

## RIPHAH **INTERNATIONAL UNIVERISTY Department Of MATHEMATICS**

# **Convolutional Neural Network**

# **Facial Emotion Recognition**

Rabia Riaz, Fiza Akram, Umm-e- Farwa, Kiran Iqbal Email: rabiariaz.rr786@gmail.com, fizaakram87@gmail.com, ummefarwa0283@gmail.com, iqbalkiran043@gmail.com Supervised by: M. Saqib Khan

Department of Mathematics, Riphah International University Islamabad (Lahore Campus)

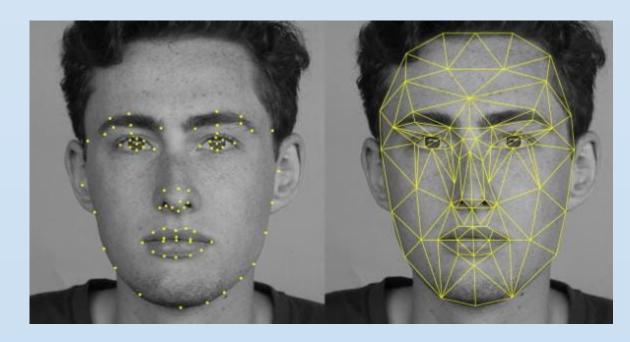
2<sup>nd</sup> Workshop on Advancement of Mathematics & it's Applications(WAMA-2024)

# **CNNs: Facial Expression Recognition via Deep Learning**

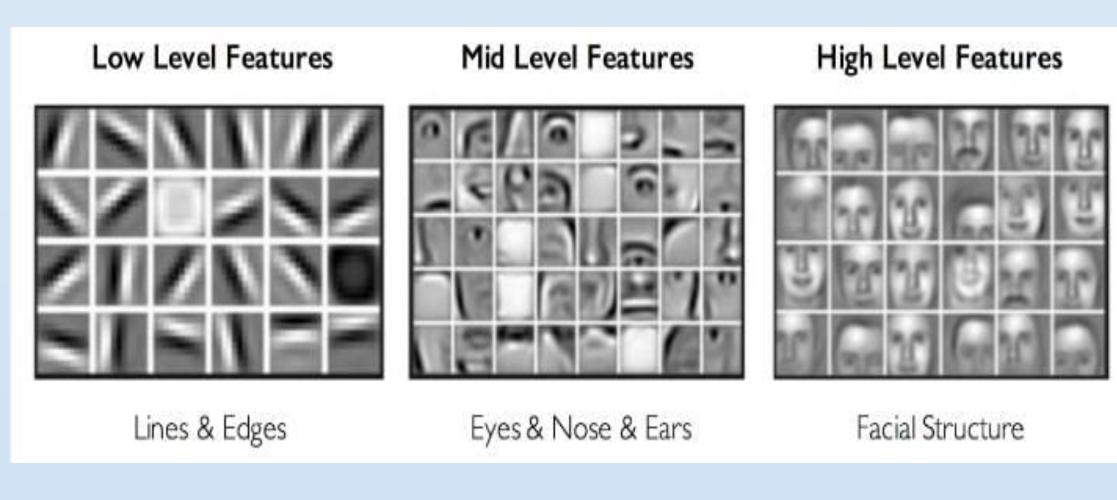
#### **INTRODUCTION**

Convolutional Neural Networks (CNNs) are a type of deep learning algorithm that is primarily used for image processing and recognition tasks. CNNs consist of multiple layers, each of which performs a specific operation to transform the input data.

The key component of CNNs is the convolutional layer, which applies convolution operations to the input image. These convolution operations involve sliding a small matrix called a kernel or filter over the input image to perform element-wise multiplication and then summing up the results to produce a feature map.



► Plus, our model uses Haar Cascades to detect faces. A pre-trained cascade of classifiers that can detect faces. This addresses most low light issues.

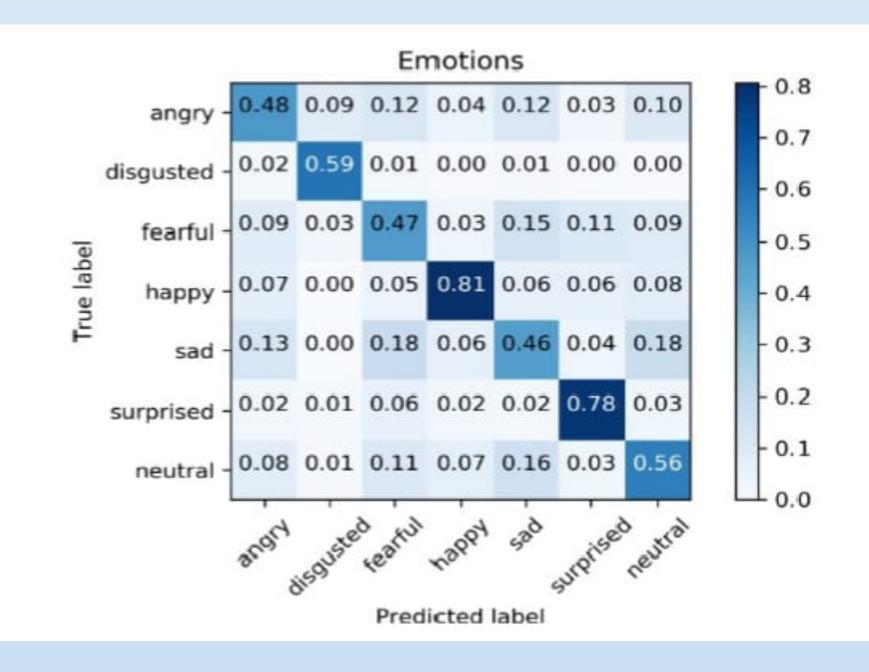


#### **PROPOSED ARCHITECTURE**

#### **CONFUSION MATRIX**

► Adam optimizer gave the highest overall accuracy.

► It does drastically better for faces showing disgust and fearful - almost 30%



**OBJECTIVE** 

► Our goal is to develop a neural network to recognize facial expressions and classify them into one of seven emotions - happy, sad, disgusted, surprised, angry, fearful and neutral. ► By identifying these emotions, we will then generate content in the style of a news feed.

There are 6 universal emotions in all of the world's cultures.

Sadness



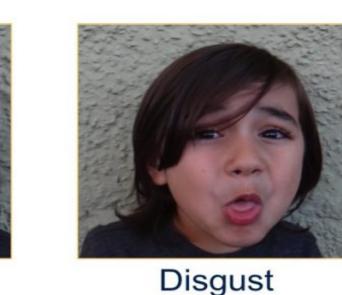




Anger

Happiness

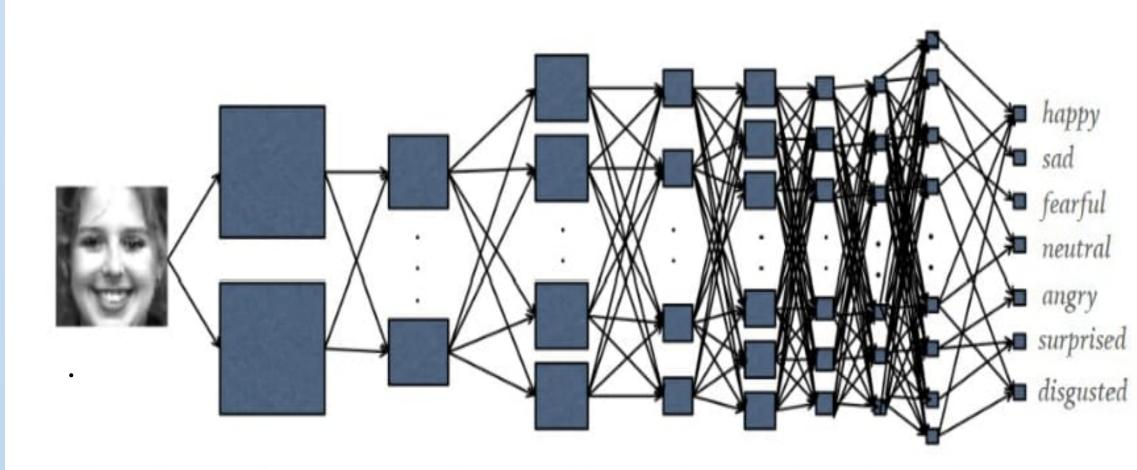




Fear

Surprise

### CHALLENGES



Max Pooling Conv Max Pooling FC Max Pooling Conv 1x1x128 1x1x256 1x1x7

#### **PREPROCESSING THE DATA**

The initial dataset was split into two sections - a string of 2304 numbers indicating pixel values for the image and a number from 1-7 indicating the emotion.

► We converted the string of numbers into a 48x48 matrix to feed into the neural network.

pixels emotion 70 80 82 72 58 58 60 63 54 58 60 48 89 115 121.

#### COMPARISON **OTHER** WITH SYSTEMS

► Similar systems that made use of emotion analysis did so on static images and not on real-time video streams.

► Some such models made use of using basic machine learning techniques such as Support Vector machine and Linear Discriminant Analysis, in combination with regular neural networks.

► A disadvantage of these systems is that they take a long time to train and their predictions are not instantaneous as required by a real-time system.

These systems take a long time to train because of the complexity of the data and the network itself.

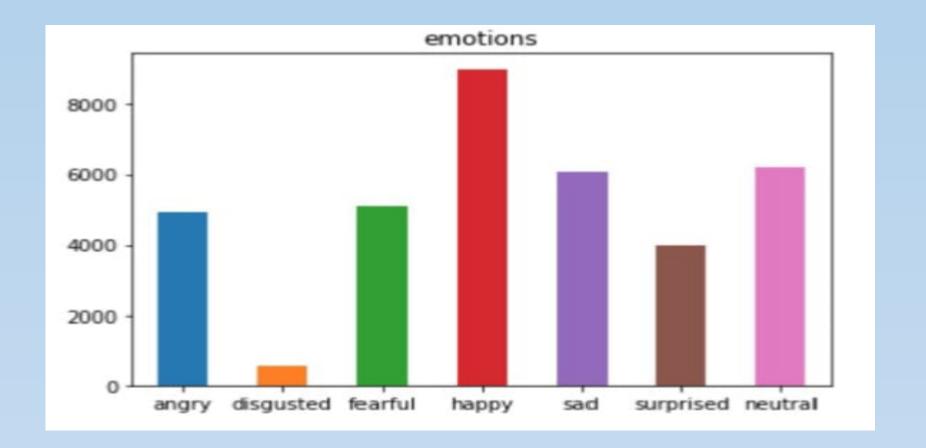
► Owing to the low computational requirements and faster training and prediction time, our model can be further developed for mobile use.

### CONCLUSION

► Thus we conclude that a real-time system in which emotions can be detected is feasible and generating content based on these emotions is a viable proposal.

► Furthermore, the established average accuracy of 60% is competent considering the complex nature of a human face and the real-time

- ► Class Imbalance Problem.
- ► Moreover, a feedforward network generally predicts the same emotion all the time.
- ► Another issue is that images have to be well illuminated. Low light / highly exposed images produce poor results.



#### **ADRESSING THE CHALLENGES**

► We have used a deep neural network - a Convolutional Neural Network which is capable of overcoming this problem by spatial locality - detecting edges and extracting certain features.

	a
151 150 147 155 148 133 111 140 170 174 182 15	

- 2 231 212 156 164 174 138 161 173 182 200 106 38...
- 24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...
- 400000000000315232848505884...

#### array([[ 70., 80., 82., ..., 52., 43., 41.], [ 65., 61., 58., ..., 56., 52., 44.], [ 50., 43., 54., ..., 49., 56., 47.], [ 91., 65., 42., ..., 72., 56., 43.], [ 77., 82., 79., ..., 105., 70., 46.], [ 77., 72., 84., ..., 106., 109., 82.]])

#### constraints.

### REFERENCES

► [1] Albert Mehrabian. Silent Messages, University of California Los Angeles, 1971.

► [2] P. Ekman and W. V. Friesen. Emotional facial action coding system. Unpublished manuscript, University of California at San Francisco, 1983.

► [3] Yaniv Taigman, Ming Yang, Marc'Aurelio Ranzato, Lior Wolf. DeepFace: Closing the Gap to Human-Level Performance in Face Verification. The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2014.

► [4] Thai Hoang Le. Applying artificial neural networks for face recognition. Advances in Artificial Neural Systems, 2011:15, 2011.

## **APPROACHES**

Model	Batch Size	Optimizer	Epochs	Accuracy
Feed Forward	128	RMSProp	10	17.386
Simple CNN	128	RMSProp	10	24.728
Decision Tree	40	~	L	30.843
Model #1	96	RMSProp	100	57.397
Model #2	64	SGD	10	55.900
Model #3	128	Adam	20	60.587