International Journal for Research in Engineering Application & Management (IJREAM)
ISSN : 2454-9150 Vol-10, Issue-01, Apr 2024

Emotion Detection Using Python

Shubham Mahajan[1], Snehal Kurle[2],Tanmay Naik[3], Srujan Chavhan[4] Prof. A. T. Sonawane[5]

UG Student ,Information Technology,SKN Sinhgad Institute of Technology and Science,India

shubhammahajan20191@gmail.com[1] snehalkurle11@gmail.com[2] tanmaynaik12003@gmail.com[3]

srujanchavan1308@gmail.com[4]

Abstract: Understanding human emotions is a complex journey into the realm of feelings and thoughts, often marked by spontaneity. Deciphering emotions through facial expressions presents a formidable challenge due to the lack of clear-cut connections and significant variations among individuals. However, with the advent of deep learning, emotion recognition has garnered widespread attention, opening up numerous practical applications in our everyday lives.

Our project revolves around analyzing images of human faces to train pre-existing models using datasets. Over the years, Machine Learning (ML) and Neural Networks (NNs) have emerged as powerful tools for this purpose. In our endeavor, we employ a Convolutional Neural Network (CNN) to sift through image features and discern emotions. Through numerical analysis, our algorithm provides probabilistic insights into various emotional states.

I INTRODUCTION

Understanding facial emotions plays a crucial role in human interaction, aiding in the interpretation of others' intentions. Typically, individuals gauge emotions like joy, sadness, and anger through facial expressions, which serve as primary channels of information in interpersonal exchanges. Consequently, research on facial emotions has garnered significant attention in the past decade, finding applications in perceptual and cognitive sciences.

The surge in interest in Automatic Facial Emotion Recognition (FER) aligns with the rapid advancements in Artificial Intelligence (AI) techniques. These technologies are increasingly integrated into various applications, becoming more prevalent in human experiences. Enhancing Human-Computer Interaction (HCI) necessitates equipping machines with the ability to comprehend their surroundings, particularly human intentions. Through cameras and sensors, machines can capture the context of their environment.

In recent times, Deep Learning (DL) algorithms have demonstrated remarkable success in comprehending environmental cues. Emotion detection is crucial for machines to fulfill their roles effectively, as it provides insights into the emotional states of humans. By leveraging DL techniques on sequences of facial images, machines can discern and respond to human emotions more accurately.

II MOTIVATION

There's been considerable interest in leveraging Facial Expression Reading (FER) technology, with Tang et al. proposing a comprehensive system for analyzing facial expressions. Their system encompasses five key stages: data collection, face detection, person identification, emotion recognition, and result processing. Utilizing methods such as K-nearest neighbor (KNN) classification and ULBGPHS (Uniform Local Gabor Binary Pattern Histogram Sequence), this approach delves into patterns to accurately identify emotions.

Furthermore, Savva et al. suggested the development of a web application aimed at analyzing students' emotions during face-to-face instruction sessions. This initiative involved setting up webcams to capture live footage, which was subsequently subjected to analysis using machine learning algorithms.

III. OBJECTIVES

In this project, we employ Convolutional Neural Networks (CNNs), a deep learning technique, to create a classification model. This model integrates feature extraction and classification to effectively detect facial emotions. Our goal is to develop a robust facial expression recognition system, leveraging machine learning algorithms within the domain of computer vision.

By detecting emotions, our system aims to enhance Intelligent Human-Computer Interaction (HCI), enabling more intuitive and responsive interactions between humans and machines.

IV Existing System & Limitations

To enhance the e-learning experience and improve content delivery effectiveness, the authors have introduced a system designed to detect and monitor emotional states, providing real-time feedback. This system discerns an individual's emotional state by analyzing subtle movements of the eyes, nose, mouth, and head.

Ayvaz et al. developed a Facial Emotion Recognition System (FERS) capable of identifying emotions through video analysis. Employing four distinct machine learning algorithms (Support Vector Machines, K-Nearest Neighbors, Random Forest, and Classification & Regression Trees), the study found that K Nearest Neighbors and Support Vector Machines achieved the highest accuracy rates.

Drawing from facial emotion recognition techniques utilizing the Haar Cascades method to pinpoint facial features on the JAFF database, the authors proposed a model for emotion recognition within virtual environments.

 DOI : 10.35291/2454-9150.2024.0193

Furthermore, Chiou et al. introduced an intelligent classroom management system leveraging wireless sensor network technology. This system enables teachers to seamlessly transition between different instructional modes, saving valuable time during lessons.

Limitations:

· Accuracy is not good [1]

· Works only with images [1]

V. MODULES

A. Face Capturing Module

Image Acquisition: Images utilized for facial expression recognition can be static images or sequences of images captured using a camera. Face detection, a crucial step in this process, involves identifying facial features within these images. In the training dataset, Face Detection is performed using a Haar classifier known as the Voila-Jones face detector, which is implemented through OpenCV. Haar-like features are integral to this detection process, encoding variations in average intensity across different regions of the image. These features are represented by connected black and white rectangles, where the feature value corresponds to the difference in pixel sums between these regions.

B. Pre-Processing Module

Image pre-processing is a vital step that involves refining images before they undergo further analysis. This process typically includes the removal of noise and normalization to ensure consistency across images. Two common techniques used for normalization are:

Color Normalization: This technique adjusts the color distribution of images to ensure consistency across different lighting conditions or camera settings. By standardizing color values, it helps mitigate variations caused by factors like brightness and contrast.

Histogram Normalization: This method aims to equalize the distribution of pixel intensities in an image's histogram. By redistributing pixel values, it enhances the overall contrast and improves the clarity of features within the image.

C. Training Module

Deep learning training is the process through which a deep neural network (DNN) learns to analyze a specific dataset and make predictions. It entails extensive trial and error until the network can accurately deduce conclusions based on the desired outcomes.

D. Face Recognition Module

A Convolutional Neural Network (CNN) is a specialized type of artificial neural network featuring one or more convolution layers, primarily employed for tasks such as image processing, classification, segmentation, and analysis of auto-correlated data. Deep learning, a subset of machine learning, utilizes artificial neural networks to identify objects within images by progressively extracting features from the data through multiple layers.

In the process of recognizing a face in an image, CNNs must be trained with human faces, as depicted in the accompanying figure. CNNs offer the advantage of constructing an internal representation of a two-dimensional image, enabling the model to grasp the position and scale of faces within it. Once the CNN is trained, it becomes capable of recognizing faces in images effectively. Utilizing Convolutional Neural Networks for image data allows for the extraction of features embedded within an image, enhancing the model's ability to understand and analyze visual data.

E. Expression Detection Module

Common expression recognition methods typically involve several stages, including image preprocessing, facial feature extraction, and expression recognition itself. During the preprocessing stage of image expression recognition, face detection is performed to isolate facial region images.

Recognition of expressions in low-resolution facial images often necessitates additional techniques like image enhancement or image super-resolution. Image enhancement aims to improve the quality of existing image information by enhancing pixel details.

In our approach, we utilize Convolutional Neural Networks (CNN) for image recognition, leveraging their ability to effectively extract features and recognize patterns within images.

VIII ALGORITHM USED

Convolutional Neural Networks (CNNs or Conv Nets) represent a class of multi-layer neural networks designed to discern visual patterns from pixel images. Within CNNs, "convolution" denotes a mathematical function, serving as a type of linear operation. This operation involves multiplying two functions to generate a third function, illustrating how one function's shape can be altered by the other. In essence, when two images are represented as matrices, their multiplication yields an output used to extract information from the image.

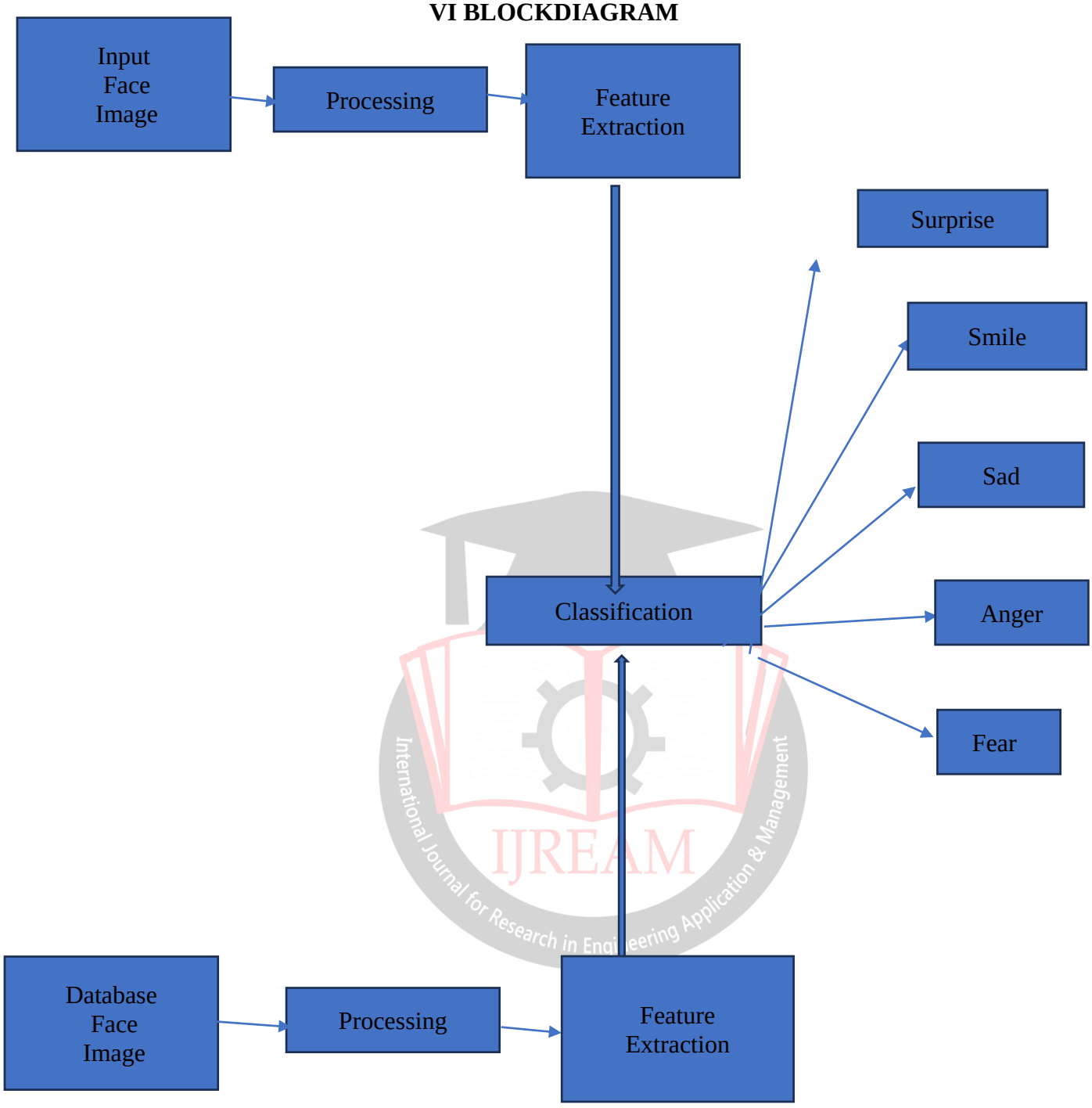
While CNNs share similarities with other neural networks, their distinctive feature lies in the sequence of convolutional layers they employ, adding complexity to the network architecture. CNNs rely heavily on convolutional layers, which are indispensable for their functioning.

CNNs have emerged as dominant players in various computer vision tasks, attracting widespread interest across multiple fields. Comprising numerous layers such as convolution layers, pooling layers, and fully connected layers, CNNs employ backpropagation algorithms to autonomously and adaptively learn spatial hierarchies of data.

Further insights into these terms will be provided in the subsequent section.

 DOI : 10.35291/2454-9150.2024.0193

VI BLOCKDIAGRAM



IX. CONCLUSION

This project presents a novel approach for categorizing facial expressions, a task with broad applicability in areas like robotics vision, video surveillance, digital cameras, security, and human-computer interaction. The primary aim of this project was to develop a facial expression recognition system by leveraging computer vision techniques to enhance advanced feature extraction and classification.

The project involved analyzing images of seven distinct facial expressions from various datasets, each representing different individuals. Key steps included preprocessing the facial images to enhance quality, followed by feature extraction using Local Binary Patterns (LBP). Classification of facial expressions was achieved through training datasets of facial images using Convolutional Neural Networks (CNN).

Through this methodology, the project aimed to improve the accuracy and efficiency of facial expression recognition,

 DOI : 10.35291/2454-9150.2024.0193

contributing to advancements in computer vision applications.

X REFERENCES

[1] Chu, William Wei-Jen Tsai, Hui-Chuan, Yuh Min Chen, and Min-Ju Liao. "Facial expression recognition with transition detection for students with high functioning autism in adaptive e-learning." Soft Computing 21, no. 1 (2017): 1-27.

[2] Tzirakis, George Trigeorgis, Mihalis A. Nicolaou, Panagiotis, Bjrn W. Schuller, and Stefanos Zafeiriou. "End-to-end multi-modal emotion recognition using neural networks." IEEE Journal of Topics in Signal Processing 11, no. 8 (2017): 1301-1309.

[3] Gampala, V., Kumar, M.S., Sushama, C., and Raj, E.F.I. "Deep learning based image processing approaches for image deblurring." Materials Today: Proceedings (2020).

[4] Aneja, Gary Faigin, Deepali, Alex Colburn, Barbara Mones, and Linda Shapiro. "Modeling stylized character expressions via deep learning." In Asian Conference on Computer Vision, pp. 136-153. Springer, 2016.

[5] Natarajan, V.A., Kumar, M.S., Patan, R., Kallam, S., and Mohamed, M.Y.N. "Segmentation of Nuclei in Histopathology images using Fully Convolutional Deep Neural Architecture." In 2020 International Conference on Computing and Information Technology (ICCIT1441).

[6] Nicholson, J., Takahashi, K., and Nakatsu, R. "Emotion recognition in speech using neural networks." Neural Computing Applications 9, no. 4 (2000): 290-296.

[7] Fasel, B., and Luettin, J. "Automatic facial expression analysis: a survey." Pattern Recognition 36, no. 1 (2003): 259-275.

[8] Krizhevsky, A., and Hinton, G. "Learning multiple layers of features from tiny images." (2009).

[9] Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., and Fei-Fei, L. "ImageNet: A large-scale hierarchical image database." In Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on, pp. 248-255. IEEE, 2009.

[10] Krizhevsky, A., Sutskever, I., and Hinton, G.E. "ImageNet classification with deep convolutional neural networks." In Advances in neural information processing systems, pp. 1097-1105, 2012.

[11] Lv, Y., Feng, Z., and Xu, C. "Facial expression recognition via deep learning." In Smart Computing (SMARTCOMP), 2014 International Conference on, pp. 303-308. IEEE, 2014.

[12] TF Learn. "TFLearn: Deep learning library featuring a higher-level API for TensorFlow." URL: http://tflearn.org/.

[13] Open Source Computer Vision. "Face detection using Haar cascades."

 DOI : 10.35291/2454-9150.2024.0193