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Facial Expression Recognition Using CNN

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ABSTRACT

This study proposes a novel method for addressing the problem at hand for detecting facial expressions has been developed. Because of the individuality associated with each human's emotions, facial expression recognition is a fascinating research area. Deep Learning is a cutting-edge area of machine learning that excels in solving picture categorization challenges. With excellent accuracy, feature extraction has been accomplished using Deep Learning techniques, mainly Convolutional Neural Networks (CNN). Each face picture in this study is categorized into one of the seven categories of human emotions using a specifically created convolutional neural network. The model was developed using the data set from the Kaggle Facial Expression Recognition Competition namely FER2013, which contains 35,887 grayscale 48 by 48-pixel images.

KEYWORDS: Deep Learning, CNN, Facial Expression Recognition

1. INTRODUCTION

Without speaking a word, it may convey a wide range of feelings. Facial expression recognition extracts emotion from a facial picture and uses it to determine an individual's mood and personality. The six universally recognized fundamental emotions—anger, fear, disgust, sad, surprise, and happiness—were identified by American psychologists Ekman and Friesen in the 20th century. Due to

its effects on clinical treatment, social robots, and education, facial expression recognition has received a lot of attention lately. Several studies have shown that emotions are significant in teaching. Exams, questionnaires, and observations are currently used by teachers as sources of feedback; however, these traditional approaches are frequently ineffective. The instructor can modify their method

and their educational materials based on the facial expressions.

The goal is to teach computers to perceive and interpret visual information in a way that is similar to how humans do, and to produce the desired output based on that input. However, achieving this level of sophistication can be a complex and challenging undertaking. One specific challenge is the need to account for individual differences in how people express visual information, which can make it difficult to develop computer algorithms that work consistently and accurately.

2.LITERATURE SURVEY

Deep Learning is a dominant subset of Machine Learning, particularly in the context of processing image data. Unlike traditional Machine Learning models, Deep Learning models are better equipped to handle large image datasets with higher efficiency. In addition, Deep Learning algorithms are capable of assessing the accuracy of their own predictions, making them more autonomous and reliable in producing accurate results. Hong Wei NG and colleagues utilized a transfer learning method that leveraged pre-trained Deep CNN architectures on the ImageNet dataset. They then fine-tuned the network in two stages by utilizing two distinct datasets. Through their experiments, they found that this multi-stage fine-tuning

approach resulted in superior performance [1]. Similarly,[2] another study proposed a face detection classification network composed of multiple deep CNNs.

Several studies have proposed different methods for facial expression recognition. Heechul Jung and colleagues utilized a two-stage approach that first detected the face using Haar-like features .They correlated two types of deep networks then found that the convolutional neural network outperformed the other neural network [3]. Similarly,[4] Ma Xiaoxi and colleagues employed a Deep Boltzmann Machine and SVM, while Ali Mollahosseini and colleagues designed a network consisting of convolutional and Inception layers [5]. A novel offered Abir Fathallah CNN-based architecture for facial expression recognition, which was fine-tuned using the Visual Geometry Group model and achieved better results [6]. Neha Jain and colleagues implemented a network hybrid Convolution-Recurrent Neural Network method that extracted image patterns using Convolution layers [7] and considered temporal dependencies during classification using Recurrent Neural Network layers. Finally, [8] Bazrafkan highlighted the importance of using consistent databases for training and testing, as using different databases can result in lower accuracy in predicting emotions.

3. PROPOSED METHODOLOGY

Our proposed the system first recognizes the face in the input image, and then it crops and normalizes the identified faces to a size of 48x48. These facial photos are then sent into CNN. The output, which includes findings for facial expression recognition.

Convolutional Neural Networks are a subset of deep learning, and their ability to independently assess if an estimate is true or not is one of the reasons that deep learning is preferred over machine learning. Moreover, Deep Learning networks outperform traditional ML algorithms when dealing with vast amounts of data, and picture categorization is an area where Deep Learning has outperformed Machine Learning in terms of quality. Convolutional Neural Networks, or ConvNets, are similar to standard Neural Networks in many ways.

3.1 CONVOLUTION LAYERS

The Convolutional Neural Network (CNN) consists of three main types of layers: the The First Layer extracts features from the input image using a filter of a particular size, generating a feature map that preserves the spatial relationship between pixels. Feature map size can be reduced using Max, Average or Sum pooling, and

acts as a bridge between the Convolution Layer and the Fully Connected Layer. The third layer contains the weights, biases, and neurons that connect neurons between two different layers and performs mathematical operations on the flattened vector from the previous layer, facilitating the classification process. Two fully connected layers are often used to improve performance and automate feature extraction. Overall, these layers work together to extract meaningful input image features and classify it accurately.

3.2 BLOCK DIAGRAM:

The objective of this project is to use a Convolutional Neural Network to accurately detect the emotions displayed on human faces. The network architecture consists of three convolutional layers go along with a pooling layer, fully connected layer at the end.

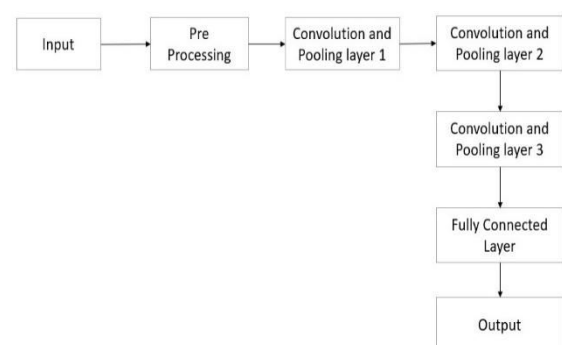


Fig 1. Flow chart

In the fully connected layer to produce the final output an activation function namely Softmax is used. The combination of these

layers enables extract meaningful features from the input image, allowing it to accurately classify the emotion displayed on the face.

3.3 DATASET:

This model has been trained using the FER2013 dataset. This dataset comprises 35,887 grayscale images of human faces, each with dimensions of 48 by 48 pixels. To evaluate the model's performance, we split the dataset into three parts in the ratio of 80:10:10 for training, cross-validation and testing.

```
WARNING:tensorflow:From /usr/local/lib/python3.8/dist-packages/tensorflow/python/compat/v2_compat.py:187: disable_resource_variables (from tensorflow.python.ops.variable_scope) is deprecated and will be removed in a future version.
Instructions for updating:
non-resource variables are not supported in the long term
model.fit_generator(train_generator, steps_per_epoch=batch_size, epochs=epochs) #train for randomly selected one
Instance length: 2104
25000 train samples
3100 test samples
Epoch 1/100: 16s 28ms/step - batch: 127.5000 - size: 253.4336 - loss: 1.7960 - acc: 0.2533
Epoch 2/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 1.5853 - acc: 0.3661
Epoch 3/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 1.4177 - acc: 0.4510
Epoch 4/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 1.2977 - acc: 0.5012
Epoch 5/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 1.2180 - acc: 0.5364
Epoch 6/100: 7s 28ms/step - batch: 127.5000 - size: 253.4336 - loss: 1.1556 - acc: 0.5626
Epoch 7/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 1.0961 - acc: 0.5853
Epoch 8/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 1.0383 - acc: 0.6054
Epoch 9/100: 7s 27ms/step - batch: 127.5000 - size: 253.4336 - loss: 0.9810 - acc: 0.6313
Epoch 10/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.9283 - acc: 0.6548
Epoch 11/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.8685 - acc: 0.6735
Epoch 12/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.8087 - acc: 0.6987
Epoch 13/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.7486 - acc: 0.7282
Epoch 14/100: 7s 27ms/step - batch: 127.5000 - size: 253.4336 - loss: 0.6881 - acc: 0.7463
Epoch 15/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.6244 - acc: 0.7677
Epoch 16/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.5657 - acc: 0.7929
Epoch 17/100: 7s 28ms/step - batch: 127.5000 - size: 253.4336 - loss: 0.5026 - acc: 0.8134
Epoch 18/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.4535 - acc: 0.8315
Epoch 19/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.4136 - acc: 0.8478
Epoch 20/100: 7s 27ms/step - batch: 127.5000 - size: 253.4336 - loss: 0.3734 - acc: 0.8634
Epoch 21/100: 7s 27ms/step - batch: 127.5000 - size: 255.1445 - loss: 0.3218 - acc: 0.8838
Epoch 22/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.2637 - acc: 0.9106
Epoch 23/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.2077 - acc: 0.9336
Epoch 24/100: 7s 27ms/step - batch: 127.5000 - size: 253.4336 - loss: 0.1553 - acc: 0.9510
Epoch 25/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.1070 - acc: 0.9639
Epoch 26/100: 7s 27ms/step - batch: 127.5000 - size: 255.1445 - loss: 0.0603 - acc: 0.9799
Epoch 27/100: 7s 28ms/step - batch: 127.5000 - size: 253.4336 - loss: 0.0734 - acc: 0.9757
Epoch 28/100: 7s 27ms/step - batch: 127.5000 - size: 253.4336 - loss: 0.0531 - acc: 0.9818
Epoch 29/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.0569 - acc: 0.9825
Epoch 30/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.0385 - acc: 0.9871
Epoch 31/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.0784 - acc: 0.9739
Epoch 32/100: 7s 27ms/step - batch: 127.5000 - size: 253.4336 - loss: 0.0606 - acc: 0.9794
Epoch 33/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.0476 - acc: 0.9831
Epoch 34/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.0564 - acc: 0.9800
Epoch 35/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.0557 - acc: 0.9800
Epoch 36/100: 7s 27ms/step - batch: 127.5000 - size: 253.4336 - loss: 0.0627 - acc: 0.9784
Epoch 37/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.0576 - acc: 0.9803
Epoch 38/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.0499 - acc: 0.9833
Epoch 39/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.0443 - acc: 0.9850
Epoch 40/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.0642 - acc: 0.9790
Epoch 41/100: 7s 27ms/step - batch: 127.5000 - size: 253.4336 - loss: 0.0494 - acc: 0.9832
Epoch 42/100: 7s 28ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.0512 - acc: 0.9822
Epoch 43/100: 7s 27ms/step - batch: 127.5000 - size: 253.4336 - loss: 0.0507 - acc: 0.9802
Epoch 44/100: 7s 27ms/step - batch: 127.5000 - size: 255.1445 - loss: 0.0454 - acc: 0.9847
Epoch 45/100: 7s 27ms/step - batch: 127.5000 - size: 253.4336 - loss: 0.0504 - acc: 0.9826
Epoch 46/100: 7s 27ms/step - batch: 127.5000 - size: 253.4336 - loss: 0.0523 - acc: 0.9833
Epoch 47/100: 7s 27ms/step - batch: 127.5000 - size: 254.2891 - loss: 0.0488 - acc: 0.9854
```

Fig: Trained model

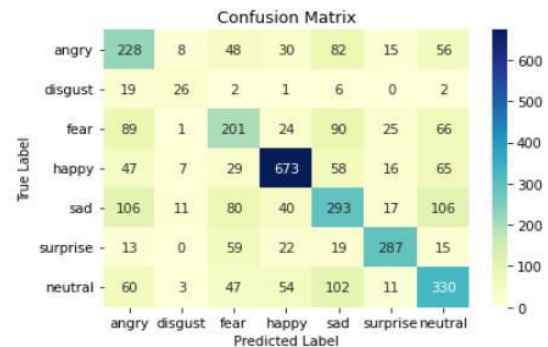


Fig : Confusion matrix

According to the dataset, detecting the emotion of happiness was the easiest task with an accuracy of 0.88, followed by

surprise with an accuracy of 0.81. However, predicting the emotion of fear proved to be difficult with least accuracy of 0.47. On average, the accuracy for all seven different emotions was approximately 0.64.

3.4 RESULTS OF TRAINED MODEL:

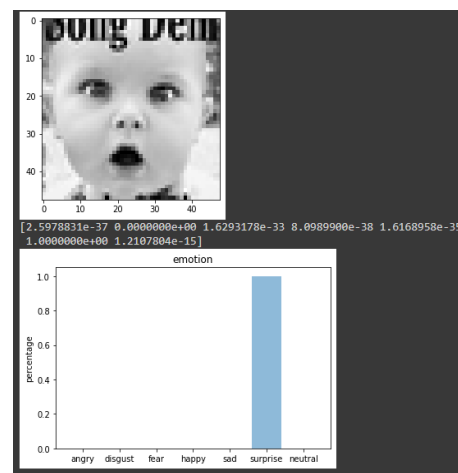


Fig: Trained model surprise image

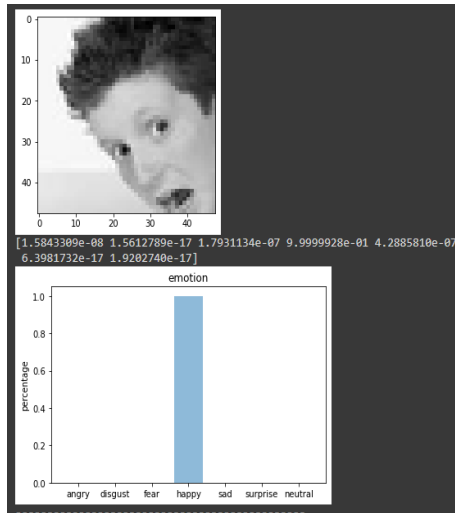


Fig: Trained model happy image

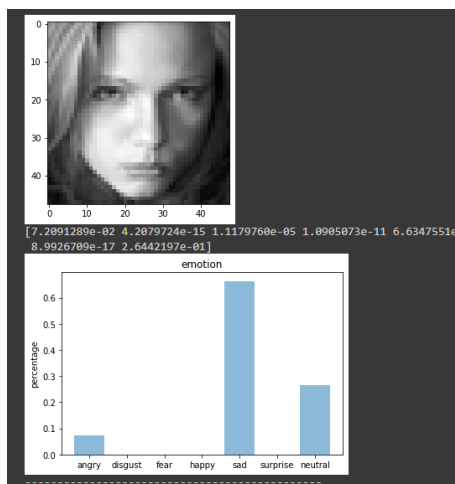


Fig: Trained model false prediction

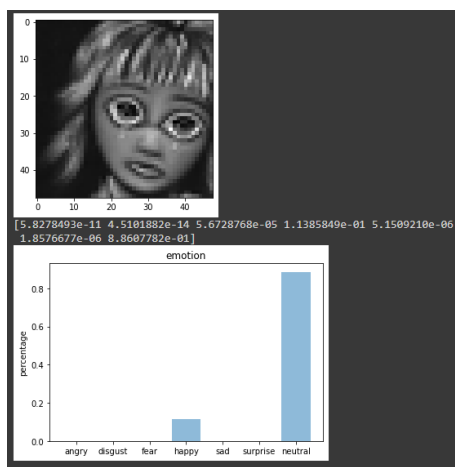


Fig: Trained model false prediction

4.RESULT ANALYSIS:

To improve the networks rate of learning, a Batch Normalization Layer has been added after the convolutional layers. Nonlinearity is introduced in the network through the Activation Layer, and the Pooling Layer. The model has been trained using 80% of the data from the FER2013 dataset for a total of 60 epochs, as indicated by the graph. The proposed architecture's configuration is presented in Table 1, which provides different stages of output layers.

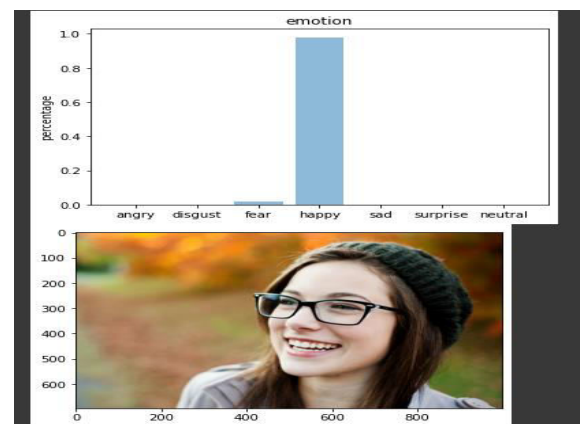


Fig : Emotion detection on an image

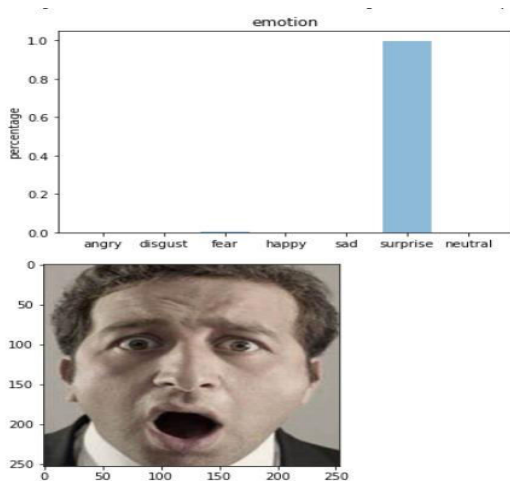


Fig : Detection of an emotion

5.CONCLUSION:

Facial Emotion Recognition has been extensively studied due to its numerous practical applications.

A neural network architecture is proposed for recognizing facial emotions in images, which includes 3 convolutional layers, 3 pooling layers, and a fully connected layer with an activation function namely Softmax.

The FER2013 is used to trained the proposed model and can be evaluated on both dataset images and saved or captured images from a webcam.

The model performs best in recognizing Happy and Surprise emotions, while it struggles to accurately predict Fear and Anger emotions.

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