



Image Emotion Classification using deep learning

V.Sharmila¹, J.Sherine Glory², P.Ezhumalai³, Madana Gopichand⁴, Madhanagopal G⁵, Karankumar S⁶

^{1,2}Assistant Professor, Department of Computer Science and Engineering R.M.D. Engineering College (Autonomous), Chennai

³Professor and Head, Department of Computer Science and Engineering R.M.D. Engineering College (Autonomous), Chennai

^{4,5,6}Student, Department of Computer Science and Engineering R.M.D. Engineering College (Autonomous), Chennai

***Corresponding author:** Assistant Professor, Department of Computer Science and Engineering R.M.D. Engineering College (Autonomous), Chennai, Email: sharmilavaradhan@gmail.com

Submitted: 19 March 2023; Accepted: 13 April 2023; Published: 11 May 2023

ABSTRACT

Behavioral poses and facial expressions and recognizing them is an interesting field of research. Humans have various emotions with multiple intentions so tremendous research has undergone to understand and analyze the emotion. In this paper, we have presented a method for image emotion detection under a study of facial expression analysis. The neural network solutions and the image processing technique are used to recognize and classify the face image expression: Happy, Neutral, Cry, and Angry. Color images of the face are taken as the input. The algorithm that we use here to implement the face image emotion deduction is Convolution Neural Network. Then we have data set images in the form of pixels with a list of trained datasets of emotions. After image-processing with multiple features extract a set of feature points from the images of the face, and training and testing data sets are split by using these features. By using various classifiers, we train the model and find the accuracy of the model. Finally, we use algorithms to predict the image emotion.

Keywords: *facial emotion recognition, deep neural networks, database, automatic recognition, etc*

INTRODUCTION

Deep Learning

Ai technology have long gone as a long way as giving computer systems the capacity to examine facts understand styles expect destiny results and take motion deep getting to know is one of the key derivatives of and with its clever computing and self-getting to know competencies it is paving the manner for the following virtual revolution throughout a myriad of industries so what precisely is deep getting to know is a complicated shape of synthetic intelligence that permits machines to method

facts and examine logical conclusions in a manner that mimics the concept method of a human using an synthetic neural community this is constituted of more than one and hierarchical layers of deep getting to know's set of rules constantly filters its inputted facts via every layer till it reaches a end at the lowest layer every layer incorporates deep neural networks which use beyond schooling facts to carry out complicated operations along with discerning styles extrapolating records and connecting more than one portions of facts the primary layer methods the preliminary inputted facts and its

operations together yields a chunk of records concerning that facts earlier than passing it right all the way down to the following layer then completes the equal method with its given records after which passes its amassed records right all the way down to the following layer this method maintains via a plethora of layers with every layer contributing a chunk of records that provides to the records given to it via way of means of the preceding layer with every degree the amassed records will become more and more complicated and finished permitting the very last layer to give the found out end basically deep getting to know is a self-getting to know

method as one layer teaches the following and so on similar to the neurons of a human mind deep-getting to know perpetuates the getting to know the method via way of means of feeding itself greater facts for greater records.

Characteristic Of Deep Learning

- ✓ Supervised, Semi-Supervised or Unsupervised
- ✓ Huge Amount of Resources
- ✓ A large number of layers in Model
- ✓ Optimizing Hyperparameters
- ✓ Cost Function

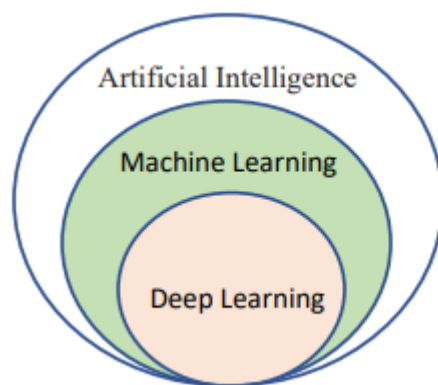


FIG 1: Venn Diagram

LITERATURE SURVEY

Emotion recognition classification methods

Author: Andrew Koch

Year: 2018

He has presented a comparison of the performances of different classification methods for the task of classifying facial emotions given a 5-dimensional principal component reduction of the local phase quantization and Pyramid of Histogram Gradients. These results are used to compare the results obtained and presented in a paper on static facial expression analysis, with a comparison being made to the methods used. It was found that a decision tree-based method was better at dealing with overfitting than a deep neural network.

PROBLEM STATEMENT

To accurately predict the facial emotion recognition from the image by a deep learning model by convolution neural network schema which efficiently classifies the results accuracy by comparing with the convolution architecture.

Existing System

They propose a commonplace for representations of non-similar features of the corpus and then search for relationships between objects and limiting the introduction of the regression. The discriminant was worn as a measure of skewness to reduce. The difference in distribution and the distinction allying both domains is important for the field problem and transformational learning algorithms for emotion recognition in speaking tasks.

Disadvantages:

- They are used to analyze sound frames but sounds alone do not contain human emotions. They cannot discover human expression based on voice.
- They are not voice-only predicting human current expression, because sad people same time expression happy speech but the human not happy, this speech only does not predict human expression.

Proposed System

To classify facial expressions, we decided to design a deep learning technique that those who use less software can also use easily. More image samples are collected, including different classes like happy, angry, sad, and neutral. Various images were collected for which class was specified into database images, an image which is given as an input. images based on directional features of shape and texture. Example screenshot showing facial emotion detection using color-based segmentation model.

Ascendency

- Facial emotional expressions also called non-oral communication
- Improves detection of image facial emotion

SYSTEM ARCHITECTURE

A disease Database is assisted with the feature Extraction module later the input is provided to the Feature selection module and cross-checked with the Feature Extraction module and further processed with the Deep Learning algorithms and classifies the emotion and gives the output.

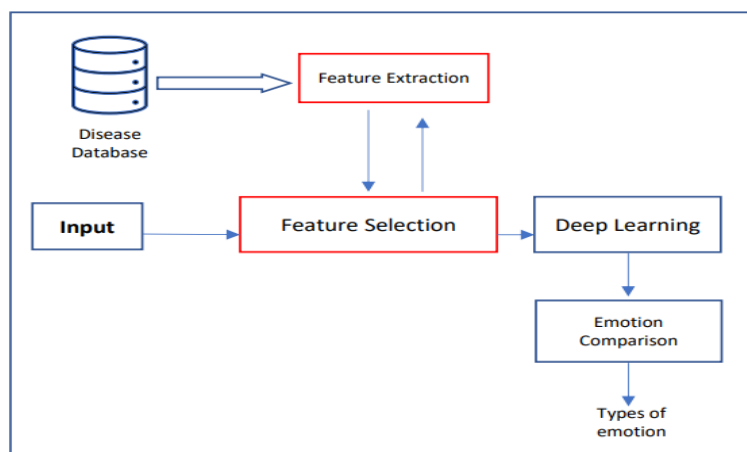


FIG 2: System Architecture

SYSTEM MODULES

This module tells what sought of information will enter and leave the system, how the data was progressed in the system, and where the data will be stored. Parallelism is not the same as traditionally flowchart structures that rely on

control flow or UML activity flow diagrams, this diagram resembles both as a confined model. A flow chart of data is also studied as a bubble_chart. This design tool is used in a Top-down path to system symbols owned by DFD and notation that describes the four components of a data flow diagram.

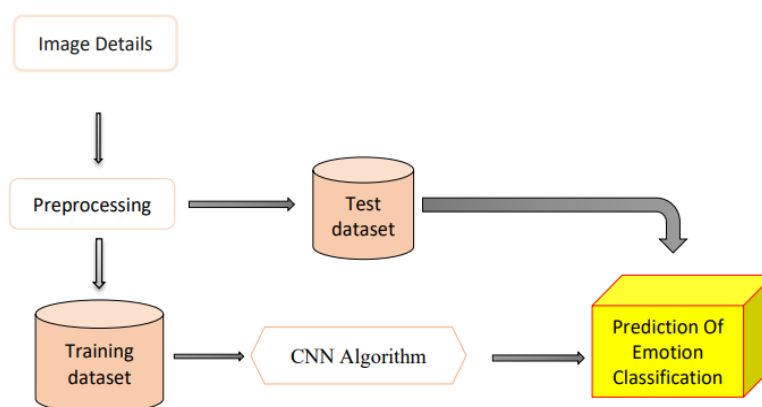


FIG 3: Process of a dataflow diagram

It is evident that the image will be processed and then passed into the Training Dataset and undergoes a convolution neural network algorithm in the other hand the processed image will be sent to the Test dataset finally, the correct emotion in the image will be sent as output by the

emotion classification prediction model and in the below convolution Diagram it is evident that the features been first extracted from the image and it sent to convolution layer and the expanded feature by the convo layer will be sent to pooling layer.

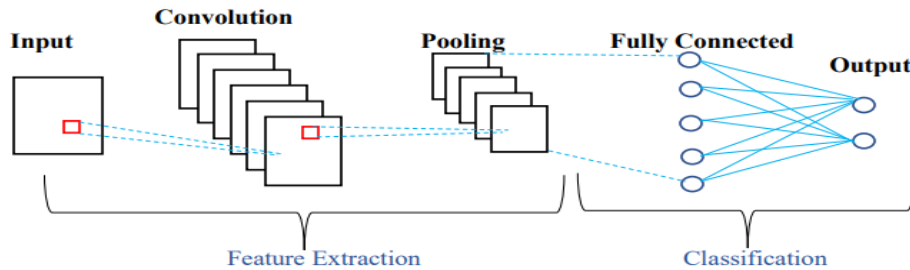


FIG 4: Convolution Diagram

Here it gets classified into various features called nodes and gives accurate results. It is also evident that the feature in the image gets extracted. Later these features are loaded and examined in the

Convolution layer and then these extracted features are figured in the pooling layer. It is then connected with various nodes called features. Finally, we will get the results.

Level 1

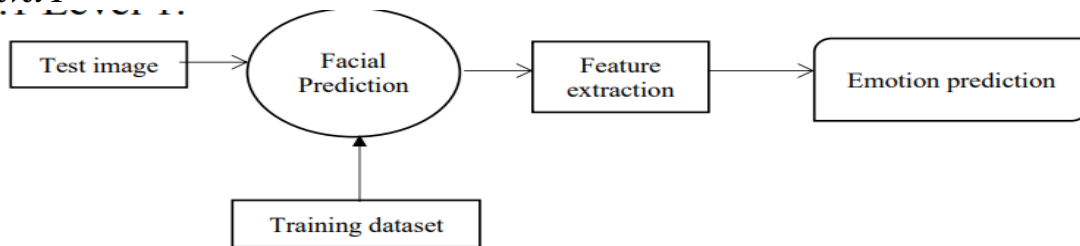


FIG 5: Level 1 Flow Diagram

Level 2

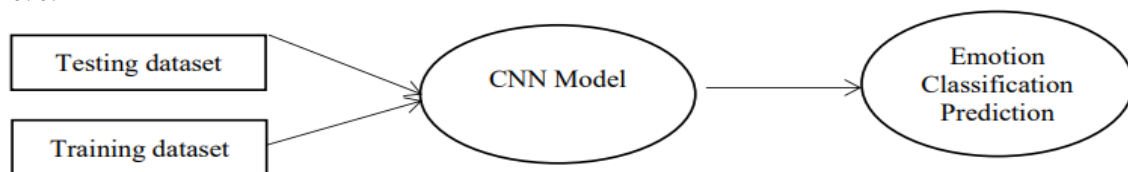


FIG 6: Level 2 Flow Diagram

Level 3

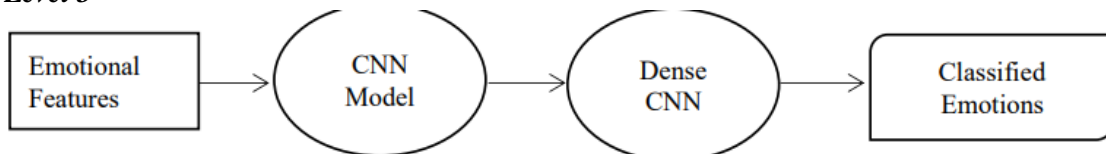


FIG 7: Level 3 Flow Diagram

Models

Conv 2d

2D convolution is like a simple calculation: you start with multiplication, it's just a small weight matrix. This kernel move over the 2D input data item multiplies with each element by the input currently above it, then aggregates the result into a single output pixel. By this, we can observe that the capacity of the core directly specifies the number of functions and is used to combine to create new output functions. In the above example, we have $4 \times 4 = 16$ input features and $6 \times 6 = 36$ output features. Suppose if it is connected standard class, we have a weight-matrix of $25 \times 9 = 225$ as parameters, with each outcome ... with their respective input. The transformation allows us to perform this transformation is done only 8 parameters, for each output characteristic. (2, 2) will get the high value of the 2x2 window group. Steps: integer, a tuple of 2 integers or none.Void. Specify the distance to move the group window for each group step. Otherwise, the group size will be used by default. Padding: one of the words real (case insensitive) "Valid" means no padding.channels) or If data_format = `channel_first`: 4_Dd tensor of the form (batch_size, channel, row, cols) and its output form If data_format = `channel_last`: 4_Dd tensor with shape (batch_si, pooled__roows, pooled__colmnn_ , channel) and If data_format = `channel_first`: 4_Dd tensor with shape (batch size, channel, poooled__roows, poooled__colmn).

Dense Layer

Dense does the operation: $\text{result} = \text{enable}(\text{dot}(\text{input}_i, \text{coefficient}) + \text{bias}_i)$ which enables a function that allows each item to be passed as an enable argument and the coefficient is a weight match due to generated class. Dense calculates the inner product within the inputs along the least axis of the input_. if the input has size (size, d0, d1), then we create a kernel of shape (d1, unit) and the kernel works along with the 3 axes input, on each sub-symbol their form (1, 1, d1_) (have batch_size * do of these subcomponents) and the arguments are unit, trigger, use bias, initializer, position bias initializer, kernel regularization, kernel constraints, bias constraints.

Input shape

N-D tensor with shape: (batch_size_, ..., input_dim).

Output shape

Tenso value ND has the shape: (batch_size, ..., units).

Epochs

It tells the number of times the model is used to train in forwarding and backward directions.

Rectified Linear Unit (ReLU)

ReLU is called a non-linear activation feature. Price was a good deal much less than zero, round it as a good deal as zero. Convolutional layers which filters are completed to unique the image and to a unique feature in CNN. Many user-certain parameters are inside the network.

Pooling layers

Pooling layers are just like convolutional layers; however, they carry out a particular characteristic together with max_pooling, which takes the most cost with a sure clear out region, or common pooling, which takes the common cost in a clear-out region. These are commonly used to lessen the dimensionality of the network.

Convo Layer

Convo layer is also called as extraction layer. There will be many features in the image so this extraction layer or the convo layer is used to extract features for the respective image. It is well known that if the image undergoes a Convolution Process or convolution operation it should relate to the convo layer and by applying this convo layer it is used to plot the dots in the image in various fields. Later, the results after the convolution operation via the convo layer are in the form of a single Integer. Next various similar features are applied to the same image several times and get stride and this process gets iterated by many times. Do it multiple times until it goes through the whole image.

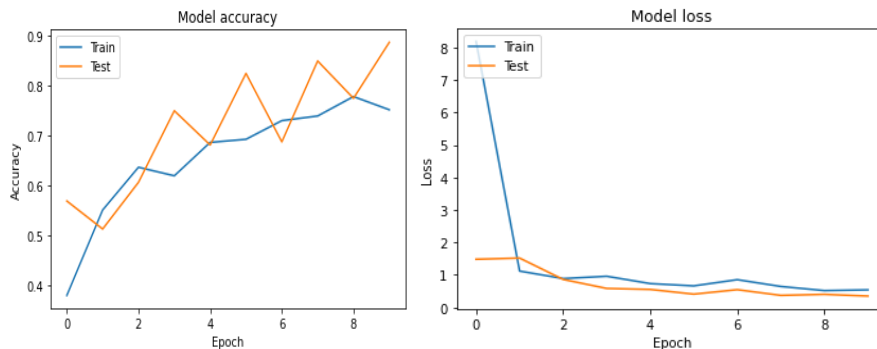


FIG 8: Accuracy and Loss Model graphs in ManuelNet Architecture

The softmax or Logistic layer is the closing layer of CNN. It is living on the quit of the FC layer. Logistic is used for binary category and softmax is for multi-category.

Output Layer

It includes the form of one-heat encrypted. Finally, results got were given a top-notch comprehension of CNN.

Layer	# filters / neurons	Filter size	Stride	Padding	Size of feature map	Activation function
Input	-	-	-	-	227 x 227 x 3	-
Conv 1	96	11 x 11	4	-	55 x 55 x 96	ReLU
Max Pool 1	-	3 x 3	2	-	27 x 27 x 96	-
Conv 2	256	5 x 5	1	2	27 x 27 x 256	ReLU
Max Pool 2	-	3 x 3	2	-	13 x 13 x 256	-
Conv 3	384	3 x 3	1	1	13 x 13 x 384	ReLU
Conv 4	384	3 x 3	1	1	13 x 13 x 384	ReLU
Conv 5	256	3 x 3	1	1	13 x 13 x 256	ReLU
Max Pool 3	-	3 x 3	2	-	6 x 6 x 256	-
Dropout 1	rate = 0.5	-	-	-	6 x 6 x 256	-

FIG 9: Layers with Activation Function

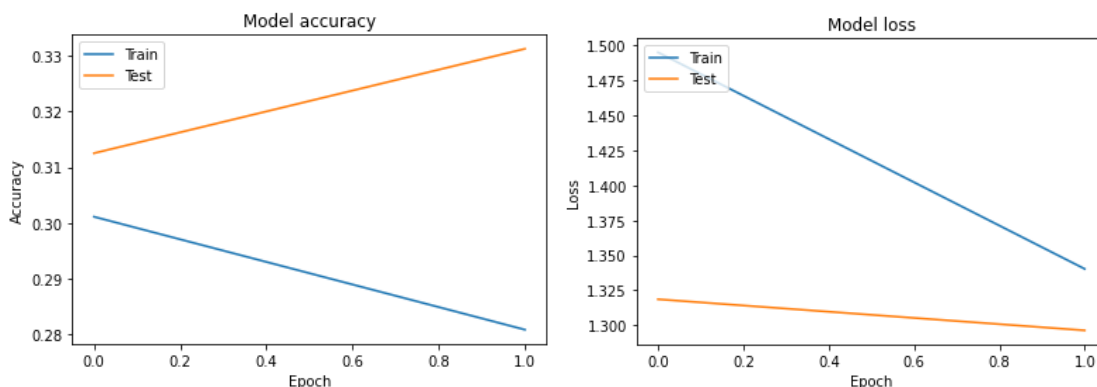


FIG 10: Accuracy and Loss Model graphs in LeNet Architecture

From the above-mentioned architecture, an overview is made and the model which has more accuracy will be used as the actual model and the required emotion from the given input image will be recognized.

CONCLUSION

In this paper, a study aimed at classifying facial emotions on static face images using deep learning techniques was developed. That's one of the promises of Deep Learning. Although feature engineering is not required, image preprocessing improves classification accuracy. Therefore, it reduces noise in the input data. The learning doesn't seem to be over yet due to a major limitation. Therefore, emotional classification can be achieved using deep learning techniques

Future Enhancement

The first is to use the entire dataset when optimizing. We should carefully use the datasets. Another technique is to assess each emotion one by one. Led to detecting what kind of emotions are demanding and difficult to categorize. In the end, utilizing a huge dataset for training appears to be beneficial. However, such datasets may not be there today. Making use of various datasets could be a solution, but a careful process is required to normalize them. Utilizing the dataset for training the images with already trained emotions and using a larger dataset kind of efficient improve network performance. Therefore, they need to be addressed in future research on this topic.

REFERENCES

1. Li Yu, Zhifan Yang, Peng Nie, Xue Zhao, Ying Zhang, "Multi-Source Emotion Tagging for Online News", 12th Web Information System and Application Conference 2015.
2. David Watson; Auke Telleger, "Towards a consensual structure of Mood", Psychological Bulletin, Vol. 98, No. 2. 219-235, 1985.
3. Niko Colneric and Janez Demsar. 2018. Emotion recognition on Twitter: Comparative study and training a unison ^ model. IEEE Transactions on Affective Computing, 11(3):433–446.
4. Christopher D Manning, Prabhakar Raghavan, and Hinrich Schutze. 2008. Introduction to information retrieval. Cambridge university press.
5. Goodfellow, Y. Bengio and A. Courville, Deep learning. MIT Press, 2016, pp. 164-223.
6. J. Han, M. Kamber, and J. Pei, Data Mining: Concepts and Techniques. San Francisco: Morgan Kaufmann, 2011, pp. 138-150.
7. Esau, Natascha, et al. "Real-time facial expression recognition using a fuzzy emotion model." 2007 IEEE international fuzzy systems conference. IEEE, 2007.
8. Zhang, Tong, et al. "Spatial-temporal recurrent neural network for emotion recognition." IEEE transactions on cybernetics 49.3 (2018): 839-847.
9. Chen, Po-Cheng. "Face recognition system and method." U.S. Patent No. 10,311,287. 4 Jun. 2019.
10. Pathar, R., Adivarekar, A., Mishra, A., and Deshmukh, A., 2019, April. "Human Emotion Recognition using Convolutional Neural Network in Real-Time", 2019 1st International Conference on Innovations in Information and Communication Technology (ICIICT) (pp. 1-7).