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Facial expression recognition using pattern analysis and machine intelligence

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Abstract
Human interaction relies heavily on communication, where emotions play a vital role in enhancing understanding. Non-verbal cues such as gestures, facial expressions, and dynamic behaviors often convey more information than spoken words. Facial expressions, in particular, are key indicators of genuine emotions and are essential in interpersonal relationships. In the context of Human-Computer Interaction (HCI), communication can be categorized into verbal and non-verbal forms, with facial expressions serving as a primary mode of non-verbal communication. Recognizing these expressions is increasingly important across various fields for improving decision-making, interaction, and emotional perception.

Keywords: Facial expression recognition, pattern analysis, machine intelligence, dynamic behaviors

1. Introduction

Facial Emotion Recognition (FER) analyzes human emotions using images or video by detecting facial movements, such as those of the eyebrows, mouth, and chin. As facial expressions reflect emotional states, FER is widely used in emotion classification for applications like biometric security, smart HCI, and mental health monitoring. This study aims to recognize emotions in real-time using efficient algorithms to ensure system robustness. Commonly used methods include CNN, SVM, and MLP. A literature review highlights past techniques, challenges, and solutions. For instance, compared various learning models and showed that their proposed MHL-based method outperformed others when tested on webcam datasets. Proposed an intelligent emotion recognition system to recognize the emotions from the input datasets. A stationary wavelet entropy technique and a single hidden layer feed-forward neural network extract the features and classify the input image. They are head-pose, image background, light intensity, and occlusion. Those mentioned above are some of the parameters seen to be challenging. The analysis results indicate that the proposed model recognizes facial emotions with more than 96.80% accuracy. FER is a non-verbal way of understanding communication. From this human emotional state, primary feature extraction and classification methods are analyzed. discussed the difficulties in achieving high accuracy in FER in uncontrolled environments. Finally, the review provides a comprehensive analysis of selected papers on FER in Computer Vision and a valuable reference for future studies in emotion recognition. Have presented Light-FER, a lightweight FER system based on the Exception model with model compression techniques. The system includes pruning unimportant connections, quantization to half-precision format for reduced memory usage, and optimization using deep learning compilers for faster inference. The system is deployed on NVIDIA Jetson Nano to demonstrate its performance on edge devices. Upadhyay & Kotak (2020) conducted research work to define the efficiency of the different feature extraction techniques in extracting the features from the input image. Generally, the features are extracted from the mouth, eye, and nose to recognize facial emotions. Various feature extraction techniques, such as geometry, template, and appearance-based methods, are used. The authors elaborately discuss the efficiency of these methods. State that facial expressions infer human emotions. There is high noise in standard emotion coding models of facial expression, adding categorical and dimensional ones new problem of facial emotion recognition with noisy multi-task annotations has been introduced formulation from the point of joint distribution match view has been suggested for the latest issue, which aims at learning more reliable correlation among raw facial images and multi-task labels.

2. An effective facial expression recognition using convolutional neural network

The study intends to develop a methodological system for CNN. The proposed model classifies the input facial images captured from the webcam into seven categories: Fear, sorrow, happiness, disgust, wrath, surprise, and neutrality, to classify human emotions. FER can be used to analyze facial expressions to better understand the system's human requirements. The micro presentation has been made recognizable in several studies.

2.1 Preprocessing

Preprocessing them with the optical flow approximation method is the initial step in the micro expression videos. Improved noise stability and flow discontinuity are two essential benefits of this method. Object vectorized notes from optical flow codes movement depict the changes in the pixel direction or the flow of z intensity. The optical flow is defined into two parts: Vertical and Horizontal.

$$\vec{v} = \left[p = \frac{dx}{dt}, q = \frac{d_y}{dt}\right]^T \quad (1)$$

$$\epsilon = \frac{1}{2}\left[\nabla u + (\nabla u)^T\right] \quad (2)$$

$$\epsilon = \begin{bmatrix} \epsilon_{xx=\frac{\delta u}{\delta x}} \epsilon_{xy=\frac{1}{2}\left(\frac{\delta u}{\delta y}+\frac{\delta v}{\delta x}\right)} \\ \epsilon_{yx=\frac{1}{2}\left(\frac{\delta v}{\delta x}+\frac{\delta u}{\delta y}\right)} \epsilon_{yy=\frac{\delta v}{\delta y}} \end{bmatrix} \quad (3)$$

Shear strain is a normal strain where the diagonal load is a standard strain component. There is a change towards x and y via everyday stress. The total amount of optical pressure of each pixel, calculated with the sum of squares of standard shear strain components, is expressed in Equations 3.2, 3.3, and 3.4.

$$|\epsilon| = \sqrt{\epsilon_{xx}^2 + \epsilon_{yy}^2 + \epsilon_{xy}^2 + \epsilon_{yx}^2} \quad (4)$$

3. Experimental Setup

The entire research work has experimented with Python software with different kinds and sizes of face datasets. Some of the datasets are fully classified and annotated. The majority of the classes belong to seven expressions. A significant portion of the datasets is preprocessed. The remaining dataset was also preprocessed using the proposed methodologies involved in this research work. From the dataset, 80% of the data is used to train the model and to make the dataset trained and labeled. The remaining 20% of the data is used for testing and validating the model. The entire process of designing, implementing, and experimenting with the proposed model is in a Core-i7, 7th generation, Intel Pentium Core processor system. It has a 1TB HDD and 12 GB RAM with other necessary elements installed.

4. Results and Discussion

Experimental results were analyzed using several performance metrics to validate the proposed model. Accuracy comparisons were made among three methods: raw, HC (high concentration), and LS (label smoothing). On the CK+ and KDEF datasets, ResNet with LS showed improved accuracy. However, accuracy slightly dropped on the RAF dataset from 81.68% to 80.89% using LS. Despite this drop, LS still outperformed other feature extraction techniques under high intra-class variation.

Further analysis using K-metal feature selection excluded two expressions, allowing a refined clustering model. It was observed that outliers appeared more frequently in clusters without smoothing, while models trained with smoothing showed more consistent labelling. HC improved the CK+ dataset accuracy from 98.17% to 98.25% by focusing on regions of interest (ROI). However, no significant accuracy gains were observed for KDEF (92.44%) and RAF (80.57%) using HC. Figure 3.8 shows that HC leads to faster convergence than other methods.

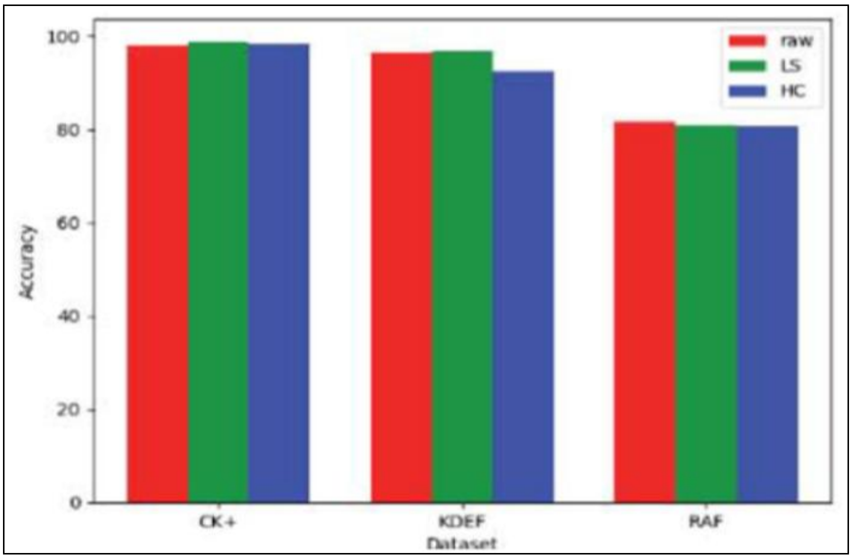

Fig 1: Accuracy comparison of different datasets

5. Conclusion and Future Work

Facial-expression recognition (FER) is increasingly vital for security, surveillance, and biometric authentication. To deliver a fast, fully automatic system, this study develops and tests deep-learning models in three steps:

- **Baseline CNN:** A streamlined pipeline (video to frames → face detection → pre-processing → CNN) achieved 98.25 % accuracy on CK+ and 92.44 % on KDEF when trained on 80 % of the data and tested on 20 %.
- **ML vs. DL comparison:** Traditional classifiers (AdaBoost, Random Forest, KNN, SVM + HMM) reached 95-99 % on small sets, but the custom CNN topped them with 99.94 % accuracy, highlighting deep learning's scalability limits on larger, more varied datasets.
- **Hybrid model:** A CNN with Bayesian Optimization for tuning, coupled with a Multilayer Neural Network and Sparse Representation (CNN-BO + MNN-SR), boosted accuracy to 99.57 % across CK+, FER2013, and DISFA, even under pose, lighting, and occlusion changes.

6. Limitations

Deep networks demand substantial compute, long training times, and struggle on low-power devices; they also miss subtle micro-expressions. Future work will focus on lightweight architectures and finer-grained emotion detection to meet real-time, resource-constrained requirements.

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