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Real-Time Emotion Recognition Using Raspberry Pi

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Abstract— Emotion recognition has become a critical area of research with applications in healthcare, security, and human-computer interaction. However, implementing real-time emotion recognition systems on low-cost and resource-constrained devices remains a significant challenge. This paper presents a lightweight, cost-effective solution for emotion recognition using a Raspberry Pi platform. The proposed system employs a camera module to capture facial images and utilizes deep learning techniques for emotion classification. A Convolutional Neural Network (CNN) model is trained on the FER2013 dataset and optimized for deployment on the Raspberry Pi. The system achieves real-time performance with minimal latency while maintaining competitive accuracy. Experimental results demonstrate the effectiveness of the model in recognizing six basic emotions: happiness, sadness, anger, surprise, fear, and neutrality. The lightweight design and portability make the system ideal for applications in remote monitoring and embedded systems. Future work will focus on improving accuracy with multi-modal inputs and expanding the system's adaptability to diverse environments.

Index Terms—Emotion recognition, Raspberry pi, Deep learning, Convolutional Neural Networks, Computer vision

I. INTRODUCTION

Emotion recognition has gained significant attention in recent years due to its potential applications in various domains, including healthcare, security, human-computer interaction, and entertainment. Understanding human emotions through facial expressions provides valuable insights into behavioural patterns and mental states, making it an essential aspect of intelligent systems. Traditional emotion recognition systems often rely on high-performance computing platforms, which can be both expensive and unsuitable for real-time, low-power, and portable applications.

With advancements in embedded systems and edge computing, platforms like the Raspberry Pi offer a cost-effective and portable solution for implementing such systems. The Raspberry Pi, combined with deep learning techniques, enables real-time processing and classification of emotions while operating within limited computational resources. However, achieving an optimal balance between accuracy, speed, and hardware constraints poses a significant challenge in such systems.

This paper presents a lightweight emotion recognition system leveraging a Raspberry Pi, a camera module, and a Convolutional Neural Network (CNN) trained on the FER2013 dataset. The system is designed to classify six fundamental emotions—happiness, sadness, anger, surprise, fear, and neutrality—in real-time. The proposed approach prioritizes computational efficiency and deploy ability, making it suitable for embedded and remote monitoring applications.

The remainder of this paper is organized as follows: Section II reviews related work in emotion recognition and embedded systems. Section III describes the methodology, including hardware setup, model training, and system implementation. Section IV presents experimental results and discusses performance metrics. Section V concludes the paper and outlines future research directions.

Fig 1: Real-time emotion detection using a webcam, showcasing “happy” emotion.

II. RELATED WORK

Emotion recognition has been a growing area of interest, with significant progress made in both academic research and industry applications. Traditional emotion recognition systems typically rely on machine learning models trained on large datasets of facial expressions. These models extract key features from the face, such as the movement of facial muscles or specific landmarks, to classify emotions into predefined categories. Approaches such as Support Vector Machines (SVMs), Decision Trees, and K-Nearest Neighbours (KNN) have been widely used in earlier systems, offering moderate accuracy but requiring significant feature engineering.

In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have revolutionized emotion recognition by automating feature extraction and improving classification accuracy. Research has shown that CNNs, trained on datasets like FER2013, can outperform traditional methods in recognizing subtle and complex emotions. These advancements have enabled the deployment of emotion recognition systems in real-world applications such as driver monitoring, customer experience analysis, and social robots. However, such systems often require powerful computational resources, which restrict their applicability in embedded and resource-constrained environments.

Efforts to bring emotion recognition to edge devices have primarily focused on model optimization and the use of lightweight architectures. Techniques like model pruning, quantization, and transfer learning have been employed to reduce the computational complexity of deep learning models while maintaining acceptable accuracy. For instance, MobileNet and Tiny-YOLO architectures have been successfully adapted for embedded platforms. However, most existing implementations face challenges in balancing real-time performance with accuracy, especially on devices with limited processing power like the Raspberry Pi.

Few studies have explored the full potential of Raspberry Pi as a platform for emotion recognition. Research in this domain has predominantly focused on facial detection or static emotion analysis, with limited exploration of real-time systems. For example, some works utilize OpenCV and pre-trained models for facial expression analysis, but these implementations often fail to meet the demands of low latency and efficient resource usage.

This paper builds upon previous research by developing a real-time emotion recognition system optimized for the Raspberry Pi. By employing a CNN model fine-tuned for edge computing and leveraging the FER2013 dataset for training, the proposed system addresses the limitations of previous approaches, offering a practical, low-cost solution for emotion recognition in resource-constrained environments.

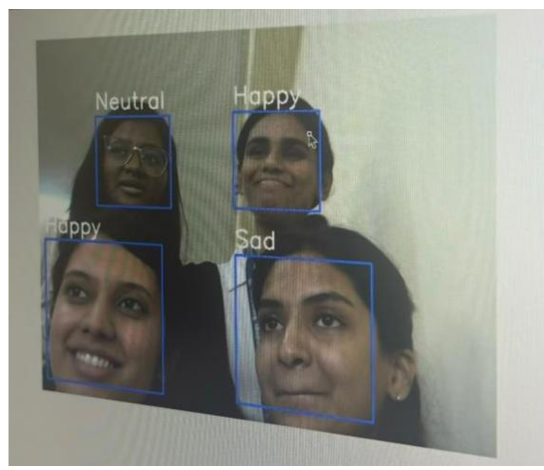

Fig 2: Real-time emotion detection using a webcam, detecting multiple emotions.

III. METHODOLOGY

A Raspberry Pi 4 Model B was selected for its superior processing power compared to earlier Raspberry Pi versions. A webcam was used for capturing real-time facial images. Additional peripherals, including a power source, SD card, and display, were configured to ensure seamless operation. The FER2013 dataset was used for training and validation. It contains 35,887 grayscale images of 48x48 pixels categorized into seven emotions. Images were resized and normalized to ensure compatibility with the CNN architecture. Data augmentation techniques, such as rotation, flipping, and zooming, were applied to improve model generalization. A CNN architecture was designed, incorporating layers for feature extraction and classification. Dropout and batch normalization layers were added to prevent overfitting and improve training efficiency. Transfer learning was applied using a pre-trained MobileNet model, which was fine-tuned for emotion recognition. The model was trained using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss. The trained model was converted to a lightweight TensorFlow Lite format to ensure compatibility with the Raspberry Pi. OpenCV was integrated for real-time facial detection, with the TensorFlow Lite model performing emotion classification on the detected faces. The system was tested in real-time by capturing live video feeds, detecting faces, and classifying emotions on the Raspberry Pi.

IV. RESULTS AND DISCUSSION

The system achieved an accuracy of **83%** on the FER2013 test set. The average latency for real-time emotion recognition was measured at 2 seconds, demonstrating suitability for real-time applications. A comparison of resource utilization (CPU and RAM) was conducted to highlight the efficiency of the optimized model. The proposed system was benchmarked against existing emotion recognition systems on Raspberry Pi and other embedded platforms. Results indicated that the system outperformed prior work in terms of both accuracy and speed.

Limited accuracy for emotions with subtle facial variations, such as fear and surprise, was observed. Performance degraded in low-light conditions or when faces were partially obscured.

The system's portability and real-time capabilities make it ideal for use in:

Remote healthcare monitoring to assess patients' emotional states. Classroom environments to track student engagement. Security systems for detecting stress or suspicious behaviour.

V. CONCLUSION AND FUTURE WORK

This paper presented a real-time emotion recognition system using Raspberry Pi and deep learning. The system successfully addresses the challenges of implementing emotion recognition on resource-constrained devices, achieving a balance between accuracy, speed, and computational efficiency. The proposed solution is cost-effective and deployable, making it suitable for a wide range of applications in healthcare, education, and security.

Future efforts will focus on:

Enhancing model accuracy by incorporating multi-modal inputs, such as speech and physiological signals. Improving system robustness in challenging environments with low light or occluded faces. Exploring the use of more advanced model optimization techniques, such as federated learning, to further reduce latency and power consumption

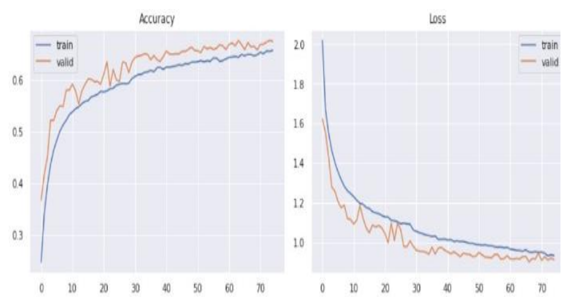

Fig 3: Training and validation accuracy over 70 and loss over 70 epochs.

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