International Journal of Scientific Research and Engineering Development-– Volume 7 Issue 4, July-Aug 2024

Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

AI-POWERED EMOTIONAL RECOGNITION IN HUMAN THERMAL IMAGES

G.Bharathikannan*, K.Sridhar**

*(Asst.Professor.CSE, Sembodai Rukmani Varatharajan Engineering College,Sembodai
Email: bharathi348@gmail.com)

** (PG Scholar CSE, Sembodai Rukmani Varatharajan Engineering College, Sembodai
Email: sridharkumar065@gmail.com)

--************************----------------------------------

Abstract:

Facial expressions convey non-verbal information between humans in face-toface interactions. Automatic facial expression recognition, which plays a vital role in human-machine interfaces, has attracted increasing attention from researchers since the early nineties. Classical machine learning approaches often require a complex feature extraction process and produce poor results. In this paper, we apply recent advances in deep learning to propose effective deep Convolutional Neural Networks (CNNs) that can accurately interpret semantic information available in faces in an automated manner without hand-designing of features descriptors. We also apply different loss functions and training tricks in order to learn CNNs with a strong classification power. The study aims to analyze facial expressions associated with various emotions, including happiness, sadness, anger, fear, surprise, and disgust.The CNN algorithm is utilized as a powerful classifier to facilitate the extraction and selection of crucial features, allowing for a robust and accurate identification of various emotional states. The integration of thermal imaging and AI-based emotion recognition holds promise for applications in diverse fields, including psychology, healthcare, and human-computer interaction. This research contributes to the advancement of emotion analysis techniques by leveraging state-of-the-art AI technologies to decode complex emotional expressions through thermal facial data.

Keywords **—**Convolutional Neural Networks, Region Of Interest.

--************************----------------------------------

I. INTRODUCTION

In recent years, combining artificial intelligence (AI) and image processing has opened new ways to understand human emotions. This study focuses on recognizing emotions like happiness, sadness, anger, panic, surprise, and disgust using thermal facial images. Unlike traditional methods that use visible light images, thermal images capture subtle changes in facial temperature linked to different emotions.

To achieve this, Convolutional Neural Networks (CNN) are used to analyze and extract key features from the thermal images. Important preprocessing steps are taken to improve the image quality and select relevant features for accurate emotion analysis. By integrating CNN algorithms, this approach offers a more detailed and precise understanding of human emotions, going beyond the limitations of conventional methods. This research aims to enhance our knowledge of emotion recognition, benefiting areas such as psychology and human-computer interaction.

II. DEEP LEARNING

Deep learning is a type of machine learning and artificial intelligence (AI) that mimics how humans learn certain types of knowledge. It is crucial in data science, which involves statistics and predictive modeling. Deep learning helps data scientists by speeding up and simplifying the process of collecting, analyzing, and interpreting large amounts of data.

III. RELATED WORKS

3.1 DEEP RESIDUAL NEURAL NETWORK FOR CHILD'S SPONTANEOUS FACIAL EXPRESSIONS RECOGNITION[2021]

Qayyum.A [2] discussed with in this paper, we present progressive light residual learning to classify spontaneous emotion recognition in children. Unlike earlier residual neural network, we reduce the skip connection at the earlier part of the network and increase gradually as the network go deeper. The progressive light residual network can explore more feature space due to limiting the skip connection locally, which makes the network more vulnerable to perturbations which help to deal with overfitting problem for smaller data. Experimental results on benchmark children emotions dataset show that the proposed approach showed a considerable gain in performance compared to the state of the art methods.

3.2THE IMPACT OF EMOTIONAL FACE MASKS ON EMOTION RECOGNITION PERFORMANCE AND PERCEPTION OF THREAT[2022]

Dernti.B [3] discussed with in the current study, we investigated whether emotion recognition, assessed by a validated emotion recognition task, is impaired for faces wearing a mask compared to uncovered faces, in a sample of 790 participants between 18 and 89 years (condition mask vs. original). In two more samples of 395 and 388 participants between 18 and 70 years, we assessed emotion recognition performance for faces that are occluded by something other than a mask, i.e., a bubble as well as only showing the upper part of the faces (condition half vs. bubble). Additionally, perception of threat for faces with and without occlusion was assessed. We found impaired emotion recognition for faces wearing a mask compared to faces without mask, for all emotions tested (anger, fear, happiness, sadness, disgust, neutral). Further, we observed that perception of threat 9 was altered for faces wearing a mask. Upon comparison of the different types of occlusion, we found that, for most emotions and especially for disgust, there seems to be an effect that can be ascribed to the face mask specifically, both for emotion recognition performance and perception of threat.

2.3FACIAL EXPRESSIONS RECOGNITION AND DISCRIMINATION IN PARKINSON'S DISEASE[2021]

LongoC [8] discussed with this study aims at assessing emotion recognition and discrimination in PD. Recognition of six facial expressions was studied in order to clarify its relationship with motor, cognitive and neuropsychiatric symptoms. Sensitivity in discriminating happy and fearful faces was investigated to address controversial findings on impairment patients and 25 control participants were also tested with a backward masking paradigm for sensitivity in happiness and fear discrimination. Results showed that PD patients were impaired in facial emotion recognition, especially for fearful expressions. The performance correlated with perceptual, executive and general cognitive abilities, but facial expression recognition deficits were present even in cognitively unimpaired patients. In contrast, patients' sensitivity in backward masking tasks was not reduced as compared to controls.

IV. PROPOSED METHODOLOGY

The proposed system aims to improve emotion recognition by combining thermal imaging and advanced AI algorithms. It captures infrared radiation from human faces to observe physiological changes linked to emotions. The thermal images go through preprocessing steps like calibration, normalization, and filtering to improve quality and accuracy. Face detection algorithms then locate facial features, defining a region of interest (ROI) for analysis.A key innovation of the system is using Convolutional Neural Networks (CNN) for automatic feature extraction and learning. The model is trained on labeled datasets to link temperature patterns within the ROI to specific emotions. During real-time use, the trained model predicts emotional states based on thermal features, providing a detailed understanding of human emotions.This system has significant potential in psychology, healthcare, and human-computer interaction, enabling more accurate and non-intrusive emotion analysis in various settings.

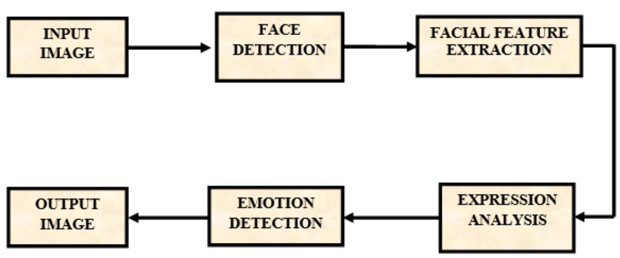

Fig. 1 System Architecture

V. SYSTEM IMPLEMENTATION

A. *System Modules*

1. Data Acquisition
2. Pre-processing
3. Face Detection
4. Region of Interest (ROI) Selection
5. Feature Extraction
6. Training the Model
7. Emotion Recognition
8. Post-processing
9. Interpretation and Visualization

B. *Module Description*

1. Data Collection

The dataset is separated into training set and test set. Each sample represents a traffic sign labeled as one of two classes. The outline of a traffic sign image is scaled to 256×256 pixels in three channel RGB representation. Below, there are a only some random samples from the dataset: vilo jones images are collected. This involves capturing thermal images using infrared sensors to identify temperature variations on human faces. The acquired data form the foundation for subsequent analysis.

2.Preprocessing

Variations that are irrelevant to facial expressions, such as different backgrounds, illuminations and head poses, are fairly common in unconstrained scenarios. Therefore, before training the deep neural network to learn meaningful features, pre-processing is required to align and normalize the visual semantic information conveyed by the face Illumination and contrast can vary in different images even from the same person with the same expression, especially in unconstrained environments, which can result in large intra-class variances Image size In the pre-processing module, raw thermal images undergo calibration to ensure temperature accuracy. Normalization and filtering techniques are applied to enhance image quality, minimizing noise and artifacts.

3.Face Detection

Using computer vision algorithms, this module locates and identifies faces within the thermal images. Techniques like Haar cascades or deep learning models are often employed for precise face detection.

4.Region Of Interest (Roi) Selection

Once a face is detected, this module defines a Region of Interest (ROI) around facial features. This step narrows the focus of analysis to the most relevant area for emotion recognition.

5.CNN Layer Feature Extraction

The Feature Extraction module involves extracting important thermal features from the defined ROI. CNN or other machine learning techniques may be utilized for automatic feature extraction.

Convolutional neural networks (CNNs) are highly effective in image recognition, mainly due to the convolution operation that distinguishes them from traditional neural networks. When given an input image, a CNN scans it multiple times to identify specific features. This scanning process, or convolution, is controlled by two parameters: stride and padding type.During the first convolution, the image is processed into new frames, each representing the presence of a particular feature. Higher values in these frames indicate strong visibility of a feature, while lower values indicate little or no presence. This process is repeated for each frame across multiple layers. In this project, we use a classic model with two convolution layers. As we move to higher layers, the CNN searches for more complex features, similar to human perception.Initially, the features a CNN looks for are random. During training, the weights between neurons are adjusted, enabling the CNN to learn which features are important for recognizing images in the training set. This learning process allows the CNN to automatically extract and identify relevant features, making it suitable for tasks like face recognition.6.2.6 Training The ModelIn this extracted features are used to train an AI model, such as a CNN. The model learns to associate specific thermal patterns with different emotional states using labeled training datasets.

6.Emotion Recognition

Trained on the extracted features, the Emotion Recognition module applies the model to new thermal images, predicting the emotional state of the subject. The model interprets temperature distributions within the ROI to categorize emotions.

8. Post-Processing

Post-processing steps refine the results, addressing any remaining noise or anomalies. Thresholds or confidence levels may be applied to filter out less reliable predictions, ensuring the accuracy of the emotional state classification.

9. Interpretation And Visualization

The involves interpreting the model's predictions and presenting the results in a comprehensible format. Visualization tools may be employed to showcase recognized emotions, offering insights into the subject's emotional state. This step facilitates the application of the system's findings in practical scenarios, such as psychological assessments or human-computer interaction.

VI. CONCLUSIONS

We have developed a comprehensive and fully automated method for identifying facial expressions using thermal imaging, leveraging both surface and subsurface facial features. Our new algorithm reliably extracts facial features and achieves higher accuracy than previous methods. This low-complexity approach is suitable for real-time applications. By using Convolutional Neural Networks (CNN), our system classifies different human expressions based on selected features and measured properties of the facial region. This enables the capture of emotional cues through thermal facial images, providing a unique and valuable perspective on emotion recognition and insights into the physiological manifestations of feelings. As thermal imaging technology and AI algorithms advance, this integrated approach leads the way in enhancing our understanding of human emotions. It offers practical applications that can positively impact various aspects of human interaction and well-being. Our method surpasses other state-of-the-art approaches, with high-quality face images providing valuable information to efficiently distinguish genuine emotions from fake ones.

REFERENCES

[1] A. C. Rafael and D. Sidney, “Affect detection: An interdisciplinary review of models, methods, and their applications,” IEEE Trans. Affective Comput., vol. 1, no. 1, pp. 18–34, Jun. 2010.

[2] A Qayyum , “Deep residual neural network for child’s spontaneous facial expressions recognition”, PP. 282–291, 2021.

[3] B Dernti, “The impact of face masks on emotion recognition performance and perception of threat”, 2022.

[4] C. Darwin, The Expression of Emotions in Man and Animals. John Murray, 1872 (reprinted by the University of Chicago Press, Chicago, IL, 1965).

[5] C Longo , "Facial expressions recognition and discrimination in parkinson's disease",PP. 554–567, 2021.

[6] G. Guo and C. R. Dyer, "Learning from examples in the small sample case: Face expression recognition," IEEE Trans. Syst., Man, Cybern. B, vol. 35, no. 3, pp. 477– 488, Jun. 2005.

[7] I. Cohen, N. Sebe, Y. Sun, M. S. Lew, and T. S. Huang, "Evaluation of expression recognition techniques," in Proc. Int. Conf. Image Video Retrieval, Jul. 2003, pp. 184–195.

[8] J Fierezz , "Facial expressions as a vulnerability in face recognition", 2022.

[9] J. F. Cohn, "Advances in behavioral science using automated facial image analysis and synthesis," IEEE Signal Process. Mag., vol. 27, no. 6, pp. 128–133,

[10] L. D. Silva and S. C. Hui, "Real-time facial feature extraction and emotion recognition," in Proc. 4th Int. Conf. Inform. Commun. Signal Process., vol. 3. Dec. 2003, pp. 1310–1314.

[11] Liton Chandra Paul, Abdulla Al Sumam. Face Recognition Using Principal Component Analysis Method. International Journal of Advanced Research in Computer Engineering & Technology (IJARCET),Volume 1, Issue 9, November 2012.

[12] M Grahlow , "The impact emotional of face masks on emotion recognition performance and perception of threat", 2022.

[13] M. Pantic and I. Patras, "Dynamics of facial expression: Recognition of facial actions and their temporal segments from face profile image sequences," IEEE Trans. Syst., Man, Cybern. B, vol. 36, no. 2, pp. 433–449, Apr. 2006.

[14] N. Sebe, H. Aghajan, T. Huang, N. M. Thalmann, and C. Shan, "Special issue on multimodal affective interaction," IEEE Trans. Multimedia, vol. 12, no. 6, pp. 477–480, Oct. 2010.

[15] P. Ekman, T. Dalgleish, and M. E. Power, Basic Emotions, Handbook of Cognition and Emotion. Chichester, U.K.: Wiley, 1999.