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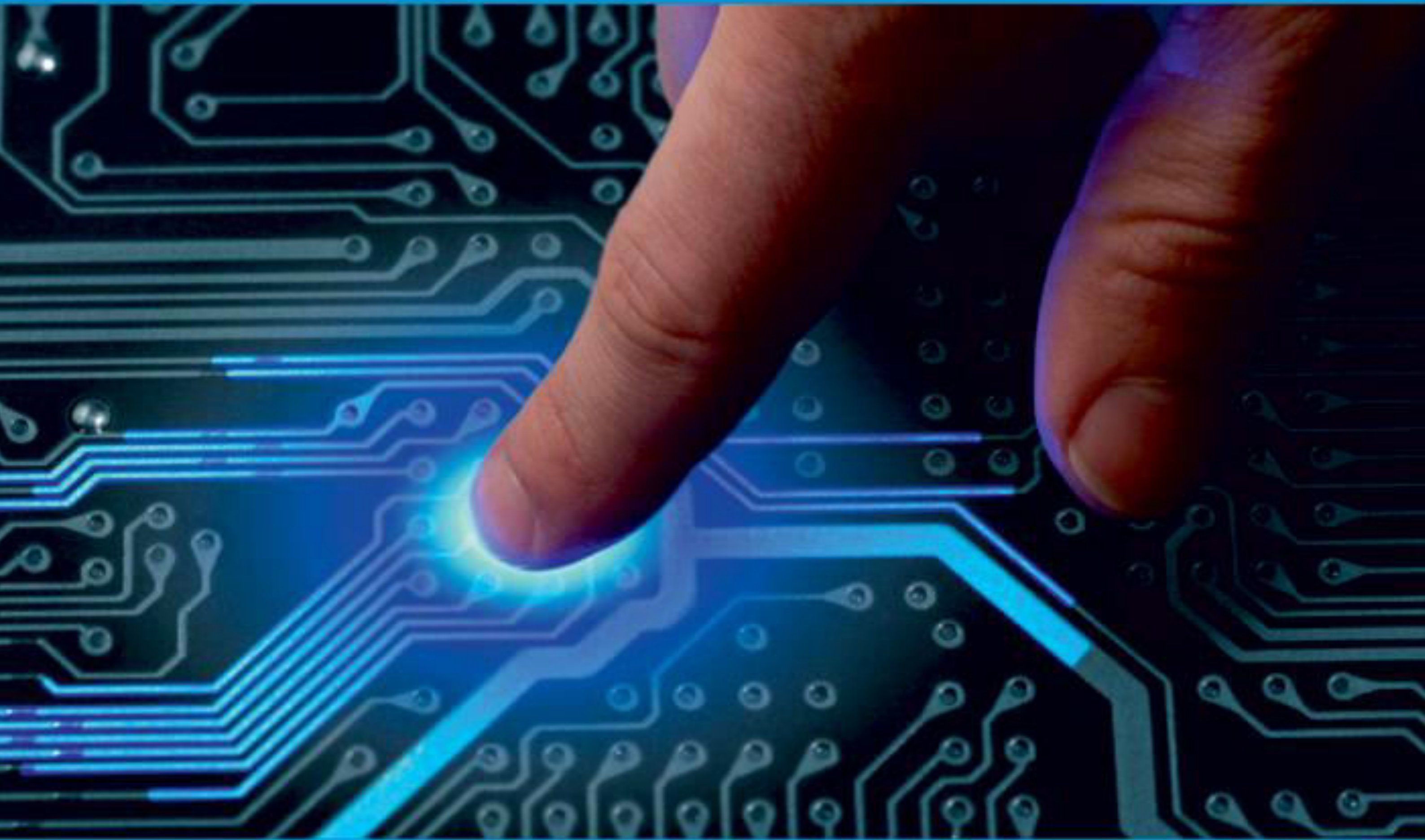

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Emotion Detection Using Facial Recognition

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ABSTRACTFacial detection of emotions of humans from the image is considered to be one of the accidents and sequential tasks in research of social communication. The method that results in better execution than any conventional method that requires the processing of images is the detection of emotions that is based on Deep Learning. This paper consists of the design of a process that can detect emotions using facial expressions. It depicts the basic three main steps in the emotion detection procedure: detection of face, extraction of features, and classification of emotions. It proposes a convolutional neural network (CNN) based deep learning architecture. The proposed method performance is evaluated using two datasets Facial Emotion Recognition Challenge (FERC-2013) and Japanese Female Facial Emotion (JAFFE).The resulting accuracies with this model are 98.65 and 70.14 percent for JAFFE and FERC2013 datasets respectively.

KEYWORDS: Artificially intelligence (AI), Facial emotion recognition (FER), Convolutional neural networks (CNN), Rectified linear units (Re004Cu), Deep learning (DL).

I. INTRODUCTION

Emotion is a conscious mental reaction (such as anger or fear) subjectively experienced as a strong feeling usually directed toward a specific object and typically accompanied by physiological changes in behavior in the body associated with the nervous system. Recognition of faces in images and videos for various applications is one of the current applications ofusing neural networks. Other applications of face detection include using it forobservation purposes by law enforcers and in civil orders. Identifying some emotions such as anger,happinesssadness, surprise,fear,and neutrality using a method presented here.

II. RELATED WORK

A. A. Human Facial Expressions

Humans interact through facial expressions and body language. Charles Darwin has already published on facial expressions in the 19th century. These play an important role in nonverbal communication. Ekman Friesen made sure that facial behaviors must be correlated with specific emotions. Humans and also animals produce particular muscle movements which get included in a specific mental state.

B. Image Classification Techniques

It generally consists of feature extraction followed by a classification stage. Also, different approaches work equally well. However, based on the current availability of training data and computational power, the performance of models can be substantially improved. Several recent milestones are listed below.

• Krizhevsky and Hinton gave a huge publication on image classification in general. This work shows a deep neural network that resembles the human visual cortex’s functionality. A model to categorize objects from pictures is obtained using a self-developed labeled array of 60,000 images over 10 classes, using the CIFAR-10

dataset. Another important result of the research is the visualization of the filters in the network.

- In 2010, the onset of the annual Imagenet challenges energized work on the classification of images, and since then the existing massive collection of labeled data is often used in publications.
- Regarding facial expression recognition, a method was presented in which a network of deep beliefs is primarily used with expanded databases. The results are comparable to the accuracy obtained below.95 percent of the same database by other methods, such as support vector machine (SVM) and learning vector quantization (LVQ).
- The dataset used now is the Facial Expression Recognition Challenge (FERC-2013) resulted in an average accuracy of 67.02 percent on emotion classification.

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III. PROPOSED SYSTEM

A.Emotion Detection Using Deep Learning

In this paper, we use the deep learning (DL) open library "Keras" provided by Google for facial emotion detection.We use two different datasets and train with our proposed network and evaluate its validation accuracy and loss accuracy. Images extracted from m given dataset which has facial expressions for seven emotions, and we detected express using of an emotion model created by a CNN using deep learning. We have changed a few steps in CNN as compared to the previous method using a keKerasibrary given by Google and also modified CNN architecture which give better accuracy. We implemented emotion detection using keKerasith the proposed network.

B.CNN Architecture

The networks are programmed on top of Kerasras, operating on Python, using Kerastase learn library. This environment reduces the code's complexity since only the neuron layers need to be formed, rather than any neuron. The software also provides real-time feedback on training progress and performance and makes the model after training easy to save and reuse. In CNN architecture initially, we have to extra can t input image of 48*48*1 from dataset FERC-2013. The network begins with an input layer of 48 by 48 which matches the input data size parallelly processed through two similar models that is functionality in deep learning, and then concatenated for better accuracy and getting features of images perfectly as shown in Fig.1 which is our proposed model, Model-A. There are two sub-models for the extraction of CNN featthatshare this input and both have thesame kernelsize. The outputs from these feature extraction sub-models are flattened into vectors and concatenated into one long vector matrix and transmitted to a fully connected layer for analysis before a final output layer allows for classification. This model contains a convolutional layer with 64 filters each witha normalization layer and, a max-pooling layer, followed by one more convolutional layer, max pool, and ng, flatten respectively. After that, we concatenate two similar models and linkthem to a softmax output layer that can classify seven emotions. We use a dropout of 0.2 for reducing over-fitting. It has been applied to the fully connected layer and all layers contain units of rectified linear units (ReLu) activation function. First, we are passing our input image to a convolutional layer which consists of 64 filters each of size 3 by 3, after that it passes through local contrast normalization and can remove the average from neighborhood pixels leading to get quality of feature maps, followed by ReLu activation function. Maximum pooling is used to reduce spatial dimension reduction so processing speed will increase. We are using concatenation for getting the features of images (eyes, eyebrows, lips, muth,etc) perfectly so that prediction accuracy improved as compared to the previous model. Furthermore, it is followed bya fully connected layer and softmax for classifying seven emotions. A second local max-pooling is added to the numberdimensionalities Here, we use batch normalization, dropout, ReLu activation function, categorical cross-entropy loss, adam optimizer,andsoftmax activation function in the output layer for seven emotion classification.
In the JAFEE data set, imagine the size of input issued to that 128*128*3. The network starts with an input layer of 128 by 128 which matches the input parallellyprocessed through two similar models as shown in Fig.1.Also, it is connected and passed through one more softmax layer for emotion classification and all procedure is the same as above.In Model-B, the network starts with a 48 by 48 input layer, which matches the size of the input data. This layer is preceded by one convolutional layer, a local contrast normalization layer, and one layer of max pooling, respectively. Two more convolutional layers and one fully connected layer, connected to a softmax output layer, complete the network. Dropout has been applied to the fully connected layer and all layers contain units of ReLu.

IV. EXPERIMENT DETAILS

We develop a network based on the concepts to assess the two models (Model-A and ModelB) mentioned above on their emotion detection capability. This section describes the data used for training and testing, explains details of the used data sets, and evaluates the results obtained using two different datasets with two models.

Datasets

Neural networks, and particularly deep networks, needs a large number of training data and the choice of images used for the training is responsible for a large part of the set that is both high quality and quantitative. Several datasets are available for research using seep learning with our proposed model which gives better results than private our model. In the proposed method, computation time reduces, validation accuracy increases and loss also decreases, and further performance evaluation is achieved which compares our model with the previous existing model. We tested our neural network architectures on FERC-2013 and JAFFE database which contains seven primary emotions like sadness, fear, happiness,anger, neutral, surprised, and disgust. Fig.2 shows theproportions of detected emotions in a single image of

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FERRecognize emotions, ranging from a few hundred high-resolution photos to tens of thousands of smaller images.The datasets primarily vary in the amount, consistency, and cleanness of the images. For example, the FERC-2013 collection has about 32,000 low-resolution images. It can also be noted that the facial expressions in the JAFFE (i.e. further extended as CK+) are posed (i.e. clean), which makes it harder to interpret the images from the FERC 2013 set, but given the large size of robustness can be beneficial for the diversity.

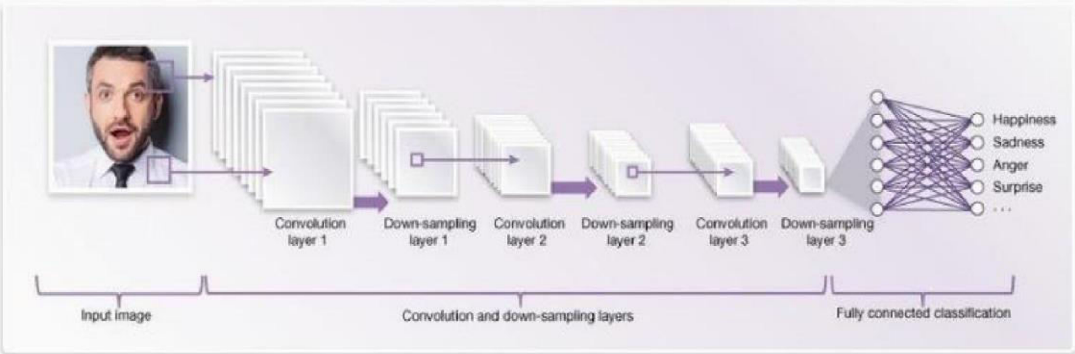

Fig I: Network Architecture

Training Details

We train the network using GPU for 100 epochs to ensure that the precision meets the optimum. The network will be trained on a larger set. Training will take place with 20,000 pictures from the FERC-2013 dataset instead of 9,000 pictures. The FERC-2013 database also uses newly designed verification (2000 images) and sample sets (1000 images). It shows a number of emotions in the final testing and validation set after training and testing our model. The accuracy will be higher on all validation and test sets than in previous runs, meaning that emotion detection using deep convolutional neural networks can improve the performance of a network with more information.

Emotions	Angry	Sad	Happy	Disgust	Fear	Neutral	Surprise
Angry	56	12	3	9	8	11	1
Sad	10	69	2	6	9	2	2
Happy	0	0	95	0	0	3	2
Disgust	7	13	0	63	8	5	4
Fear	9	8	3	2	65	10	3
Neutral	2	1	8	1	7	75	6
Surprise	7	3	11	0	3	8	68
Average accuracy = 70.14(%)							

TABLE I: Confusion Matrix (%) for emotion detection using the proposed model

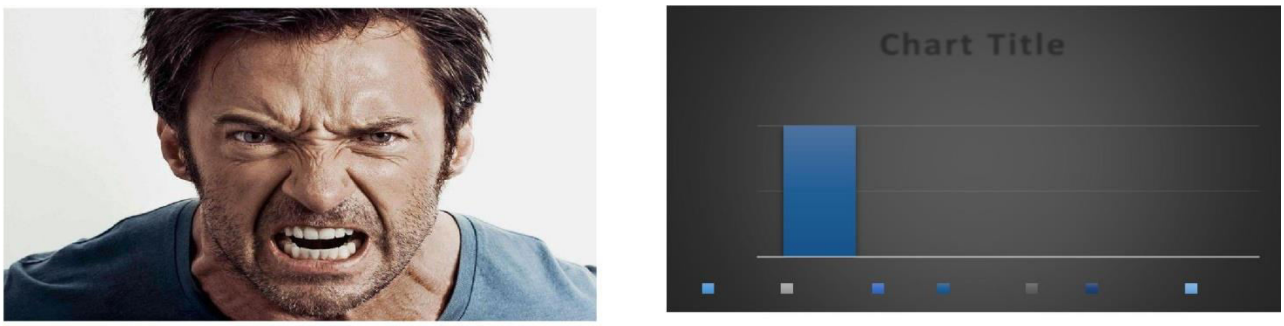

Fig 2: (a) Image , (b) Properties of emotions

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Results using Proposed Model

In emotion detection we are using three steps, i.e., face detection features extraction and emotion classificationdataset. Fig.2(a) shows the image, whereas the detected emotion proportions are shown in Fig.2(b). It is clearly observable that anger has a higher proportion than other emotions. That means the emotion detected in this image (in Fig.2(a)) is anger. Similarly, Fig.3 showsanother image and corresponding emotional proportions. From Fig.3(b), it is observable that happy emotion has a higher proportion than others. That suggests that the image of Fig.3(a) detects happy emotions.Similarly, performance is evaluated for all the test images of the dataset. We have achieved 95% for happy, 75% for neutral, 69% for sad, 68% for surprise, 63% for disgust, 65% for fear, and 56% for angry. On average we are getting average accuracy of 70.14% using our proposed model. The confusion matrix of classification accuracy is shown in TABLE I. We get an average validation accuracy of 70.14% using our proposed model in facial emotion detection using the FER dataset.

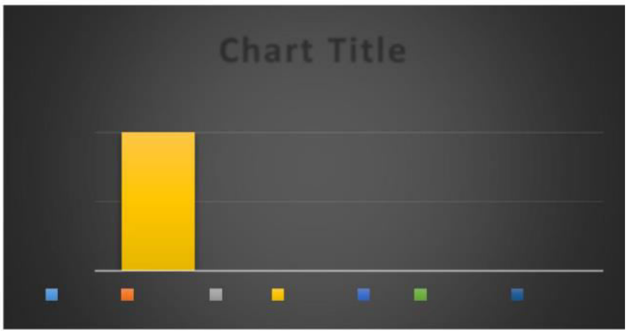

Fig 3: (a) Image , (b) Properties of emotions

V. PERFORMANCE EVALUATION

In the FER dataset, we train on 32,298 samples which arevalidated on 3589 samples, and in the JAFFE dataset, we train 833 samples, which are validated on 148 samples Different combinations of these parameters have been tested to find out how to achieve the better recognition rate. From Table II, it is observed that our proposed model shows 70.14% average accuracy compared to the 67.02% average accuracy reported in model B FOR FER dataset. In this case of the JAFFE database, we achieved an average accuracy of 98.65% which is also higher than model B.

VI. CONCLUSION

In this paper, we have proposed a deep learning-based facial emotion detection method from images. We discuss our proposed model using two different datasets, JAFFE and FERC-2013. The performance evaluation of the proposed facial emotion detection model is carried out in terms of validation accuracy, computational complexity, detection rate, learning rate, validation loss, and computational time per step. We analyzed our proposed model using trained and test sample images, and evaluate their performance compare to a previously existing model. Results of the experiment show that the modelproposed is better in terms of the results of emotion detection than previous models reported in the literature. The experiments show that the proposed model is producing state-of-the-art effects on both two datasets.

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