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Facial Emotion Recognition Based on Deep Learning: A Review

Nabeel N. Ali*, Adnan M. Abdulazeez
IT Dept., Duhok Technical College, Duhok Polytechnic University, Duhok, Iraq

Email: *nabeel.ali@dpu.edu.krd

Abstract. Numerous domains, including safety, health, and human-machine interfaces, have garnered significant attention from researchers. Within this field, there is a notable interest in developing methodologies for interpreting and encoding facial expressions, as well as extracting pertinent features for more accurate computer-based predictions. Leveraging the remarkable advancements in deep learning, various architectural approaches are explored to enhance performance outcomes. The primary objective of this paper is to conduct an examination of recent research endeavors pertaining to automatic facial emotion recognition (FER) through the utilization of deep learning techniques. We emphasize the treatment of these contributions, elucidate the architectural frameworks employed, and outline the databases that have been utilized. Additionally, we present a comprehensive assessment of the progress achieved by comparing the methodologies proposed and the corresponding results obtained. This paper aims to provide valuable insights and guidance to researchers in this field by reviewing recent developments and suggesting avenues for further enhancements.

Keywords: Facial Emotion Recognition, Deep Learning, Emotion, Human Computer Interaction.s

1. Introduction

Facial Emotion Recognition (FER) is a crucial field in non-verbal communication, impacting areas such as surveillance and healthcare. An intriguing concept within this domain is the variety of methods available for interpreting emotions, including observing someone's facial expressions, body language, and variations in how they speak. Our facial expressions create distinct patterns corresponding to the specific emotions we are attempting to express, making facial expression a potent, innate, and widespread method for people to communicate their feelings and intentions [1]. Achieving high recognition rates in FER systems is computationally intricate and challenging when using standard methods of feature extraction and classification [2].

To attain optimal performance, many researchers are actively engaged in enhancing new FER algorithms. However, only a minority have shared their results publicly. The Extended

Cohn and Kanade (CK+) datasets, along with FER 2013, are widely recommended by scholars for evaluating their specific FER algorithms. These datasets, FER 2013 and CK+, are frequently utilized and are considered well-constructed for the field [3].

The paper proposes various machine learning and deep learning techniques for identifying facial expressions and speech in hospital patients [4], [5]. Techniques like Gabor filters, SVM, and CNN models are used, and Mel-frequency cepstral coefficients from speech data are extracted. The study shows high accuracy in predicting emotions, potentially enhancing healthcare and human-computer interaction [6]. Additionally, the research introduces a technique for identifying facial expressions by employing a selective local binary pattern (SLBP) in conjunction with convolutional neural networks. This system effectively handles variations in head posture and lighting conditions, resulting in impressive accuracy rates when tested on the KDEF and JAFFE datasets [7].

A novel framework for facial expression identification employs feature sparseness-based regularization, surpassing the performance of L2-norm regularization. Through rigorous testing on several datasets, the model has exhibited exceptional performance and a strong ability to generalize, hence confirming its efficiency in enhancing facial expression detection and emotion analysis [8]. There exist six globally recognized varieties of human expressions: normal, happy, sad, surprised, furious, and fearful. Figure 1 depicts an individual displaying these six distinct facial expressions. Emotion recognition can be challenging due to its connection with ideas, feelings, behavioral responses, and personal satisfaction or dissatisfaction.

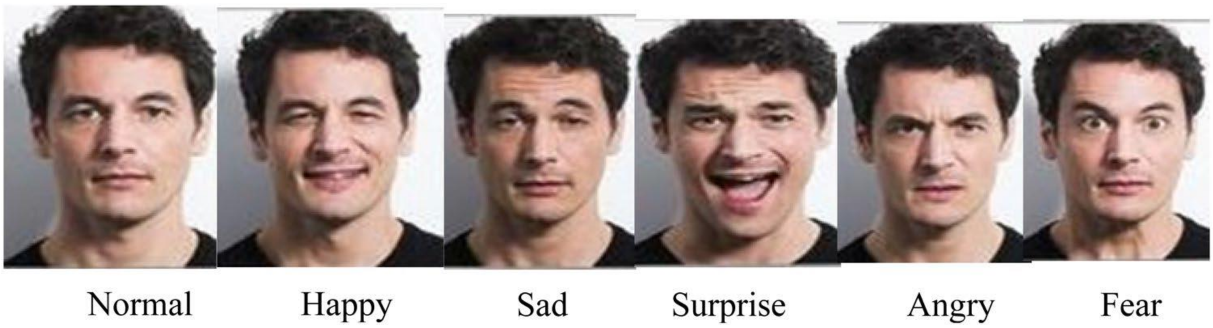

Figure 1. Variety of Emotions Captured in One Person's Face [9].

The fundamental approach for identifying emotion involves these steps: An image is inputted, followed by the detection of the face, allowing the algorithm to focus on the region of interest. Next, key features such as the eyes, nose, and mouth are extracted as these are critical in discerning emotions. The process is detailed further in the architecture description.

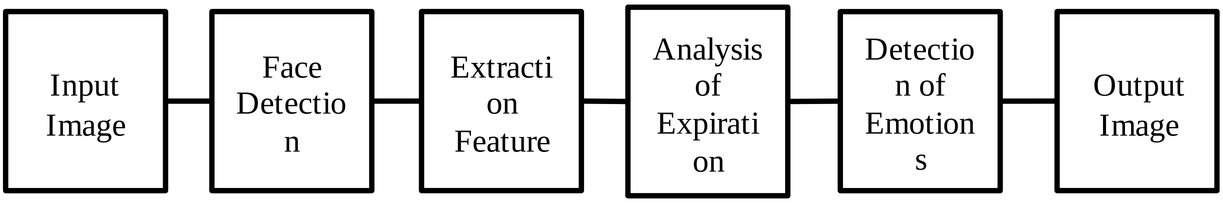

Figure 2. Steps of Facial Emotion Recognition.

This study presents a comprehensive overview of the latest developments in detecting emotions through the identification of facial expressions using several deep-learning

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frameworks. We provide a comprehensive overview of the latest findings spanning from 2019 to 2024, along with an analysis of the challenges and advancements made in the field. The organization is structured in the following manner: In part two, we provide an overview of many publicly accessible databases. In Section 3, we discuss the most up-to-date advancements in facial expression recognition (FER) utilizing deep learning techniques. Sections four and five are dedicated to a discussion and comparison of the findings, followed by a general conclusion that includes suggestions for future research.

2. Facial Emotion Recognition

Facial Emotion Recognition (FER) is a technology employed for the analysis of emotional states through the examination of facial expressions in both static images and videos [10]. It falls under the category of technologies associated with "affective computing," a multidisciplinary field focused on the computer's capacity to recognize and interpret human emotions and affective states, often leveraging Artificial Intelligence (AI) technologies [11].

Facial expressions serve as a form of non-verbal communication, offering subtle cues about human emotions. This aspect has been a subject of research interest in psychology [12] and Human-Computer Interaction (HCI) [13] for many decades. Recent advancements in biometric analysis [14], deep learning [15], [16], and pattern recognition [17], coupled with the widespread availability of cameras, have significantly propelled the development of FER technology.

Various companies, ranging from tech giants like NEC and Google to smaller firms such as AFFECTIVA and EYERIS, have invested in this technology, underscoring its growing importance. Additionally, numerous European Union research and innovation programs under Horizon 2020 have explored the potential applications of FER technology [18].

The process of FER analysis involves several stages (Figure 2). Emotion detection relies on the analysis of facial landmark positions, such as the end of the nose and eyebrows [19]. In video data, changes in these positions are also scrutinized to identify contractions in specific facial muscles. Depending on the employed algorithm, facial expressions can be classified into basic emotions (e.g., anger, disgust, fear, joy, sadness, and surprise) or compound emotions (e.g., happily sad, happily surprised, happily disgusted, sadly fearful, sadly angry, sadly surprised) [20]. Alternatively, facial expressions may be linked to physiological or mental states, such as tiredness or boredom.

FER technology can utilize various sources of images or videos, ranging from surveillance cameras to cameras positioned near advertising screens in stores, as well as data from social media, streaming services, and personal devices [21]. Additionally, FER can be integrated with biometric identification, and its accuracy can be enhanced through the analysis of diverse data sources, including voice, text, health data from sensors, and inferred blood flow patterns from images [22]. Also, facial emotion recognition utilizes neuroscience principles [23], [24] to analyze facial expressions, enhancing security [25], [26] by detecting emotional cues in individuals, potentially identifying suspicious or deceptive behavior

3. Facial Expression Recognition Databases

Deep learning algorithms excel when trained on a wide variety of examples. In the field of Facial Expression Recognition (FER), researchers have access to an array of databases. These databases vary significantly in terms of image and video quantity, size, resolution, illumination conditions, participant demographics, and the range of facial poses they encompass. Below is a table summarizing key FER databases:

Table 1. Facial Expression Datasets Overview

Ref.	Dataset Name	Emotions Captured	Description
[27]	CK+ (Extended Cohn-Kanade)	Anger, Contempt, Disgust, Fear, Happiness, Sadness, Surprise	Includes 593 video sequences of 123 participants (aged 18-50) showing transitions from neutral to peak expressions. Captured at 30 fps, resolutions are either 640x490 or 640x480 pixels.
[28]	JAFFE	6 Basic Facial Expressions	Features 10 Japanese female participants expressing 7 posed emotions across 213 images in 8-bit grayscale Tiff format, uncompressed.
[29]	FER2013	7 Emotional States (0=Angry, 1=Disgust, etc.)	Contains around 30,000 RGB photos, each 48x48 in size, showing various facial expressions.
[30]	MultiPie	Anger, Disgust, Neutral, Happy, etc.	Over 750,000 photos from 337 individuals, captured in 4 sessions with 15 viewpoints and 19 lighting conditions.
[31]	CASME II	Disgust, Happiness, Repression, etc.	Offers precise data on emotional states, action units, and frame indices. Images are 170x140 pixels, cropped.
[32]	IFEED	Range of Emotions (Angry, Sad, Happy, etc.)	Curated collection from the 'Friends' TV series, pre-processed for training deep learning models in facial expression recognition.
[33]	AffectNet	8 Specific Facial Emotions	Over 400,000 photos annotated for specific facial emotions, with additional valence and arousal data.
[34]	DEAP Database	Facial Reactions to Music Videos	Involves 32 volunteers assessing 120 music videos, with EEG and physiological signals recorded.
[35]	LFW-Gender Dataset	Various	13,233 images from the internet, identified by the Viola-Jones face detector, featuring diverse individuals.
[36]	KDEF	6 Basic Emotions	Analyzed 240 video clips, categorized by observers, and assessed for expressions and facial action units using morphing software.

Each database has unique characteristics, making them suitable for different research objectives in the realm of FER. This variety allows for comprehensive training and testing of deep learning models, ensuring robust and accurate facial expression recognition.

4. Facial Emotion Recognition Using Deep Learning

Over the past decade, there has been a significant shift in academic research from traditional facial recognition systems [37], which relied on manually crafted features, to deep learning techniques [38] due to their superior automatic feature detection capabilities [39]. This study delves into the latest advancements in Facial Expression Recognition (FER) [40], [41], particularly focusing on deep learning methods that have enhanced the precision of emotion detection [42], [43]. It also discusses the training and testing of these methods using various static and sequential databases. Below is a summarized table of recent studies in FER using deep learning, highlighting the year, dataset used, methodology, and performance:

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Table 2. Facial Expression Recognition Methodology and Performance Summary

Ref.	Year	Dataset	Methodology	Accuracy
[44]	2017	MMI, CASME II	CNN-LSTM	78.61% and 60.98%
[45]	2018	RAF-DB, AffectNet	ACNN	80.54% and 54.84%
[2]	2019	JAFFE, CK+	CNN	95.23% and 93.24%
[46]	2019	CK+	CNN	99.14%
[47]	2020	FER2013	CNN	65%
[48]	2020	CK+, Oulu-CASIA, MMI	DCBiLSTM	99.6%, 91.07%, 80.71%
[42]	2020	FER and JAFFE	CNN	70.14%, 98.65%
[49]	2020	NCUFE, CK+, FER2013	LBP	94.33%,98.68% and 75.82%
[50]	2021	FERA, Webcam.	Deep learning-based approaches	98.75%,
[51]	2021	Cohn- Kanade, JAFFE and FER2013	CNN, ELM,ViolaJones Algoritm	86.5%, 96.8%, and 62.5%
[9]	2021	JAFFE, CK+, Pie dataset, and Real-world images	DCNN, Cat Swarm optimization	96.76%, 94.59%, 95.34% and 96.28%
[52]	2021	LFW,The Extended,Yale Face B,Google Facial expression comparison	CNN	~93%
[53]	2021	FER2013	CNN	69.85%
[54]	2022	KDEF, GENKI 4K, CK+	CNN, Tree-Structured Part Model (TSPM)	82.79%, 94.33%, and 97.69%
[55]	2022	Celeb A, SCUT-FBP and SCUT-FBP5500	LDCNN	82%, 89% and 85.9%,
[56]	2022	Celeb A	CNNs	82.8%.
[57]	2023	SCUT-FBP, SCUT-FBP5500, and ME Beauty	DCNN	PC value: 0.879, 0.886 and 0.888
[58]	2023	Camera	CNN	89.60%
[59]	2023	CK +, SFEW, and FER-2013	neural networks coevolutionary (FERC)	54%
[60]	2023	CK +	Resnet50, vgg19, Inception V3	96%

The proposed Deep Convolutional Neural Networks (DNN) model classifies images into six facial emotion categories, using the Extended Cohn-Kanade (CK+) and Japanese Female Facial Expression (JAFFE) datasets. It outperforms existing emotion recognition methods, demonstrating higher accuracy thanks to the integration of FCN and residual block clouds, achieving accuracy rates of 95.23% and 93.24% [2].

A new convolutional neural network (CNN) technique has been developed to address the challenges of low recognition rates and complex algorithms in traditional facial expression detection. This method uses batch regularization and ReLU activation to prevent gradient vanishing and overfitting, leading to a substantial 99.14% increase in accuracy for facial expression image recognition on the CK+ dataset [46].

The study presents a convolutional neural network (CNN) enhanced with an attention mechanism (ACNN) (see Figure 3), specifically tailored to identify occluded facial areas while focusing on the most distinctive un-occluded regions. This ACNN framework incorporates multiple representations from specific facial areas, achieving accuracies of 80.54% and 54.84% [45].

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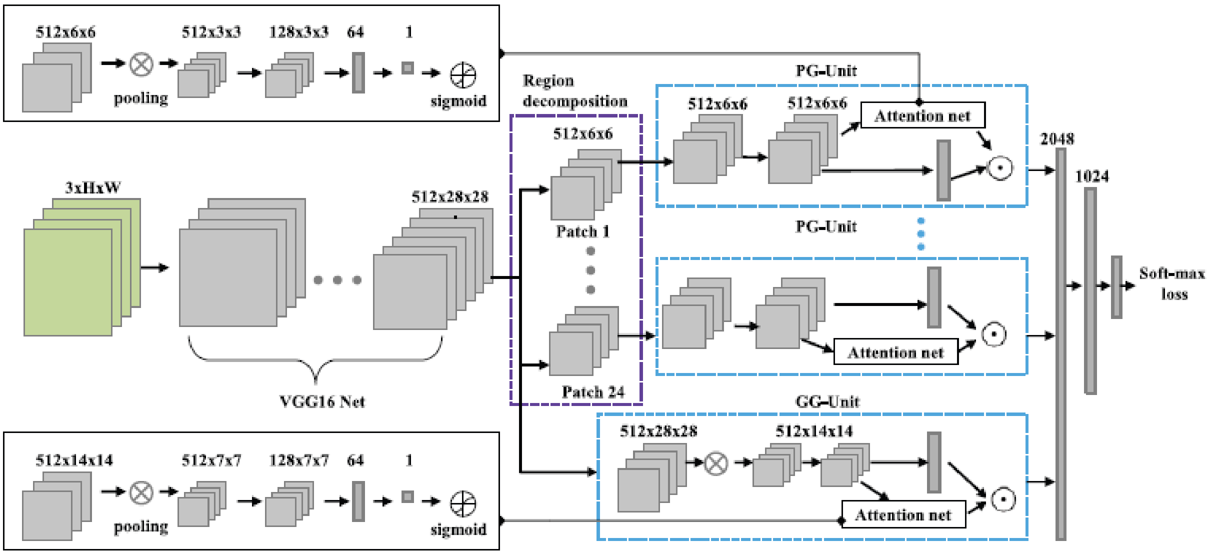

Figure 3. ACNN with VGG-16 Net for facial encoding; segmented for PG-Unit and gACNN optimization using Softmax loss [45].

The study investigates how CNN parameters like kernel size and filter count impact classification accuracy on the FER-2013 dataset. It introduces two novel CNN architectures, achieving an impressive 65% accuracy, on par with human performance. These models provide a benchmark for standardizing base models in this field [47].

The proposed method encodes facial expressions by using representative states, spatially analyzing images via a convolutional neural network, and capturing temporal aspects with long short-term memory. Experiments on the MMI (purposeful expression) and CASME II (spontaneous micro-expression) datasets yielded recognition rates of 78.61% and 60.98% [44].

A new convolutional neural network (CNN) approach has been developed to address low recognition rates and complex algorithms in traditional facial expression detection systems. This method incorporates batch regularization and ReLU activation to counteract gradient vanishing and overfitting, resulting in a significant 99.14% improvement in facial expression recognition accuracy on the CK+ dataset [48].

The study introduces an AI system using a convolutional neural network to analyze emotions from facial expressions. Tested on the FERC-2013 and JAFFE datasets, it achieved accuracies of 70.14% and 98.65% [42].

The network architecture with an attention mechanism for facial expression recognition includes feature extraction, attention, reconstruction, and classification as shown in Figure 4. Tested on a new dataset and others like JAFFE, CK+, FER2013, Oulu-CASIA, it demonstrated accuracies of 94.33%, 98.68%, and 75.82% [49].

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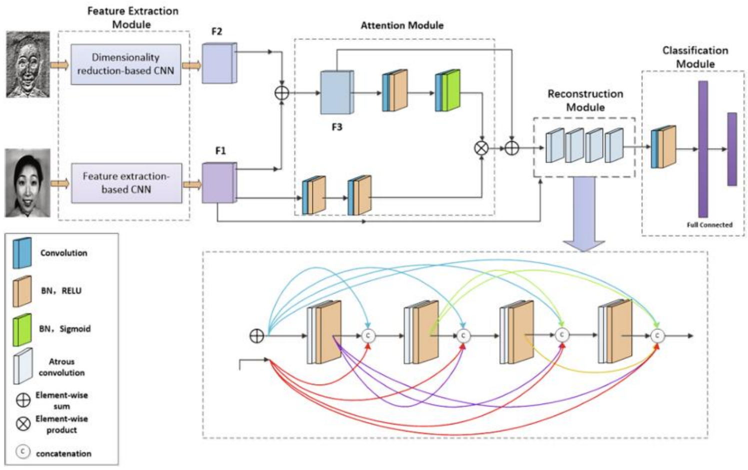

Figure 4. The Architecture of the Network [49].

The CNN-BiLSTM method, an enhanced deep learning convolutional neural network, achieved a 98.75% accuracy in simulation experiments, outperforming other algorithms by 3.15%. It also exceeded a 90% recall and recognition rate, making it valuable for emotion identification and facial expression analysis in educational settings [50].

The research employs lecture videos for face detection and feature extraction, using a Regularized Extreme Learning Machine (RELM) classifier. Tested on a new facial expression dataset and established benchmarks, it showed improved accuracy: 86.5% for CNN, 96.8% for the Learning Machine, and 62.5% for Viola-Jones [51].

The Improved Cat Swarm Optimization (ICSO) algorithm (see Figure 5), an advancement in facial expression recognition, combines a Deep Convolution Neural Network with optimized feature selection. It outperforms existing methods, achieving accuracies up to 96.76% on various datasets including JAFFE and CK+ [9].

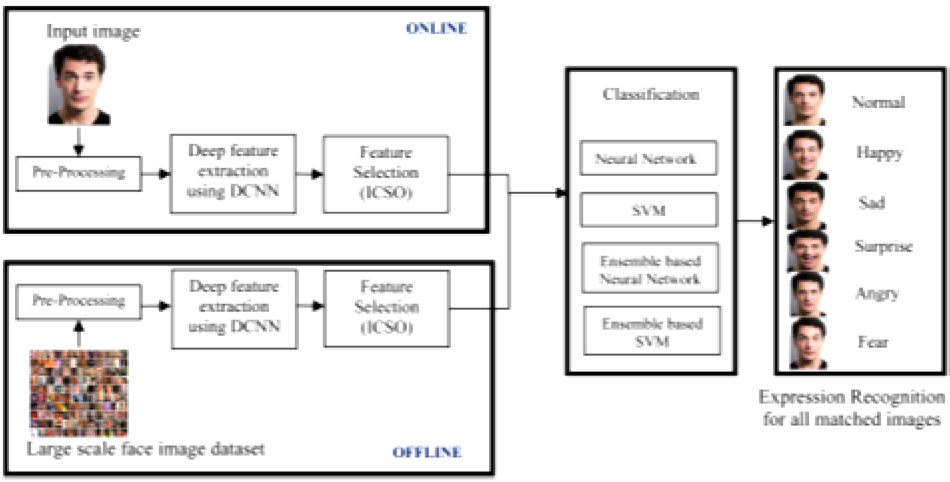

Figure 5. Overall system design [9].

The study uses a Convolutional Neural Network-based model to understand facial emotion recognition using three facial datasets: LFW, The Extended Yale Face Database B, and the Google Facial expression comparison dataset. The model calculates six discrete emotions:

happy, sad, angry, surprised, bored, and disgusted. The experiment compared to existing techniques showed a 93% accuracy rate, surpassing existing research [52].

The CNN method for facial expression recognition, using the FER2013 dataset (see Figure 6). It classifies images into seven emotions and demonstrates improved accuracy over 70 epochs, suggesting further enhancements with more epochs in future research [53].

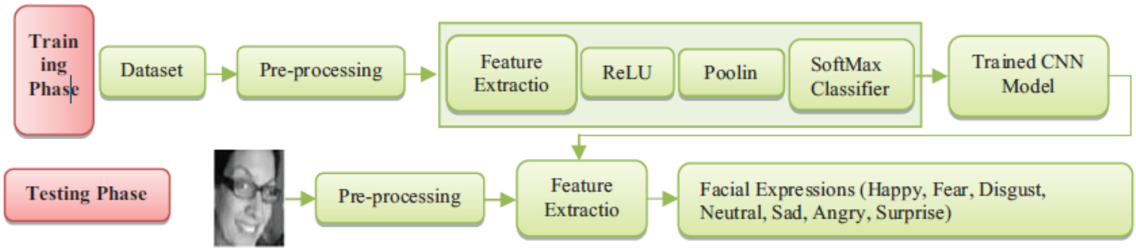

Figure 6. The General Architecture of the Proposed Study [53]

The research introduces a system for facial expression recognition, combining facial detection, a deep learning CNN, data augmentation, and fine-tuning. It outperformed existing methods with accuracies of 82.79% on KDEF, 94.33% on GENKI-4k, and 97.69% on CK+, demonstrating its superiority [54].

FIAC-Net as shown below in Figure 7, a deep convolutional neural network, assesses facial attractiveness using minimal parameters and soft labels based on SCUT-FBP and SCUT-FBP5500 datasets. It achieved accuracies of 82% on Celeb A, 85.9% on SCUT-FBP5500, and 89% on SCUT-FBP [55].

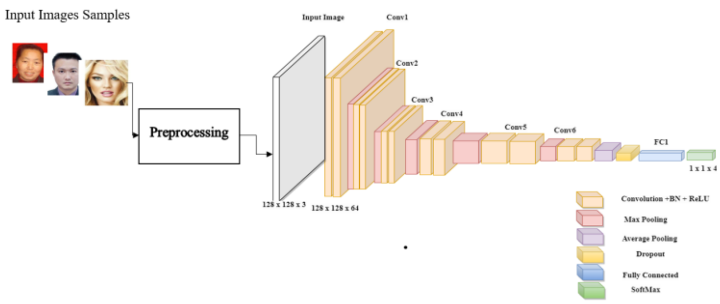

Figure 7. The architecture of FIAC-Net [55].

The study evaluates four pre-trained CNN models (AlexNet, GoogleNet, ResNet-50, VGG16) on the CelebA dataset for facial attractiveness rating. GoogleNet leads with 82.8% accuracy. Transfer learning and fine-tuning with new data enhance model performance, with the optimized GoogleNet outperforming others in aesthetic classification on Celeb A [56].

A novel ensemble-based regression model combines assessments from three distinct CNNs to predict face attractiveness scores. It highlights important facial features using Grad-CAM and performs well on datasets (SCUT-FBP, SCUT-FBP5500, ME Beauty). This method can be applied to assess pre and post-operative conditions in plastic surgery and evaluate facial image enhancements [57].

The FERC model described in [59] uses a two-part CNN network. The first part removes the image background, while the second part removes the facial features. The FERC model uses the expressional vector (EV) to identify five different types of common facial expressions.

Researchers in [60] employs pre-trained convolutional neural networks such as VGG19, Resnet50, Inception V3, and MobileNet, all trained on the ImageNet database, for facial emotion recognition.

5. Discussion and Comparison

Kim et al. [44] introduce an innovative method for Facial Expression Recognition (FER) that excels in handling a broad range of expression intensities through a novel spatio-temporal feature learning framework. This approach significantly improves the accuracy and robustness of FER systems. However, its complexity and computational demands could limit its practical application in real-time or resource-constrained environments.

In the paper [2], the authors present a new deep learning model for better facial emotion recognition, improving on their previous work with convolution layers and deep residual blocks. It shows higher accuracy on CK+ and JAFFE datasets, outperforming current methods, particularly in robust feature learning and adapting to various image sizes and intensities. However, the model's complexity may increase computational needs, and its performance in diverse or real-world settings, as well as its generalization across different demographics, is not fully examined. Despite these issues, the study is a notable progress in deep learning-based facial emotion recognition.

This paper [46] introduces an enhanced convolutional neural network (CNN) for facial expression recognition, offering higher accuracy and reduced complexity compared to traditional methods. Its integration of batch normalization, ReLU, and Dropout improves performance but may face limitations in generalizability due to dataset and expression specificity.

The paper [48] advances FER by developing a unique deep learning framework. It fuses both spatial and temporal information through a convolutional BiLSTM network, capturing detailed visual features and short-term dynamics while accumulating long-term context. This innovative approach outperforms existing methods on key datasets, demonstrating the framework's effectiveness in analyzing facial expressions. However, its focus on 2D images may require modifications for handling video data, 3D facial models, or depth images in future applications.

CNN model in [42] lies in improved feature extraction and image processing, leading to faster computation and stronger validation results. However, large datasets may still be needed for robust training, and potential overfitting remains a point of consideration.

This research [49] tackled facial expression recognition (FER) by crafting a novel network architecture. It combined the strengths of LBP features for capturing subtle details with an attention mechanism to focus on crucial aspects, leading to improved performance in recognizing nuanced expressions. However, further work is needed to adapt the method for video and 3D data, as its current focus lies on 2D images.

This study [50] innovated a CNN-BiLSTM algorithm for intelligent learning environments, excelling in both speech and visual emotion recognition with faster, more accurate results than existing methods. However, expanding the image database and real-time optimization remain key areas for future improvement.

The paper [9] innovatively integrates deep learning and optimization for facial expression recognition. It builds an automated system, featuring DCNN for feature extraction and ICSO for selection, combined with ensemble classifiers for accurate classification. This leads to improved accuracy, faster processing, and scalability, but also introduces complexity and raises questions about broader applicability and adaptability. Overall, the paper significantly advances the field while highlighting areas for further exploration.

The authors in [52] paper presents a significant advancement in the field of facial emotion recognition using deep learning. The CNN-based approach demonstrates high accuracy and real-time application potential. However, the model's dependency on specific datasets and potential computational constraints poses limitations that warrant further exploration and research.

The study in [54] presents a fascinating approach to facial expression recognition, cleverly managing the delicate dance between data augmentation and deep learning features. While it yields improved accuracy and resilience, its practical implementation necessitates careful consideration of computational costs and data quality dependencies.

The paper [57] proposes an ensemble DCNN model for facial beauty prediction, achieving improved accuracy and highlighting key features influencing attractiveness. Employing Grad-CAM for visualization and testing on diverse datasets, the model demonstrates robustness across demographics and transparency in decision-making. However, it faces computational demands and concerns about generalizability and aligning with subjective beauty standards.

The research [59] leverages convolutional neural networks (CNNs) for impressive facial emotion recognition, outperforming simpler models like decision trees or feedforward networks. By experimenting with various architectures and carefully preprocessing the FER-2013 dataset, a robust CNN model emerges, boasting enhanced accuracy and improved generalization. However, its complexity demands substantial computational resources, and potential bias in the dataset and overfitting risks warrant further consideration. While limitations exist, this study significantly advances the field of emotion recognition through its innovative use of CNNs and comprehensive model evaluation.

The study [60] leverages pre-trained CNNs for facial emotion recognition, achieving high accuracy rates with ResNet50 and efficiency with MobileNet. Comprehensive testing on CK+ database revealed strengths and weaknesses of each model. While dependent on pre-trained models and potentially limited in generalizability, this work offers valuable insights into model suitability for real-time emotion detection, especially regarding efficiency and resource limitations.

These research papers represent various advancements in the field of facial expression and emotion recognition using deep learning techniques. Each approach has its strengths and limitations, and the choice of which method to use would depend on specific application requirements and constraints. Further research and exploration are needed to address the identified limitations and improve the practicality and generalizability of these models.

6. Conclusion

In conclusion, this paper has provided a comprehensive overview of recent advancements in Facial Emotion Recognition (FER) research. We have discussed various deep learning architectures proposed by different researchers and introduced diverse datasets to enhance the precision of human emotion detection. The impressive success rates achieved by researchers indicate a promising future where machines will become increasingly proficient at interpreting human emotions, fostering more natural and effective human-machine interactions. However, it is evident that the current focus on recognizing only the six basic emotions and a neutral state in FER falls short of the complexity of emotions encountered in everyday life. This limitation underscores the necessity for future research to expand datasets and develop powerful deep learning models capable of recognizing a broader spectrum of emotions, including secondary and more nuanced emotional states. Furthermore, the evolution of emotion recognition from unimodal analysis to complex multimodal systems highlights the need for a holistic approach to understanding and interpreting human emotions. As technology continues to advance, bridging the gap between machine understanding and human emotional experience remains an exciting challenge, paving the way for more sophisticated and empathetic human-computer interactions.

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