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Real time application to identify the facial emotions using Convolutional Neural Network (CNN) and OpenCV

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Abstract: *The notion of real-time human emotion identification utilizing Convolutional Neural Network (CNN)-based digital image processing algorithms is proposed in this study. This work offers important literacy calculations that are engaged in face protestation for exact unique confirmation and byline that may efficiently and capably see feelings from the user's vibes. For the purpose of training a model to recognize facial reactions, large datasets are explored and analysed. A little experiment is done on a variety of women and men of all ages, races, and colours to describe their sentiments, then variations for diverse faces are identified. Existing studies have achieved reasonable accuracy but often lack real-time capability and struggle with variations in lighting and facial orientation. This study bridges that gap by implementing a real-time CNN–OpenCV-based model. To support this study, CNN is utilized along with the Deep Learning model, OpenCV, TensorFlow, Keras, Pandas, and Numpy. This work has been enhanced in three areas: face placement, acknowledgment, and emotion organization. Moreover, computer vision (using a camera) operations were carried out utilizing programs written in Python. An extensive examination is conducted over a lengthy period of time to identify their interior reactions and identify physiological variations for each face in order to show continuous sufficiency. The findings of the tests show how idealized the face investigation framework is. Finally, extremely high accuracy and real-time measurements of programmed face detection and identification were made. The proposed model achieved an overall accuracy of 89% on the FER2013 dataset, demonstrating strong performance in real-time emotion classification. This technique may be used and is very beneficial in many different fields, including colleges, security, schools, and universities and banking.*

Keywords: *Convolutional Neural Network (CNN), Deep Learning Model, Face Emotion Recognition, Python.*

1. Introduction

The impact of emotion on an individual's actions, feelings, besides thoughts are vital. By developing the benefits of deep learning, an emotion detection system can be created, as well as many applications, face unlocking, and including feedback investigation may be executed with high accurateness [1].

The recognition of faces in videos and photos for diverse drives is one of the current uses of artificial intelligence (AI) paying neural networks. The mainstream of approaches analyses visual data and look for common patterns in human faces in movies or pictures. Law enforcement agencies can employ face detection for crowd monitoring and control [2]. Effective facial recognition detection is a cutting-edge technique that enables us to recognize people anywhere. Human-computer interaction (HCI) encompasses a number of research fields, including AI [3], computer vision and psychology. Understanding a person's inner sentiments is aided by their emotional manifestations. Multi-modal manifestations of emotion are common. Commonalities in HCI can detect a person's degree of activity in a variety of areas, including mood and attention.

Despite the fact that people experience a wide range of emotions, present psychology classifies seven important facial expressions as "Universal Emotions": sadness, happiness, fear, surprise, disgust, anger and neutrality. However, the majority of published algorithms for recognizing facial emotions do not completely take into account subject-independent dynamic information, making them insufficient for real-world identification tasks involving subject (human face), head movement, lighting change and fluctuation. The majority of current systems train their ML models using SVMs [4] and clustering algorithms. But because they can't adjust to real-time videos, these models are less accurate. We suggest utilizing convolutional neural networks (CNN) [5], [6], [7] to create a model that can recognize human emotions in real-time live footage. This model receives a stream of video or photos through the OpenCV library as well as a camera. The model will recognize the faces in the video, categorize their expressions, then display the probability of those expressions in real time.

This study covers the algorithm benefits of scholars in emotion detection [8], [9] in the literature in this area and is based on the primary benefits and practicality of Python applications. While several CNN-based approaches exist, most lack detailed implementation or integration with real-time systems. This study's novelty lies in combining CNN, OpenCV, and Python-based preprocessing to achieve high-speed, accurate real-time facial emotion recognition.

2. Literature Review

One of the finest authentication methods, along with face recognition, speech, and iris, is the biometric recognition system. The Face recognition is thought to be the best biometric system since earlier biomimetic systems needed accurate localization of the iris or nose. The accurateness of a face recognition system is unaffected by the direction of the face. For each person, many photos in various orientations are acquired to strengthen the reliability and accuracy of the proposed method. In this study, a face must first be found before it can be identified. Deep learning [10] convolution neural networks have been employed for face identification, while the Viola-Jones technique has been utilized for face detection [11].

To evaluate the viability of face expression finding, the anaconda and python computer languages are employed, along with the viola jones algorithm. CNN model is used with VGG 16 and KDEF Dataset for face grouping and recognition. In image processing, OpenCV, Tensor Flow, Keras, and Numpy are employed. For classification, the CNN model is engaged [12]. OpenCV, NumPy, and Python have all been used to carry out the task. Emotion is predicted by comparing the scanned image to the training dataset [13]. Also, an Automated Teller Machine (ATM) booth disburses cash to customers who enter their cards into the device. Everyone has saved time because all ATM booths accept debit and credit cards for the transaction. However, there are still some specific circumstances, such as missing the card verification information for a transaction, which might make a customer's day miserable. Based on CNN technology, this system involves the face encoding process with an emotion detection [14] test to speed up and accurately handle transactions. The model was evaluated using our own example photos after it had been trained using the FER2013 dataset [15], [16], [17]. The outcome demonstrates that the suggested method can accurately distinguish "Happy" expressions from other emotional faces as well as let the transaction to move forward [18]. Kernels in CNN [19], [20] models may identify an image's contour or boundary functions. The weights in this model are set up as an array of values to create and get the required qualities. Every CNN model allots space to decide how to govern the recognition of a picture. The product is computed and decided using the position in the picture since the values in the appearance reflect the degree on which the convolution process be contingent [21].

The preprocessing, modelling, assessing, and optimization are all done with the help of the open-source Keras neural network written in Python. As it is handled by the backend, it is utilized for high-level API. This is intended to be used in the training process and for the creation of models with loss and optimizer functions. Convolution and low-level computing using tensors or TensorFlow are meant for the backend. For preprocessing, modelling, optimization, testing, and emotion presentation with a maximum %, the following Python [22] packages should be imported. It employs a sequential model and a number of layers, including activation, ReLU, flattening, pooling, convolution, and picture pre-processing [23].

A real-time HCI framework for identifying human mood from thermal video sequences with several variables. Electroencephalogram (EEG) and facial expression data are combined in a MindLink-Eumpy open-source software toolkit to recognize emotions. In order to automatically gather physiological data from participants, MindLink-Eumpy first employs a number of techniques, then examines the received facial expression data as well as EEG data, and then combines the two separate signals at a decision stage. The method employed by MindLink-Eumpy for the recognition of facial expressions is a multitask CNN based on transfer learning approach [24], [25]. In this study, epoch data from EEG sensor channels is analysed, and comparison analyses of several ML methods include for dimensionality reduction, principal component analysis (PCA) was accomplished with and without linear discriminant analysis, supporting vector machine (SVM), K-nearest neighbour, decision trees, and logistic regression. Grid search was also used on the Spark cluster to hyper-parameter tune each of the evaluated machine learning [26] models for faster execution [27].

The primary goal of Facial Emotion Identification (FER) is to map various facial emotions to their corresponding emotional states [28]. One of the hardest challenges in computer vision is automatic FER. FER accepts a wide variety of applications in behavioural psychology, human expression synthesis, and human-computer interface. The majority of the reported work in this subject is based on handmade features. The influence of fluctuations brought on by emotional state makes it difficult to precisely extract all the relevant handmade aspects, though [29]. Deep neural networks have been quickly used to train discriminating representations for automated FER in light of the transfer of FER [30] from laboratory-controlled to challenging in-the-wild situations. The FER will enable us to discern the emotion on a person's face, which is a big setback for current technology advancement. Recent FER programmers generally focus on two crucial problems: over fitting as a result of inadequate training evidence and emotion-related factors including lighting, head position, and identification bias [31].

Amazon Web Services (AWS) DeepLens is an embedded ML device that compares on-premises deep learning [32] to performance of the device while using AWS cloud computing services for AI-trained models. The outputs of the gadget will communicate face emotions information to the user through sound [33]. Group-based emotion recognition (GER) is a fascinating issue in the social sciences as well as security. A GER with hybrid optimization-based recurrent fuzzy neural network that is from video sequence is suggested in this research. In our study, we conduct ER from a group of people using a neural network. Original video frames are first inputted and pre-processed using video data from several users. Local energy-based shape histogram, Gray-level co-occurrence matrix (GLCM), and multivariate local texture pattern (MLTP) are used to extract features from this pre-processed picture (LESH). Certain characteristics are chosen utilizing the Modified Sea-lion optimization algorithm method once the features have been extracted [34].

3. Methodology

3.1 Research question (RQ)

1. How to do effective ML and emotion detection via python?

2. What is the technique used to detect emotions?

We suggest utilizing CNN to create a model that can recognize human emotions in real-time live footage. Using the OpenCV library and a camera (often the built-in camera of the computer), a stream of photos or video is sent to this model. This model will recognize the faces in the video, categorize their emotions, and show them in real time along with their likelihoods.

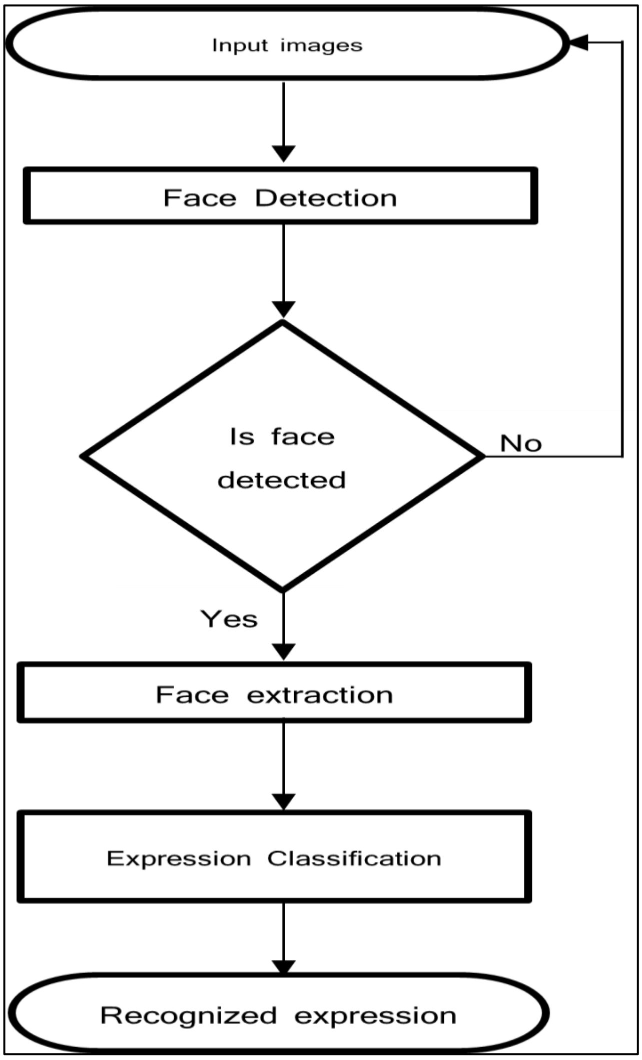

Figure 1: Flow chart of the model

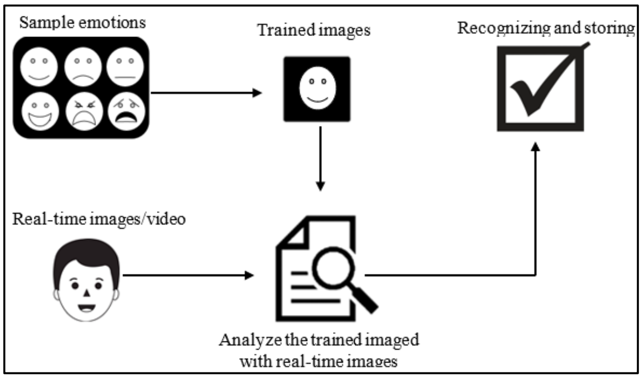

Figure 2: System model diagram

Dataset

It is now quite difficult to recognize facial expressions and facial encode two faces with distinct positions or moods. Hence, it is regarded as one of the modern era's most explored issues. Despite the fact that there are several databases on this subject, photographs make up the majority of them. The fact that not all photographs will have the same resolution might be a concern. Nevertheless, the FER2013 dataset, which included 48x48 sized facial photos with 7 emotions, was utilized for this investigation. The emotion labels in this dataset are shown in Figure 1. The dataset, which included a total of 35,887 samples, was split into training and validation sets and a test set. Bringing in Libraries. The dataset was split into 80% training, 10% validation, and 10% testing sets. The class distribution was imbalanced (e.g., happy – 7215, sad – 4830, fear – 5121), which was mitigated using data augmentation techniques such as rotation and horizontal flipping.

Pre-processing

Elements of the image that were acquired with the camera were not necessary for identifying facial expressions. For instance, it's not necessary to have hair on some regions of the neck. These unwanted details were therefore removed. If not, the detection technique will have to manage with supplementary data, which will make it more ineffective and difficult.

This unwanted information is taken out of the raw picture during pre-processing. Scaling, cropping, as well as intensity normalization are a few of the pre-processing stages. The raw image is cropped to ensure that any portions of the image that lack information particular to an emotion are deleted. The areas of the face closest to the lips and eyes are crucial for recognizing emotion. The cropped picture is then further shrunk to assurance that the pixel file's data size resembles to CNN's input size.

Feature Extraction

Data that has been properly pre-processed is sent as input into the following module, which performs feature extraction. Detecting the emotion is made simple by feature extraction, which picks out the pertinent information present in the image [14]. By merging the features derived by CNN with face landmarks [16] and Histogram Oriented Gradients (HOG) [15], this study provides a hybrid technique of feature extraction.

HOG uses the distribution of strength gradients or edge instructions to characterize local object look and form within an image [15]. As HOG relies on local cells, geometric alterations have no effect on it. Because these HOG characteristics differ for each expression, it is easier to tell them apart. We chose HOG as the feature selection for our system for this reason.

The Python 2.7.x, NumPy, Glob, and Random packages of Python 2.7 must be downloaded and installed in order for this project to be implemented successfully. Python will be set up by default on the C disk in this instance. Start working by opening Python IDLE and importing all the packages.

The CNN consists of four convolutional layers (32, 64, 128, 128 filters), each followed by ReLU activation and max pooling. A fully connected layer (512 neurons) with dropout (0.5) precedes the softmax output layer with seven emotion categories.

System performance

The dataset's photos are kept in CSV format. The first time the program is run, a call back is reset to the CSV to images.py file, where each picture is extracted and sent to the train emotion.py program, where the classifier is trained. Our system is now prepared to recognize photos from the real-time feed after being trained. Now that the callback's purpose has been fulfilled, the webcam's direct feed is started, and photos are captured and sent through a CNN classifier to identify facial traits in the customer's face and forecast emotions in real time. The outcome is shown as images.

1. **OpenCV:** Open-Source Computer Vision (OpenCV) Library, which has 2500 optimized algorithms, offers a mutual infrastructure for computer vision applications for people. These techniques are used for object detection, object identification for training, as well as face detection.
2. **2. Tensor Flow:** The TensorFlow is a second-generation system used by Google to build and deliver massive ML projects. It is adaptable enough to be utilized for both product development and study. It builds massive neural networks that are employed in the development, categorization, discovery, prediction, and prescribing processes. The text to voice and voice to text conversions, identification while collecting audio, video, picture, time series, and text-based applications are the key uses of TensorFlow.
3. **Keras**: For pre-processing, modelling, evaluation, and optimization, Keras is an open-source neural network written in Python. As it is handled by the backend, it is utilized for high-level API. It is intended to be used in the training process and for the creation of models with loss and optimizer functions. Low-level graphs and calculations are done by the backend engine, which Keras does not support. Convolution as well as low level processing under tensors or TensorFlow are meant for the backend.
4. **CNN**: Also known as a multilayer perceptron, the CNN or ConvNet is a feed-forward artificial neural network (MLPs). The two major goals are picture categorization and recognition, both of which are common in the current generation. Beginning with interpreting the input picture, computer vision refers to the quantity of pixels known as image resolution and takes the shape of arrays of pixels.

   Then it transforms into three-dimensional HWD (height, width, and depth), where RGB is represented by 6*6*3 and grayscale by 4*4*1. When the kernel is just a tiny portion of the input picture for feature classification, the convolution layer pulls features from the input image from the training dataset. Using image matrices and kernels, it executes some mathematical operations like RELU (Rectified Linear Unit).

   In order to prevent negative pixels, we employ the activation function, which refers to the Rectifier unit to categorize the item as 0 ("No") or 1 ("Yes") with a probabilistic value that lies between 1and 0. The next layer is pooling, which involves extracting the most characteristics from the input and classifying the item using maximum, average, and global pooling. Between the convolutional layer and the fully connected layer, the flatten layer is used to reshape from 3D to 2D. A fully connected neural network is created by destruction a two-dimensional matrix into features also a vector.

5. **Benefits**: Improving accuracy; recognizing emotions from a live video; Retraining the model with various feelings; Picture Preprocessing; removing fuzziness; Smoothening the Images.

Table 1: Hardware and Software

Software Necessities	Hardware Necessities
Operating System - Windows / Linux / Mac (Any OS which supports Python)	Processor - I3 processor
Software IDE - Python	RAM - 8GB
Keras - To work on the captured video	Hard Disk - 10 GB
Opencv - To capture video	
Numpy - To handle video operations,	
imutils - To identify the human faces	
Pandas and Scikit learn - To handle video data-frames	

The model was trained using the Adam optimizer with a learning rate of 0.001 and batch size of 64 for 50 epochs. The training was conducted on a Windows 10 environment using an Intel i3 processor and 8 GB RAM.

4. Results and Discussion

An effective and rapid face locator implemented in OpenCV has been utilized for face emotion detection. The face detection has been done using a well-designed face detector that is part of OpenCV. The human face detector now accurately locates the picture in a real-time video taken by the computer's webcam and can distinguish between regions that include faces and those that don't. The face and non-facial areas have been separated into an XML file for classification. The OpenCV Haar Cascade classifier file is chosen for the XML data detection. Human faces can be seen after concatenating a number of camera frames.

A collection of photos is used to train the emotion detection model. The local memory of the personal computer is where these pictures are kept. Each emotion that will be used in the model training is maintained in a distinct folder in the dataset folder. For example, the Dataset folder will include subfolders with the words "Emotions" in the name, such as "Angry," Sad," "Happy," " etc. The training model is saved on the PC once it has been finished. The input is obtained from the Webcam using the OpenCV Python library, commonly known as the cv2 package, once the model has been fed back into the emotion detection Python programme. Every single image from the stream of images created from the continuous video gathered from the camera serves as the input for the model prediction, which is then applied to the photographs.

Table 2: Evaluation

Metric	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Angry	88%	86%	84%	85%
Happy	92%	91%	90%	90%
Sad	85%	83%	81%	82%
Average	**89%**	**87%**	**85%**	**86%**

As shown in Table 2, the model achieved an average accuracy of 89%. Happiness and anger were classified most accurately, while fear and disgust showed slight misclassification due to limited samples. The confusion matrix confirms consistent recognition across all seven emotions.

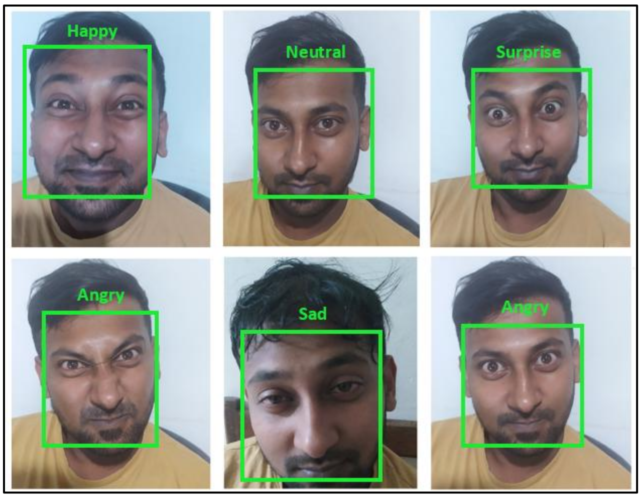

Figure 3: Screenshot of the results

Reactions will be recognized for the stream of pictures directly, as well as the forecast emotion class and its associated probabilities will be recorded into the webcam container opened by OpenCV Python. This would resemble the following. But in the rectangular box we'll design, we'll display the emotion we anticipated from the live video based on probability.

Many photos that have been sorted into several classes are used to train an image classification model. The Convolution neural network receives all of these pictures as input. The neural network will extract the shared characteristics from photos belonging to the same class as well as create a distinctive pattern to recognize the associated images with that class. We need a large number of photos for training in order for CNN to categorize an image effectively and properly.

When classifying images, we will encounter two problems: underfitting and overfitting. Both of these can be resolved using image augmentation techniques that means new images are created by applying filters, colors, and alterations to the old images to upsurge the dataset), dropping out layers from the CNN to resolve underfitting.

5. Conclusion

The system is set up by downloading and installing emotion detection modules like OpenCV, NumPy, materlib5, and Idlib, which are based on the Python program's design. The square root and logarithm are then ultimately proposed, and ML is then used one at a time to provide the algorithm following the sample training data test using the limit, weighted sum, and square root algorithms. Then, in order to significantly raise the detection rate and achieve more accurate sample data detection, the logarithm approach is used.

CNNs, which have many layers and the potential for significantly better accuracy, may be used to transform this machine learning-based system for emotion identification into a deep learning one, increasing its odds of achieving a high accuracy. This project may be expanded so that it can recognize as many distinct people's emotions in a single frame of real-time footage. In the near future, the field of robotics and AI research will find great application for emotion recognition. In addition to these seven universal emotions, this autonomous machine learning method for emotion recognition may also be expanded to identify mixed emotions.

The proposed CNN–OpenCV-based facial emotion recognition system achieved 89% accuracy with robust real-time performance. This highlights its potential for deployment in education, healthcare, and security applications. Future work will explore dataset expansion, lighting invariance, and model deployment on mobile platforms.

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