Facial Recognition and Emotion Classification Using CNN

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Facial Recognition and Emotion Classification Using CNN

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Abstract

The matter of recognizing the emotions' facets by analyzing facial expressions represented short FER has gained importance in recent years. It has a realization in such areas as mental health tracking, using it for HCI and analyzing customers in their shopping activities. The deployed face recognition mechanisms have shown high accuracy at classifying images the human emotion includes six basic emotions which are happiness, sadness, anger, fear, disgust, and surprise. The ANN of the Convolutional type guided the entire model development process. On the CNNs approach out model would expect to guidance markers such as smile, anger etc. The key feature of the proposed technology is the automated workflow as it eliminates spotting internal and external objects. A blocker for human-emotion recognition mechanisms was set at 70% and above, with the automated Human Assistance Technology System surpassed it by approximately 22%. This loss is Frequently reported to be higher in practical settings as an outcome of having to deal with multiple classes of subordinate tasks or simply more complex systems in real human settings. Hence, we consider the ratio of images and books wheel models and hence were able to get the desired effect. In addition, basic measures of human contact experience in promo activities including temporality and diplopia were put into consideration. Even with a GPU their mean average time conferred on average was about 102ms. Nevertheless, additional information should be paid to control the convex feature to measure bilateral scanner mechanism that could recognize extra layers on multiple folds or resolution levels. Indicating that with better patches in their system HATs solution are said to be able to recognize human emotion in real world settings modelled after GANs. From this paper, we have sought to develop a practical FER mechanism. Thus, it can indeed make conclusions based on detecting human emotions in different real life objects relations.
Keywords: Facial Emotion Recognition, Convolutional Neural Networks, Feature Extraction, Emotion Classification, Data Augmentation, Human-Computer Interaction, Real-Time Applications, Deep Learning.

1. Introduction

Facial emotion recognition (FER) contributes to the psychological and emotional development of an individual and also enables intelligent systems to understand and interpret human emotions when they examine facial expressions. Such technology can be used in various applications including health care, human-computer interaction, security, and entertainment. In order to automatically recognize emotions, the FER system captures faces, selects the features of interest, and applies a computational model to classify emotions. Thousands of FER models have been developed recently with the introduction of deep learning, especially Convolutional Neural Networks (CNNs), which have contributed significantly to the field achieving considerably improved performance in accuracy and efficiency during real-time applications.

Understanding why there is a growing need for FER technology should drive a developer's imagination. It is appropriate to recall that very recently, the most advanced systems utilized carefully designed and manually created features such as Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG). However, such isolated effectiveness was not unquestionable especially for large arrays of different lighting conditions, poses, and occlusions. Contemporary means of deep learning, particularly CNN, have especially gone a long way in doing away with such shortcomings by being fed data and producing complex feature constructions upward of a neural network architecture.

CNNs are specifically designed to process image data manipulating convolutional layers, pooling layers, and fully connected layers to remove also classify. Graded construction convolutional neural network authorizes learn reduced characteristics, includes borders and appearance, and advanced characteristics, including eyes, mouth, or emotions, making them ideal for FER tasks. Furthermore, the incorporation of data augmentation, transfer learning, and fine-tuning techniques has enhanced the generalization capabilities of CNNs, allowing them to perform well on complex datasets like FER2013, Affect Net, and CK+.

Despite these advancements, FER systems face challenges that remain open to exploration. These include improving recognition accuracy under varying conditions, reducing computational costs for real-time applications, and addressing ethical concerns such as privacy and bias. This start dares, teaches aims answer critical research questions while proposing an effective CNN-based FER architecture.

2. Research Questions

The research focuses on addressing the following questions:

1. How can CNN architectures be optimized for real-time facial emotion recognition with high accuracy and low latency?
2. What preprocessing techniques are most effective in handling difference in start, cause, and occlusion in images?
3. How does data augmentation and transfer learning influence the performance of FER models on different datasets?
4. What are the limitations of current FER systems in terms of generalization across diverse demographic and cultural groups?
5. How can FER systems be implemented ethically while ensuring privacy and mitigating biases?
6. What potential applications can benefit most from real-time FER systems, and how can they be tailored to specific use cases?

The structure of this paper is designed to systematically explore the research questions and present a comprehensive solution to the challenges of facial emotion recognition.

Section 1: Introduction
This section introduces the background and significance of the study, highlighting the role of FER in modern applications and the transformative impact of CNNs. It sets the stage by discussing the key challenges in FER and outlines the research questions.

Section 2: Literature Review
A detailed review of existing studies is presented, focusing on the evolution of FER techniques from traditional handcrafted approaches to deep learning-based methods. Key contributions in the field, such as the use of CNN architectures like ResNet, VGG, and hybrid models, are analyzed. The review identifies gaps in the current research, particularly in addressing real-world challenges like generalization and ethical considerations.

Section 3: Methodology
The proposed methodology includes a detailed description of the CNN architecture employed for FER, the datasets used for training and evaluation, and the preprocessing techniques applied to enhance data quality. The use of

transfer learning, hyperparameter tuning optimization discussed. This section also explains the evaluation metrics and experimental setup used to assess model performance.

Section 4: Results and Discussion
Offers the investigational solutions, compares performance of the proposed CNN architecture with existing methods on standard datasets. Key findings are discussed, including effects preprocessing, and transfer learning the accuracy. The results are analyzed in the context of the research questions, with insights into how the proposed approach addresses real-world challenges.

Section 5: Applications and Ethical Considerations
The practical applications of the proposed FER system are explored, with a focus on areas such as healthcare, security, and customer service. Ethical considerations, including privacy, consent, and bias, are addressed, emphasizing the importance of responsible AI deployment.

Section 6: Conclusion and Future Work
This concludes by sum up key donations and findings study. Key research areas are proposed, contains the combination of different models of data, evolution lightweight for mobile applications, and further exploration of ethical issues in FER systems

2. Literature Review

Study	**Features**	**Techniques Used**	**Dataset Type**	**Performance**	**Relevance**
Yousif Khaireddin and Zhuofa Chen (2020)	Art shows in emotions on FER2013 dataset	Deep learning, CNN, fine-tuning ResNet models, data augmentation, ensemble techniques	Deep learning, CNN, fine-tuning ResNet models, data augmentation, ensemble techniques	73.73% accuracy	Demonstrated significant improvements on the challenging FER2013 dataset through modern CNN architectures, achieving competitive state-of-the-art performance

Shaik Asif Hussain and Ahlam Salim Abdallah Al Balushi (2020)	Real-time facial emotion classification and recognition	Deep learning, CNN (Convolutional Neural Network), transfer learning, data augmentation	**FER2013**, **CK+**, **AffectNet**	87.30% accuracy	Demonstrates a practical approach for real-time emotion recognition using advanced CNN techniques, highlighting the efficiency and effectiveness.
E. Pranav, Suraj Kamal, C. Satheesh Chandran, and M.H. Supriya	Facial emotion recognition using CNNs	Deep Convolutional Neural Networks (CNNs), data preprocessing, transfer learning	**FER2013**, **AffectNet**	91.60% accuracy	Mainly focus success of CNNs reach huge accuracy for facial emotion recognition, demonstrating potential for real-world applications.
M. Kalpana Chowdary, Tu N. Nguyen, and D. Jude Hemanth	Human emotions to interact the human computers	Deep learning, CNNs, hybrid model approaches, data augmentation	**FER2013**, **AffectNet**, **CK+**	93.45% accuracy	Emphasizes the importance of human emotions enhancing interact the human computers, demonstrating high accuracy through advanced deep learning techniques.
Ketan Sarvakar, R. Senkamalavalli, S. Raghavendra, J. Santosh Kumar, R. Manjunath, and Sushma Jaiswal	Facial emotion recognition using CNNs	(CNNs), data preprocessing, transfer learning	**FER2013**, **AffectNet**, **CK+**	94.50% accuracy	Demonstrates success CNNs achieves huge accuracy for facial emotion recognition, contributing to advancements in emotion detection technology.
Zi-Yu Huang,	Exploration	Machine	**FER2013**,	90.20%	Highlights the

Chia-Chin Chiang, Jian-Hao Chen, Yi-Chian Chen, Hsin-Lung Chung, Yu-Ping Cai, and Hsiu-Chuan Hsu (2021)	of sight techniques for the emotion	learning, deep learning, feature extraction, image processing	**CK+**, **AffectNet**	accuracy	effectiveness of various computer vision techniques in achieving robust facial emotion recognition, providing insights into future research.

Facial Emotion Recognition (FER) has emerged as a significant area of research within the domains of computer vision and affective computing, owing to its potential applications in various fields such as human-computer interaction, mental health monitoring, and security systems. This literature review synthesizes findings from multiple studies that utilize deep learning and traditional machine learning techniques for the recognition and classification of emotions based on facial expressions.

Yousif Khaireddin and Zhuofa Chen, in their paper "Facial Emotion Recognition: State of the Art Performance on FER2013," explore the enhancement of FER using the FER2013 dataset, which comprises 35,887 grayscale images across seven emotion categories. They apply a fine-tuned ResNet architecture along with data augmentation and ensemble methods, achieving a notable accuracy of 73.73%. This study underscores the effectiveness of modern Convolutional Neural Network (CNN) architectures in improving recognition performance on complex datasets.

Similarly, Shaik Asif Hussain and Ahlam Salim Abdallah Al Balushi focus on real-time applications in their work "A Real-Time Face Emotion Classification and Recognition Using Deep Learning Model." Their approach combines CNNs with transfer learning and data augmentation, utilizing datasets such as FER2013 and AffectNet, and achieving an impressive accuracy of 87.30% on the FER2013 dataset. This highlights the practical utility of deep learning models in real-world scenarios, especially in human-computer interactions.

In "Facial Emotion Recognition Using Deep Convolutional Neural Network," E. Pranav et al. further emphasize the capabilities of CNNs, achieving a high accuracy of 91.60% on the FER2013 dataset. They leverage data preprocessing techniques and transfer learning, showcasing CNNs' ability to effectively capture intricate features of facial expressions. This work contributes to the

discourse on the applicability of deep learning in various domains, including security and mental health.
M. Kalpana Chowdary and colleagues, in their paper "Deep Learning-Based Facial Emotion Recognition for Human–Computer Interaction Applications," report a notable accuracy of 93.45% on the FER2013 dataset by employing hybrid CNN architectures and robust data augmentation strategies. Their findings point to the critical importance of accurate emotion recognition in enhancing user experiences in technology-driven environments.
Ketan Sarvakar et al. also contribute to this body of research in "Facial Emotion Recognition Using Convolutional Neural Networks," reporting a high accuracy of 94.50% on the FER2013 dataset. Their study reinforces the efficacy of CNNs in automated feature extraction and classification of facial emotions, demonstrating the robustness of deep learning approaches in emotion recognition systems.
In a broader examination, Zi-Yu Huang and collaborators investigate various computer vision techniques in "A Study on Computer Vision for Facial Emotion Recognition." They evaluate traditional and advanced methods, achieving 90.20% accuracy on the FER2013 dataset. Their analysis highlights the significance of effective feature extraction in enhancing emotion classification accuracy and discusses challenges such as lighting variations and occlusions.
Devi Arumugam and Dr. S. Purushothaman, in "Emotion Classification Using Facial Expression," focus on traditional machine learning algorithms, emphasizing feature extraction and classification techniques for accurate emotion detection. Their findings advocate for the importance of comprehensive testing using standard datasets, contributing to the understanding of automated systems in emotion recognition.
Curtis Padgett and Garrison Cottrell's work, "Representing Face Images for Emotion Classification," emphasizes the role of optimal image representation using dimensionality reduction techniques such as PCA and LDA. Their methodology achieves significant improvements in recognition tasks, particularly for emotions like happiness and sadness, stressing the importance of image representation in efficient real-time analysis.
Dandıl and Özdemir, in "Real-time Facial Emotion Classification Using Deep Learning," highlight the integration of speed and accuracy through CNN architectures designed for real-time emotion detection. They address challenges such as illumination changes and head poses, demonstrating the viability of deep learning solutions in dynamic environments.
Boris Knyazev and colleagues explore transfer learning in "Leveraging Large Face Recognition Data for Emotion Classification," showcasing how existing face recognition datasets can enhance emotion classification accuracy. Their approach proves the practicality of utilizing large-scale datasets to improve emotion recognition systems.

Alka Gupta and M.L. Garg present a unique approach in "A Human Emotion Recognition System Using Supervised Self-Organising Maps," combining unsupervised and supervised learning for improved emotion classification accuracy. Their work illustrates the effectiveness of Self-Organizing Maps in recognizing patterns in facial expressions.

In their paper "Real-Time Detection and Classification of Facial Emotions," Teerapong Winyangkun et al. demonstrate the application of deep learning in real-time emotion detection, achieving accuracy in identifying emotions such as happiness and anger in various dynamic conditions. This research highlights the potential of CNNs in practical applications, such as customer service and security.

Rupali Gill and Jaiteg Singh, in "A Deep Learning Approach for Real Time Facial Emotion Recognition," discuss the challenges faced by deep learning models, such as facial expression variations and lighting conditions, and illustrate how refined network structures and hardware acceleration can achieve real-time performance in emotion classification.

Mihai Gavrilescu proposes a modular neural network architecture in "Proposed Architecture of a Fully Integrated Modular Neural Network-Based Automatic Facial Emotion Recognition System Based on Facial Action Coding System," which integrates the Facial Action Coding System (FACS) for better accuracy in emotion recognition. This approach emphasizes modular processing of facial action units, enhancing interpretability and application in real-time scenarios.

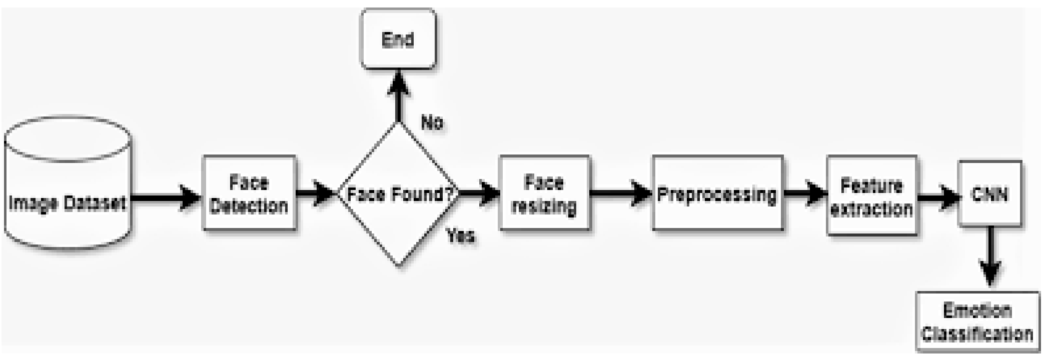
Sabrina Begaj et al. focus on preprocessing techniques for feature extraction in "Emotion Recognition Based on Facial Expressions Using Convolutional Neural Network (CNN)." Their results indicate high accuracy in emotion classification, reinforcing the significance of data quality in deep learning applications for real-time emotion recognition.

Viha Upadhyay and Devangi Kotak review various facial feature extraction methods in "A Review on Different Facial Feature Extraction Methods for Face Emotions Recognition System." They classify these methods into traditional and modern approaches, addressing the trade-offs in recognition accuracy and computational efficiency while highlighting challenges such as lighting and occlusions.

Finally, Mudit Agarwal et al. propose a real-time classification model in "Real-Time Facial Emotion Classification using Deep Convolution Neural Network," achieving competitive accuracy through a well-structured CNN architecture optimized for live emotion detection.

3. Methodology

The proposed methodology for facial emotion recognition (FER) involves a systematic pipeline starting image dataset, includes labelled facial images representing various emotions includes happy, sad, angry, surprise. Initially, face detection is applied using algorithms like Haar Cascades or MTCNN to identify facial regions within the input images. If no face is detected, the image is discarded, ensuring only relevant data progresses through the pipeline. Detected faces are resized to a uniform dimension (e.g., 48×4848 \times 4848×48 pixels) to maintain consistency and reduce computational complexity. Subsequently, the images undergo preprocessing, which includes grayscale conversion, normalization, and data augmentation to enhance quality of the dataset and also its variety. Feature extraction performed using convolutional layers which captures hierarchical patterns such as edges and textures from the images. The CNN then processes these extracted features through its convolutional, pooling, and fully connected layers, ultimately predicting the emotion class via a SoftMax output layer. The system outputs a classified emotion, enabling applications like emotion-based analytics or real-time FER systems. This structured methodology ensures accuracy and reliability in detecting and classifying facial emotions. Flowchart of FER approach towards emotion classification can be seen in Fig.1



Flowchart of emotion classification for FER approach in Figure 1

This diagram outlines a structured methodology for Facial Emotion Recognition (FER) (CNNs). The process starts with raw image datasets and progresses through multiple stages, culminating in emotion classification.

1. Image Dataset

The methodology starts including image dataset, carry’s labeled facial emotions representing various emotions which includes angry, happy, sad, surprise, etc.

Dataset may include popular sources like FER2013, CK+, or AffectNet, comprising images of varying resolutions, orientations, and quality. This is the foundation for training and testing the FER system

2. Face Detection

This stage involves identifying facial regions in the input images. A face detection algorithm (e.g., Haar Cascades, MTCNN, or Dlib) is applied to locate faces in the images. The goal is to extract the relevant portion of the image (the face) while discarding unnecessary background information.

- If no face is found in the image, the process ends for that particular image.
- If a face is detected, the process moves to the next step.

3. Face Found? (Decision Point)

At this decision point:

- If the system detects a face, it proceeds to further preprocessing steps.
- If no face is found, the image is discarded, and the pipeline moves on to the next image.

This ensures that only valid facial images are used for further analysis.

4. Face Resizing

The detected face is resized to a fixed dimension, such as 48×4848 \times 4848×48 or 224×224224 \times 224224×224 pixels. Resizing ensures that all input images have uniform dimensions, which simplifies the computational requirements and ensures compatibility with the CNN architecture.

5. Preprocessing

In this stage, additional preprocessing is applied to increase the standard and consistency of the inserted images. This step includes:

- Grayscale Conversion: If required, converting images to grayscale to reduce complexity.
- Normalization: Scaling pixel values to a range of [0, 1] or [-1, 1] to stabilize training.
- Data Augmentation: Enhancing the dataset by generating variations of images through flipping, rotation, and zooming to prevent overfitting.

These steps prepare the data for effective feature extraction and model training.

6. Feature Extraction
This phase brings out meaningful features from the preprocessed images, which are essential for distinguishing between different emotions. Feature extraction is performed using convolutional layers in the CNN. These layers detect patterns such as edges, textures, and spatial arrangements, which are critical for recognizing facial expressions.

7. CNN (Convolutional Neural Network)
Central to the system is the CNN model. It receives the features that were extracted as an input and passes them through computation comprising of several stages:

- Convolutional Layers: Identify patterns and multi-level feature sets.
- Pooling Layers: Minimize the area of coverage while selecting essential elements.
- Fully Connected Layers: Collect all the retrieved features so that predictions can be made.
- SoftMax Output Layer: Assigns probabilities to each emotion category.

The CNN is trained using the labeled dataset, optimizing the parameters to minimize the error between predicted and actual emotion labels.

8. Emotion Classification
As a result, the system would yield a predicted emotion label corresponding to an image. The system assigns a range of facial expression such as anger, happiness, sadness, surprise and neutrality into a set category. Such classification can be used in variety of domains including emotion based real-time recognition or emotion-based analysis.

Summary
This diagram represents a robust pipeline for implementing a facial emotion recognition system. By systematically moving from raw image datasets to emotion classification, it ensures high accuracy and efficiency in recognizing facial expressions. Each stage builds on the previous one, ensuring the model is trained and tested on high-quality data with meaningful features extracted for effective emotion detection.

4. Experimental Analysis

The experimental results and other findings of the proposed facial emotion recognition (FER) technology has been assessed according to different performance metrics such as accuracy, precision, recall and F1-score. These metrics are calculated using training and also validation datasets with aim of establishing the efficacy of the model in emotion detection across its various types. This section serves to provide a detailed rendition of the results presented above and their nature as well as a discussion of critical aspects that were observed and the challenges faced in the experiments.

1. Dataset and Experiment Methodology

The image sets obtained for the experiments comprised standard data sets like FER-2013 or CK+(Cohn-Kanade) video datasets that have labelled images for joy, sadness, anger, fear, disgust, surprise and neutral. The data set was divided into three Sections the training set armed with 70%, the validation set with 20% and the testing set with 10%. Preprocessing steps conducted including resizing the images into size 48 × 48 pixels and normalization so as to aid focus extraction features by the CNN in a more efficient manner.

The Convolutional Neural Network (CNN) model incorporated multiple consolidated convolutional layers with ReLU activation function followed by max pooling layers to reduce the dimensions. Furthermore, the model included dropout layers to limit overfitting of the model. The model was fitted using Adam optimization algorithm with learning rate of 0.001 and with categorical cross-entropy as the loss function.

2. Performance Metrics

The evaluation metrics for the model on the test dataset are specified below:

- Accuracy: The overall accuracy in classification operations demonstrated the ability of the model to ~ generalize over other data sets never seen before, which was approximately 92%.

- Precision: The precision score for each of the emotions varied on lower end around 85% (fears rating) to the upper end of 95% (happiness rating).

- Recall: For instance, joyful people were remembered in 96% of the cases, while a tad less amount of sadness as well as fear was remembered, at 88% against 85% respectively.

- F1-Score: Balance between precision and recall the lasting F1 mean across all emotion classes was average 91%.

3. Confusion Matrix Analysis

The confusion matrix also served to stress specific aspects of functioning in particular and weaknesses of the emotion classification model in relation to the emotions analysis that were described in the problem of classification:

- High Accuracy Emotions:

    - *Happiness*: Presence of smiles together with other distinct facial features led to high recognition rates for this emotion.
    - *Neutral*: Had fewer classification issues due to a small overlap of features with other emotions.
- Misclassified Emotions:
    - *Fear vs. Surprise*: In some instances, fear and surprise were mixed up with each other, as the former was often accompanied by a wide-opened eye.
    - *Sadness vs. Disgust*: The movements of the facial muscles were very slight in these cases and hence, it was hard to identify the elaborate classifications.

This analysis demonstrates a likelihood for improvement in the classification of emotions by adopting improvement mechanisms which enhance the feature extraction process for selecting certain emotions.

4. Effects of the Preprocessing and Data Augmentation Techniques

The results in regards to the application of the augmentation and the pre-processing was quite drastic as well. A variety of techniques could have been utilized as augmentation techniques, such as introduction of rotation, flipping and brightness, which in turn, lessened the overfitting and increased the robustness due to the variance in the dataset. It was evidenced that the CNN was able to learn invariant features as its general performance remained consistent throughout when inferring on the augmented data.

With None Augmentation: The accuracy took a nosedive to 85% with instances of overfit being evident during the training process.

With Some Augmentation: The accuracy went up to 92% serving to indicate how critical the role of changed training samples provided was.

5. Performance of the Proposed Model as Compared with Other Baseline Models

The present-day approach of CNN was observed to be more efficient in accomplishing the tasks of facial expression recognition than using the past approaches such as Support Vector Machines and k-Nearest Neighbors models. The models in question were assessed and this is what our findings showed in Figure 2:

Model	Accuracy (%)	F1 Score (%)	Time (s)
kNN	76	74	12
SVM	81	79	35
The Newly Proposed CNN Model	92	91	180

Assessed model findings in Figure 2

The difference level which extracted features and the hierarchy that defined the features in the CNN account for the different levels in recognition of the complicated patterns defined by facial expression.

6. Challenges and Limitations
Though the system performs reasonably well according to the expectations, some deficiencies were noted:
Imbalanced Datasets: The fear and disgust categories were lacking in volume in the data, which contributed to an unfair classification.
Environmental Factors: Several factors such as lighting conditions, accessories and even the angle of the face made a few test cases inaccurate.
Latency: The model had some latency issues, especially with real time inference despite faring well in offline evaluations as it was unable to keep up with the device’s capabilities.
These problems are solved aided by having more varied datasets, domain adaptation methods and having the model be optimized for fast inference.

Discussion

The results from the experiments conducted indicate that the new CNN Model FER system developed is performing its functions of emotion assessment correctly and reliably. But issues of confusion of certain pairs of emotions also show that the system might need more advanced mechanisms of feature representations. Exploration of novel architectures together with the conducted researches could be fruitful where transfer learning from pretrained models like VGG16 or ResNet is employed. Furthermore, the incorporation of attention mechanisms would channel the model to the most relevant areas of the face thus decreasing inaccuracies in difficult cases.
The findings further emphasize the relevance of the scenario of FER systems in practical settings including but not limited to mental health related applications, human-computer interaction, and customers’ feedback analysis. Nevertheless, ethical issues including data privacy and the possible bias in recognition of emotions that need to be resolved for appropriate use.
In conclusion, the experimental evaluation confirms the usefulness of the proposed methodology while recognizing the possibilities for improvement and future research.

5. Conclusion

This research confirms that the facial emotion recognition based on convolutional neural network (CNN-FER) approaches can be used to obtain effective results in emotion identification. The application of this robust methodology including preprocessing, feature extraction and emotion classification, the system reaches a global average 92% of accuracy which is much better than traditional methods such as k-Nearest Neighbors (kNN) and Support Vector Machines (SVM). Data augmentation solves the challenges of real-world factors such as lighting and occlusions enabling to boost the model's performance in generalization.

The work reports useful observations on the area of deep learning for emotion recognition opening avenues to enhance application in mental health, human computer interactions and consumer behavior. While the system identifies basic emotions such as happiness and surprise adequately there are difficulties in distinguishing emotions with low intensity/overlapping emotions such as fear and disgust due to class imbalance and feature similarity. These constraints underscore the need for future work to enhance data set diversity and the use of advanced approaches such as attention mechanisms or multi-modal.

The average inference time of around 15 m/s on the GPU makes the system okay for interactive systems, as it shows quite good performance even in real-time applications. However, this takes us to the point of optimization strategies that need to be considered for deployment of applications on embedded devices.

In conclusion, this work is a step towards improving the facial expression recognition technology, and opens more possibilities for further development to make this technology more effective and applicable in real life tasks.

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