

Facial emotion analysis through image processing using AI

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Abstract

Recognizing emotions from facial expressions is challenging due to the variability of human emotion patterns, which are influenced by factors such as facial orientation, lighting conditions, and subtle differences in complex emotions. To address these complexities and enhance real-world applications, I focus on the use of a deep convolutional neural network (VGG19) trained with precision. We will use the CK+ and FER2013 datasets. We aim to enhance interactions and expand the scope of its application.

1- Interdiction

Within the scope of human-computer interaction, a highly important technology has emerged: facial emotion recognition, which is used in many fields. Accurate interpretation of human facial emotions is essential in our era and is the foundation for many applications, including psychological assessments, digital marketing, virtual reality experiences, and the improved use of AI. However, despite recent advances, reliable interpretation of facial emotions remains challenging due to the subtleties of expression variations influenced by environmental factors such as facial orientation, lighting conditions, and subtle differences in individual emotions. We can overcome these challenges by using AI to improve accuracy, which will be satisfactory to both users and systems.

Regarding current research, much of it is focused on approaches to dealing with unpredictable real-world facial conditions. These systems often face difficulties in consistency and generalization, especially when facing a changing environment. Therefore, in this project, we will try to address the challenges by using the powerful VGG19 convolutional neural network model based on the ready-made facial expression data CK+ & FER2013.

2-Problem Definition:

the problem addressed by this project is the accurate classification of human emotions from facial expression images. This is formally known as a multi-class classification problem, encompassing emotions such as happiness, sadness, anger, disgust, surprise, neutrality, and fear. This approach leverages the deep convolutional neural network known as VGG19, which is pre-trained for image-based emotions using publicly available and pre-curated datasets such as CK+ and FER2013. These datasets are subject to constraints on consistent image quality and lighting conditions. These constraints include the availability of computational resources and the reliance on annotated dataset, which is problematic due to the large size and diversity of the data. The primary goal is to understand facial emotions and the accuracy of their classification. Through VGG19, we will explore the performance and efficiency of the network, which may facilitate practical applications such as psychological assessment, automation, and user experience design for interested users.

3-Motivations

The ability to accurately recognize human emotions through facial expressions has implications that benefit various fields. In practical applications, emotion recognition systems improve user experiences in customer service, marketing strategies, health diagnosis, and ultimately human-computer interaction. Academically, research is pivotal in the field of computer vision and AI. This provides an opportunity to address limitations and develop new methodologies for

accurately detecting emotions. This interest is growing due to its potential to revolutionize gaming, virtual reality, and psychographics. However, significant gaps remain, particularly in generalization across diverse datasets and dealing with a changing environment. Personal motivations stem from the ability of technologies to significantly enhance daily interactions between humans and intelligent systems, thus improving overall quality of life.

4-Objectives

In this project, we aim to implement systems and examine their effectiveness in recognizing facial emotion outputs using the VGG19 deep convolutional neural network model through transfer learning. We aim to reliably classify emotions across seven different categories using the VGG19 model. The objectives also include evaluating the model's performance across multiple reference datasets (CK+ & FER2013), applying appropriate preprocessing and amplification techniques, and analyzing the system's ability to adapt to noise and variance in image data. We also aim to compare the performance of the proposed models with current state-of-the-art technologies to highlight strengths and potential areas for improvement.

In the long term, the project aims to understand the mechanism of facial emotion recognition using artificial intelligence. This will have implications for healthcare, education, security, and interactive AI platforms, enhancing user experience

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5-Literature Review

Paper 1 :Efficient Facial Emotion Recognition Using An Optimized Deep:

Facial expressions are a fundamental component of nonverbal communication and formed the basis of early studies in emotion recognition, as Ekman and Friesen (1978) argued. Mehrabian (2017) pointed out that current methods struggle to cope with varying environmental conditions, including lighting and posture, making them less effective in practical applications. Advances in deep learning,

particularly convolutional neural networks (CNNs), have improved the performance of facial expressions, as Sajjad et al. (2023) noted. These challenges include high computational costs and the need for large-scale training data (Hi et al. 2021). This study aims to address these issues by integrating optimization techniques inspired by feature selection and quantum mechanics to improve model efficiency.

Paper 2:EmoCNN Unleashing human emotions with customized CNN using different optimizers:

According to Smith et al. (2019), traditional machine learning methods such as KNN and SVM achieved emotion recognition accuracy of up to 84%. However, Gautam (2020) demonstrated that deep learning models, especially CNNs, significantly outperform traditional techniques based on spatial features. EmoCNN (2024) demonstrated that using the Adam optimizer improved classification accuracy to 89%. However, others, such as Johnson (2023), point out that real-time emotion detection remains a challenging task due to computational limitations. This study aims to enhance the efficiency of CNN architectures by leveraging transfer learning to improve generalization.

Paper 3:Emotion categorization fromfacial expressions A review of datasets

Shihon et al. (2025) highlight that deep learning, such as CNN, achieves high accuracy in recognizing facial emotions, but is sensitive to subtle changes in the image, and this sensitivity reduces its reliability.

Zhang et al. (2023) argue that datasets such as AffecNet and RAF-DB improve generalization, but exhibit some biases that affect real-world performance.

Hong et al. (2024) point out that models such as ResNet-50 and VGG-16 focus on the pixel-level features rather than the actual emotional context, making them vulnerable to adversarial attacks.

To address these challenges, this study explores a hybrid approach of combining deep learning with facial action coding (FACO) systems to improve robustness and accuracy in real-world applications.

Paper 4: Sentiment Analysis from Images using VGG19 based Transfer Learning Approach

According to Mina et al. (2022), using transfer learning with the VGG-19 model significantly improved image sentiment analysis, achieving up to 99% accuracy on the CK+ dataset. Hua et al. (2019) argue that real-time sentiment detection remains a challenging challenge due to computational and dataset limitations, especially when using models like ResNet101. This study aims to address and find solutions to this problem by improving and developing the VGG-19 architecture and tuning hyperparameters to improve classification performance and reduce model complexity.

Paper 5: Sentiment analysis on images using different transfer learning

According to Hua et al. (2019), deep learning models used for CNNs have significantly improved the accuracy of facial expression recognition, providing stability. However, Bogda et al. (2022) argue that traditional feature extraction techniques, such as Gabor filters with genetic algorithms, can further improve classification performance, achieving accuracies exceeding 90% on the CK+ dataset. Falah et al. (2021) showed that fine-tuning deep learning models such as Alexnet-DCNN can achieve high recognition accuracy exceeding 92% on CK+. Hong et al. (2019) assert that dataset-dependent variation significantly impacts performance, as some models trained on a regular dataset tend to outperform on a more diverse dataset. This study aims to address these challenges by conducting a comparative analysis of transfer learning (TL) models across multiple datasets, optimizing their hyperparameters, and disaggregating their effectiveness on real-time emotion classification tasks.

In conclusion, the VGG19 model remains one of the most effective and widely used models for facial emotion recognition. This literature review highlights the necessary improvements for practical application.

6- Proposed Methodology

The proposed approach relies on deep learning techniques, specifically the VGG19 convolutional neural network model, known for its powerful precursor in

image classification, and its deep architecture based on transfer learning. This model is trained on the ImageNet dataset, using facial expression datasets to effectively classify emotions. This model also has the ability to extract deep spatial features in images, which is important for capturing subtle facial cues associated with different emotions.

Preprocessing includes face detection, cropping, grayscale transformation, normalization, and data augmentation techniques such as scaling, rotation, and flipping. These steps are essential for ensuring consistent input quality and enhancing the model's generalization ability. Features are extracted internally by the model's convolutional layers, eliminating the need for manual feature engineering.

The project will be implemented using the PyTorch framework, thanks to its flexibility, dynamic drawing, and robust GPU acceleration support. Supporting libraries include NumPy and Pandas for data processing, OpenCV for preprocessing, and Matplotlib for visualization. Training parameters, such as learning rate, batch size, and number of stages, will be optimized through experimentation, along with performance, precision, recall, and the F1 score of the confusion matrix.

This methodology is designed to produce an efficient, scalable, and effective emotion recognition system that performs well under a variety of conditions and provides a foundation for future improvements or deployment in real-time applications.

7- Dataset Description

The study uses two widely known open-source facial emotion recognition datasets: CK+ and FER2013. These datasets were chosen due to their availability and importance in analyzing facial expressions and representing diverse emotional states.

FER2013 is a large dataset containing 35,887 grayscale images (approximately 15 GB) with dimensions of 48 x 48 pixels. It classifies the seven emotions: disgust,

anger, fear, happiness, sadness, surprise, and neutral. It is derived from the Kaggle platform and is used repeatedly to train deep learning models and measure their performance.



CK+ consists of 920 images (approximately 18 GB) that are displayed in a sequential frame and labeled with one of the seven standard emotions. All images undergo preprocessing steps such as resizing, grayscale normalization, histogram equalization, and augmentation techniques (flip, rotate, and scale) to improve model generalization and reduce overfitting.



Challenges facing these two groups include class imbalances (e.g., a lack of samples expressing fear and disgust), discrepancies in resolution between images,

and inconsistent facial orientations. These challenges are mitigated through data augmentation, balanced sampling strategies, and processing pipelines.

8- Project implementation timeline

Week	Description
1	Download CK+ database preparation (Apex peak image extraction)
2	Literature study on the application of VGG19 to CK+
3	Setting up the working environment (Keras/TensorFlow) and image processing
4-5	Building and training the model using VGG19 Transfer Learning
6	Applying Augmentation and Performance Improvement Techniques
7	Model evaluation using performance metrics and confusion matrix analysis
8	Writing the final report and presenting the presentation

9- Data source:

<https://www.kaggle.com/datasets/msambare/fer2013>

<https://zenodo.org/records/11221351>

10- References

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