

A Real-Time Visage Expression Detection Using Convolutional Neural Network (RTVED)

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ABSTRACT

In this work, the purpose is to implement parts of seven Real-Time Visage Expression Detection using Convolutional Neural network (RTVED), Data Augmentation to get high accuracy, and focus on the Methodology of Real-Time Visage Expression Detection using CNN. In this paper, considered a convention Convolutional Neural Network model and utilized it to prepare and test diverse look pictures with the Keras, TensorFlow, and deep learning library. Real-Time human visage Expressions Detection has two sections, recognizer Validation, and data preparation, and a training model for data preparation and training. The recognizer contains a visage Expression detector and a visage Expression recognizer. The visage expression detector extricates facial pictures from the camera and the visage Expression recognizer recognizes the extracted pictures. The Data Training model utilizes the Convolutional Neural Network to prepare data and the recognizer likewise utilizes Convolutional Neural Network to identify the emotional condition through their visage Expressions. The framework perceives the six widespread emotions as anger, disgust, happiness, sadness, surprise neutral, and contempt.

Keywords— CNN, Keras, TensorFlow, visage Expression detector and recognizer, CK+, FER2013.

1. Introduction

For facial visage emotion recognition, the traditional approaches usually consider a visage image that is distinguished from an information picture, and facial visage fragments or achievements are perceived from the appearance locale. After that diverse spatial and common features are isolated from these facial visage fragments. At last dependent on the separated highlights a classifier, for example, Keras library, TensorFlow, sequential, is trained to produce recognition results [1]. Since the Convolutional Neural Network technique requires at least hours of training, the training phase must be separate from the front-end monitoring system. In this paper, design a proper Convolutional Neural Network for Real-time human Visage Expression detection. The other one is the facial visage identification and Recognition program that accesses a camera for input video and applies facial visage detection on video frames. Next, it utilizes the facial visage pictures from facial visage detection and the yield from the preparation program for expression recognition.

Significant research has been conducted in the past to increase efficiency and resolve the issues and problems, several methods have been proposed. The following (Table 1) are some of the most important and current works that address visage expression detection challenges.

1.1. Artificial Neural Networks: An ANN is a bunch of methodologies that execute label forecasts. On the off chance that the ANN is analyzed as a black box; the info would comprise labeled models, and the yield would be a vector containing a bunch of forecasts [1] [8].

1.2. Affective Computing: The fundamental establishments at the back full of Affective processing i.e. without feelings, people would not appropriately work as sane decision-making creatures. A few researchers show that there is nothing of the sort as "pure reason" [2] [10].

1.3. Human Visage Expression Recognition: This will give Computer graphical countenances that give a more normal communication. With regards to Recognition, computers have had the option to perceive some facial visage classes: happy, surprise, anger, and disgust [3] [9].

Table 1: Table representing the summary of the latest related works [7].

Issues/ Problems	Methods	Networks Types	Datasets	Expressions /Classes	Classifier	Performance %
Imbalance and over-fitting problems	[3]	ACNN	LEW CelebA	6 classes	kNN	99.62% 88.78%
	[4]	DCNN	AffectNet	8 classes	SVM	60.70%
Intra- Class variation of FER and over-fitting problems	[4]	DCNN	AffectNet	8 classes	SVM	60.70%
	[5]	SD-CNN	CK+	8 classes	6 DiffNets	99.7%
	[6]	CNN	Oulu-CASIA RAF-DB AffectNet	6 classes 7 Classes 8 classes		NN
Illumination ,Contrast Variation and over-fitting problems	[8], [7]	CNN	CK+,KDEF, JAFFE, SFEW2.0 **	7 & 8 classes	SVM	High and Good **
	[9]	ACNN	RAF-DB AffectNet	7 Classes 8 classes	NN	85.54% 54.84%
occlusion problem	[10]	ACNN	FERPlus, RAF-DB, AffectNet, SFEW	7 & 8 classes	NN	**
Eyeglasses	[11]	ERGAN	CelebA	6 classes	NN	96.35%

1.4. Machine Learning (ML): The ML algorithm makes models based on the input data and information. These models produce a yield that is typically a bunch of expectations or choices. Then, at that point, when another necessity shows up, the model could deal with it or answers without the need adding new code [4].

1.5. Deep Learning: DNN is a piece of ANN with various mystery layers of units between the underlying and last layers. In their system, scale-invariant element change (SIFT) features contrasting with a lot of achievement centers are first removed from each facial appearance picture [5] [9].

1.6. CNN (Convolutional Neural Network): Convolutional Neural Network is a sort of feed-forward ANN. Where the organization plan between its neurons is pushed by the relationship of the animal's visual cortex. It is engaging for a few, Deep learning tasks like scene acknowledgment, NLP, and facial look appearance acknowledgment [1] [6].

2. Implementation and Framework

RTVD contains 2 parts:

1. Recognizer for validation

2. Pre-train program for data training.

The recognizer contains a facial visage detector and a visage expression recognizer. The pre-train program uses a CNN deep learning training model and all steps of the process are shown in Fig.1, 2, 3, and 4.

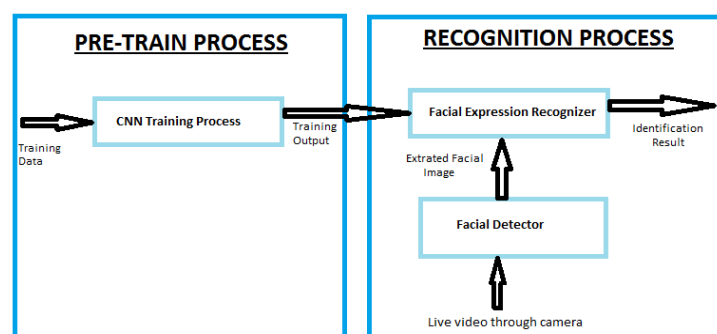


Fig1: System Design

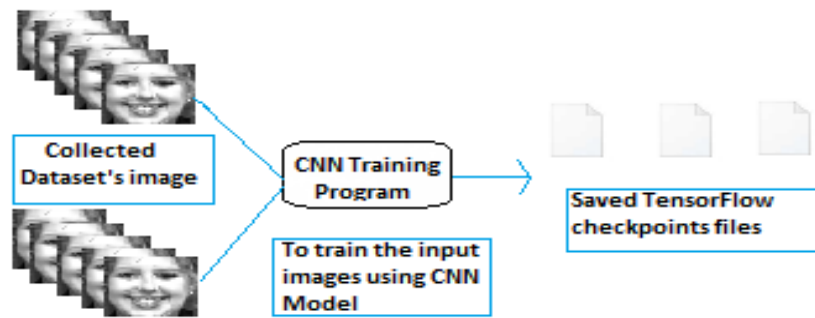


Fig. 2. The facial visage expression recognizer requires the complete result from the pre-train program to validate the facial visage image.

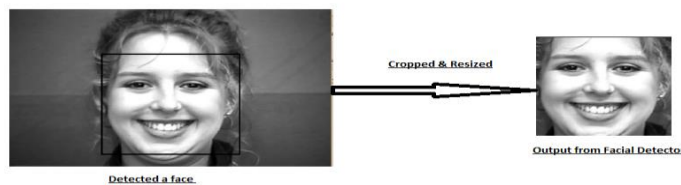


Fig. 3. Facial visages Detector - detect and extract image from video.

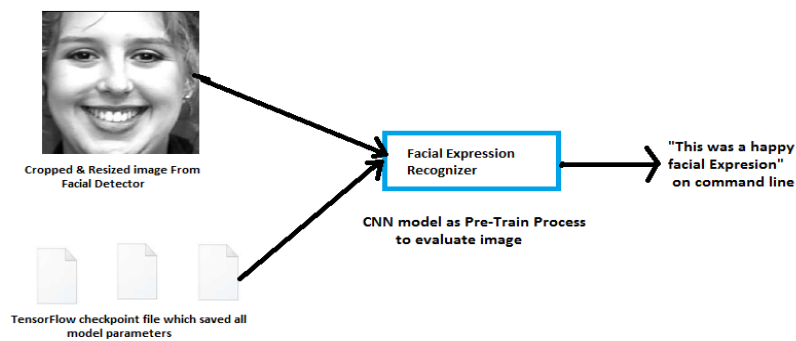


Fig. 4. Facial visage Expression Recognizer design. It uses checkpoint files from the pre-train program to evaluate the images extracted from the facial visage detector.

The facial visage expression recognizer uses the pre-train data for facial visage expression identification. The dataset is trained in the pre-train system using deep learning technology and the results are stored in checkpoint files. While the facial visage expression recognizer receives an image input, it transforms the input image into a tensor and uses the inference from the pre-train program to hypothesize the input image (Fig. 2). The output from the facial visage expression recognizer is a single expression label and it is the final system output. The facial visage detector was developed with OpenCV in python and the facial visage expression recognizer was developed with Tensorflow using the deep learning technique in python. Besides the six universal facial visage expressions: anger, disgust, fear, happiness, sadness, and surprise, the method also recognizes a neutral face. The proposed system has four options for the user. A first option is a train-only option with the command python system.py -t train file checkpoint name input size. In fig.4, the checkpoint name is the name of the checkpoint file without an extension and the name of a folder that is used to save the tensor board file. The second option is the validation-only option with the command python system.py -v validation file checkpoint name input size. This option requires a checkpoint file with completed

training data for validation purposes. The input can be either a tfrecords file or an image. The third option is the train-validate option with the command `python system.py -b train file validation file checkpoint name input size`. This option is a combination of options one and two. The last option is the live option with the command `python system.py -l checkpoint name input size`. This option requires a checkpoint file and an RGB camera for live video input.

System Model

The method used in the system is a custom CNN method to train and validate facial visage images. In the training phase, the learning rate is set to $1e-4$, the batch size is set to 32, the quantity of epochs is set to 100 and 200 (mentioned in Table 2), and drop-out is set to 50%. All input data is divided into groups of 20 and each group needs to be trained 50 times. All images that use for training purposes need to be labeled manually and converted into a binary file, tfrecords which is recommended input format for TensorFlow, with labels as the input dataset. Test dataset/data can be a single tfrecords file or a single image file. An image converter can convert all labeled images into a tfrecords file and it provides an image re-size function and image channel transform function. The CNN train Process provides a re-size function and the input data can be re-sized to a fixed size after the input layer and before the first convolutional layer as shown in Figure 5.



Fig. 5. CNN Model

3. Performance Evaluation

In this paper, applied CNN Model to our datasets and predict the outcomes. The outcomes are deciphered utilizing the confusion matrix (Fig. 7) and performance metric as accuracy metrics Fig. 6). The train: test split was 75:25. We additionally cross-validation the dataset to eliminate any predispositions. The worth of the split was picked as 5 because the resultant parts will have the same number of pictures as our 25% test set. The outcomes are Fig.6, 7, 8, and 9 as per the following:

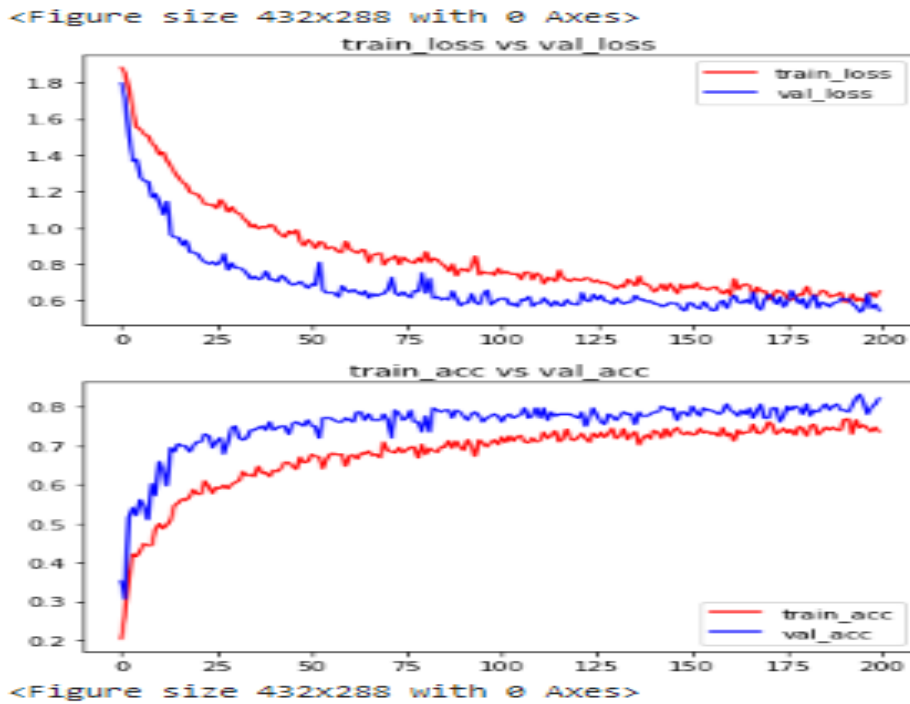


Fig. 6. shows the Visualization of the predicted testable dataset loss and accuracy curve.

		CNN Emotion Classify						
		anger	contempt	disgust	fear	happy	sadness	surprise
True class	anger	23	1	0	0	0	1	0
	contempt	3	3	3	0	0	0	0
	disgust	0	1	42	0	1	0	0
	fear	0	0	5	0	5	0	0
	happy	0	0	0	0	36	0	1
	sadness	2	0	0	0	1	5	3
	surprise	0	0	0	0	0	4	57
			anger	contempt	disgust	fear	happy	sadness

Fig. 7. Shows the plotting of the confusion matrix.

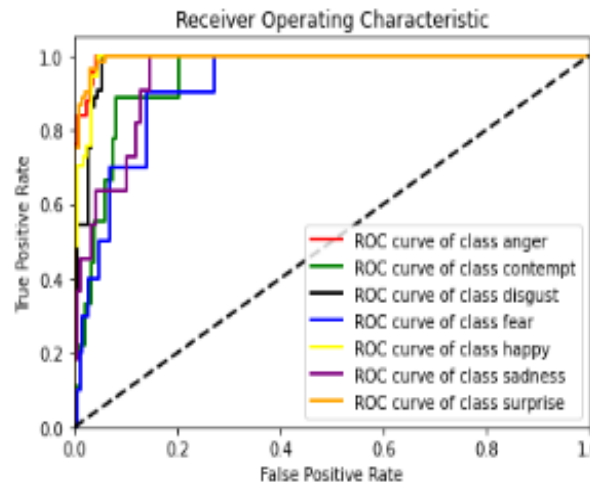
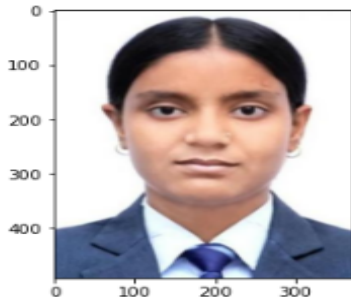


Fig. 8. Shows the plotting of the Receiver Operating Characteristic curve (ROC).

```
img = cv2.imread('/content/drive/MyDrive/nandani/nandaniimage.jpg')
plt.imshow(img[:,:,:-1])
plt.show()
```



```
result = DeepFace.analyze(img, actions = ['emotion'])
```

Fig.9. shows the result of the RBG image as an output.

Table 2: comparative summary results of ck+ and fer2013 datasets

Factors/datasets	CK+		FER2013
	100 epochs	200 epochs	100 epochs
Number of Facial visage Expressions	6 Universal emotions added with contempt		6 Universal emotions added with neutral
Number of Experimental Images	981		28812
Score Accuracy	79.08(H)	83.23(H)	69.34 (H)
Score Loss	57.01(L)	60.29(L)	30.98 (L)
Train Accuracy & Loss	69.68 & 30.31	73.50 & 26.49	62.43 & 30.32
Test Accuracy & Loss	78.06 & 21.93	82.14 & 17.85	70.0 & 34.09
Batch size	8 & 32	8 & 32	32
Value Index	4		4
Total and Trainable Parameters	217983		217983
Predicted Test Accuracy & Loss	82.23 & 48.21	84.26 & 40.39	70.56 & 30.43

The proposed scheme was compared with some other schemes table 1 to table 2 like DCNN [4], CNN [6] and ACNN [9]. It is found that the proposed scheme performs better in terms of in types of networks and layering with CK+ and FER2013 Datasets.

CONCLUSION

This paper evaluation and categorize Human facial visage Expression over static facial visage pictures utilizing a Deep learning methodology. This is a difficult issue that has effectively been moved toward a few times with various Techniques and methodologies. While great outcomes have been accomplished utilizing visage learning techniques, this paper focused on including CNN, which is one of the Deep Learning guarantees with FER2013 and CK+ datasets.

In this paper, the efficiency of detection and recognition is increased and achieve this by planning a CNN model to recognize human facial visage emotions of the six widespread Expressions in addition

to Neutral and contempt utilizing TensorFlow and Keras.

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