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CATEGORIZATION OF EMOTIONS BASED ON FACIAL EXPRESSIONS

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INTRODUCTION

01 Emotion refers to the display of a particular type of feeling or thought

02 Emotions play a primary role in one’s daily life

03 Detection of emotions is important for immaculate human to human and human to machine interactions

04 Real-time facial expression based emotion categorization system that classifies seven basic emotions, i.e. angry, disgust, fear, happy, neutral, sad, surprise

LITERATURE

PHYSIOLOGICAL SIGNAL BASED MODELS

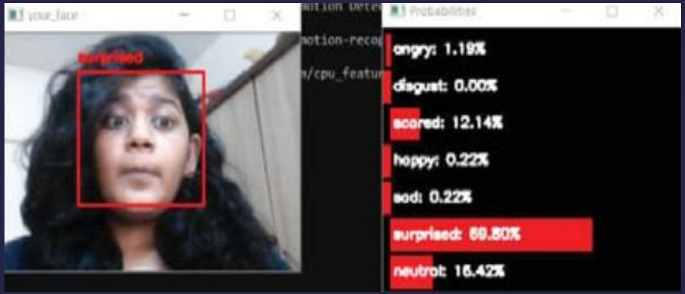
Authors	Learning Techniques	Algorithm	Datasets	Accuracy	Summary
M. S. Aldayel, M. Ykhlef and A. N. Al-Nafjan [2020]	Electroencephalogram signals	Distance metric learning (DML) and 3-D CNN algorithms	(CK+) and (JAFFE)	87%–96%	Power spectral density (PSD) and of the EEG were extracted. Each trial displayed 2,367 unique features of EEG signal.
M. R. Islam et al [2021]	EEG based	Deep learning and shallow learning	SEED, Self-Generated and IAPS dataset	96%	Comparison based on methods, classifier, the number of classified emotions, accuracy, and dataset.
Gruebler and K. Suzuki [2014]	EMG technique	ANN	Video and bioelectrical signals	89 %	The proposed device design was verified by evaluating continuous Spontaneous expressions using the device.

LITERATURE

COMPUTER VISION BASED MODELS

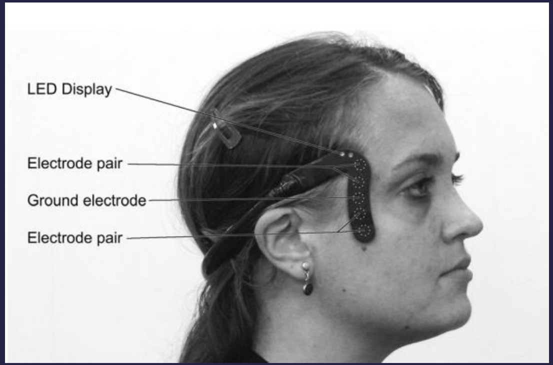
Authors	Algorithm	Datasets	Accuracy	Summary
S. Miao, H. Xu, Z. Han and Y. Zhu [2019]	CNN	FER-2013.	64%.	SHCNN's architecture classified both static and micro expressions.
D. Dagar, A. Hudait, H. K. Tripathy and M. N. Das [2016]	CNN	FER-2013	66%	A model that recognized the seven basic human emotions. It used the haar cascade method to detect faces from images captured via webcam.
K. Mohan, A. Seal, O. Krejcar and A. Yazidi [2021]	HOG-TOP, Major CNN, Shallow CNN	FER-2013	78%	This proposed architecture examined the 25 different advanced algorithms.
K. Mohan, A. Seal, O. Krejcar and A. Yazidi. [2021]	FF, CFF, RNN and LSTM.	FER-2013	80.5%.	The model was able to detect complex emotions such as - angrily disgusted, Sadly surprised, sadly fearful.

LITERATURE



D. Dagar, A. Hudait, H. K. Tripathy and M. N. Das [2016]

K. Mohan, A. Seal, O. Krejcar and A. Yazidi [2021]



Gruebler and K. Suzuki [2014]

LITERATURE

RESEARCH GAPS OF EXISTING METHODS

1. The systems proposed in recent literature use computationally heavy architectures that are not fit for deployment on an embedded system.

2. Most of the models that use the FER-2013 dataset and pure CNN architecture have low accuracy

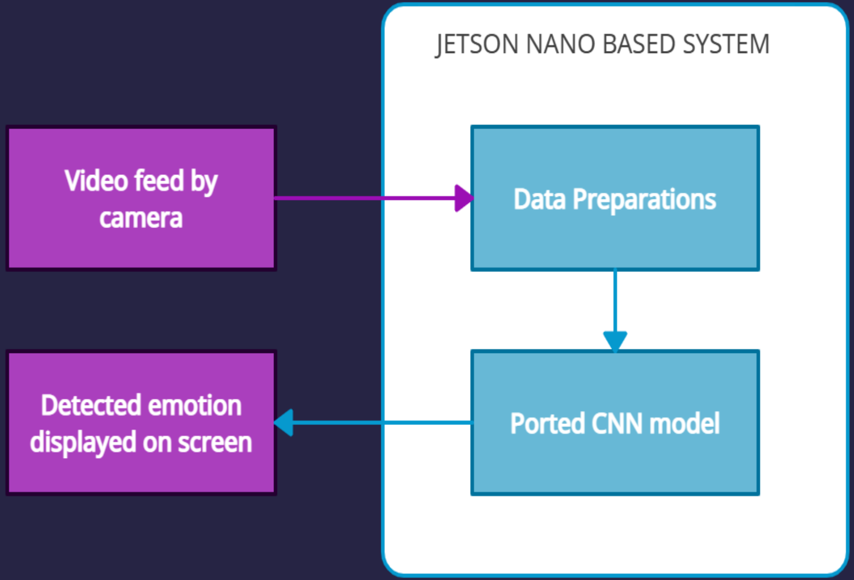
3. Other models that provide higher accuracy do not have provisions for real-time emotion recognition.

4. The systems that use physiological signals for classification are accurate but need a bulky setup, hence they are not portable.

METHOD

BLOCK DIAGRAM OF SYSTEM

The **novelty** of the system is that it is a **lightweight CNN architecture** that can be ported on target **Jetson Nano board**, which enables **accurate real-time emotion recognition**.



METHOD

FLOW OF THE SYSTEM

- The proposed system is deployed on JETSON NANO 4GB
- The system captures a single frame from the video feed
- This frame of image is processed by the Jetson Nano
- The processing is done by passing it through the Convolutional Neural network(CNN)
- Emotion in that frame is identified by passing it through various filters of the CNN
- The identified emotion is then displayed on the screen

METHOD

DATASET

- The dataset used was FER-2013 which was taken from Kaggle.
- A total of 35,887 images of 7 different emotions were used.
- The 7 emotions were angry, fear, happy, neutral, sad, surprise, disgust.
- All the images were in grayscale and had dimensions 48x48.

METHOD

PRE-PROCESSING

ImageDataGenerator

- The training and testing images were converted into a batch of 64 images.
- These images had height and width of 48x48.
- All the images were converted to greyscale.
- This batch of image was then given to the model for training and testing.

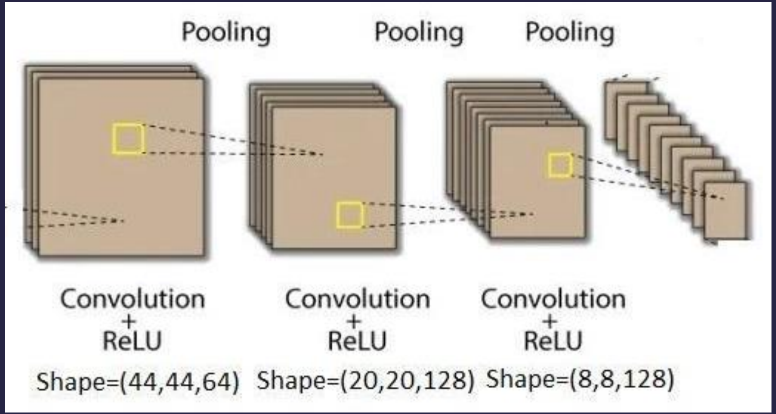
```
batch_size = 64
target_size = (48,48)
train_datagen = ImageDataGenerator(rescale=1./255)
train_generator = train_datagen.flow_from_directory(
        train_path,
        target_size=target_size,
        batch_size=batch_size,
        color_mode="grayscale",
        class_mode='categorical',
        shuffle=True)
```

FEATURE EXTRACTION

- The process of feature extraction was done with 3 feature extraction layers.

- The first layer had a filter of 32 neurons. Filter in Convolutional Neural Network detects features present in the image.

- Every layer was associated with a kernel of (3,3) which defined how much part of the image the model would learn.



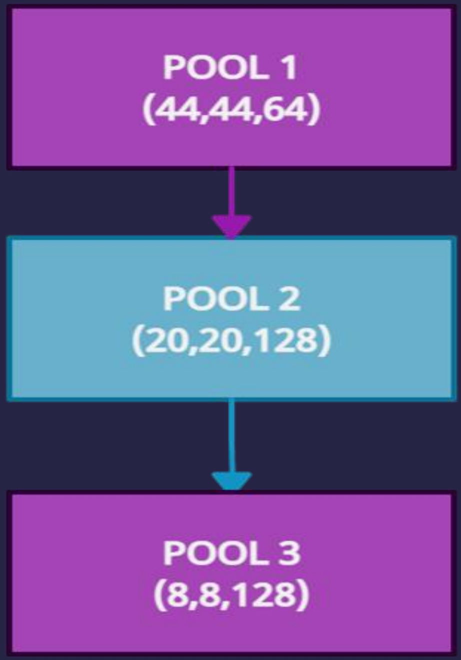
- After every layer the neurons were increased by a multiple of 2 in the feature extraction process.

- The output of each layer was the number of features extracted mapped into a 3 dimensional array.

METHOD

DIMENSIONONALITY REDUCTION

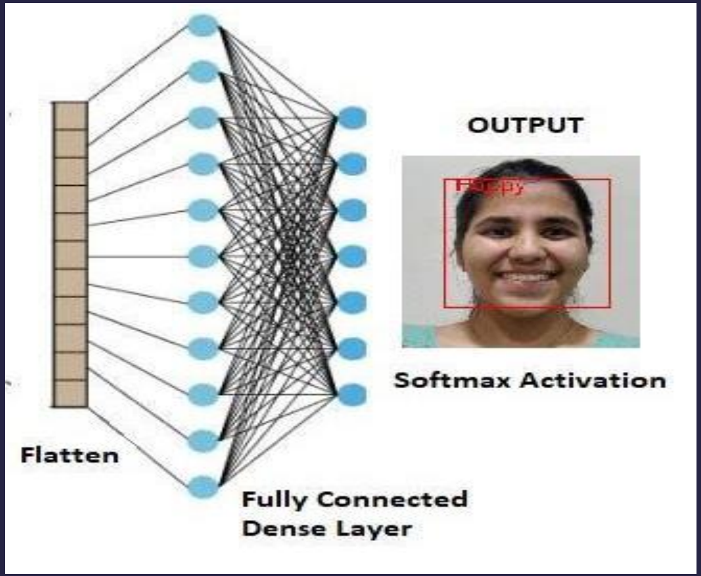
- Each layer after feature extraction was done was followed by a pooling method in the form of max-pooling method.
- Max-pooling down samples the feature map created by the filter and hence reduces the spatial dimension of the data.
- We have used a Max-pooling of size 2x2.



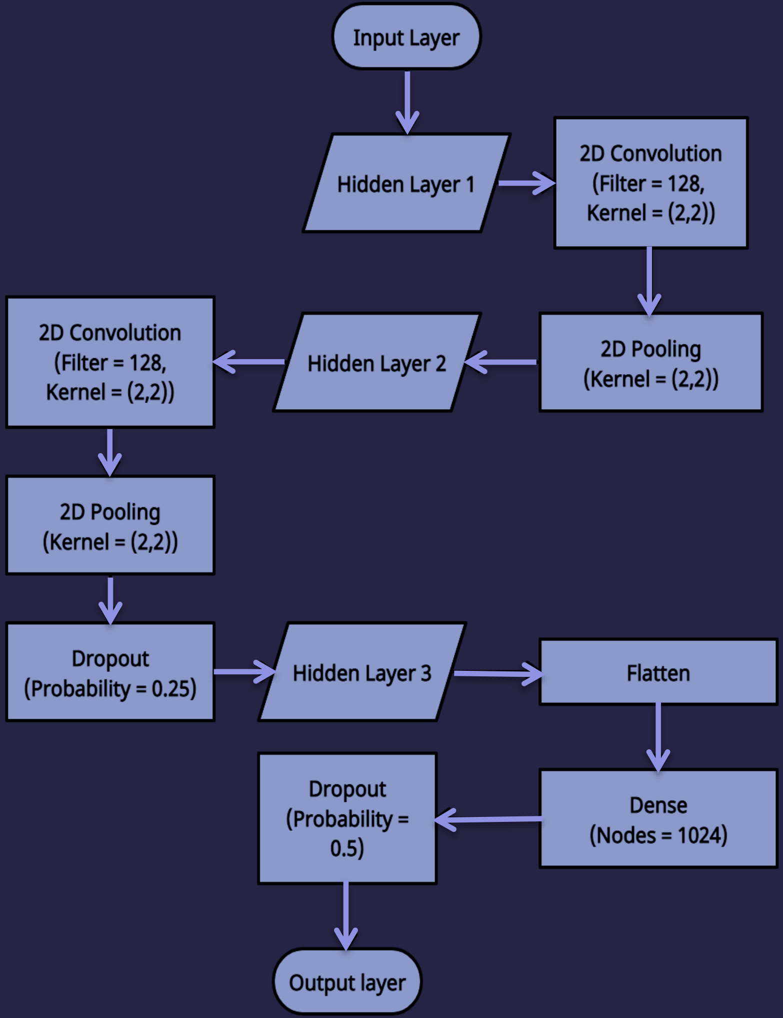
METHOD

CLASSIFICATION

- The final feature map generated was three dimensional vector. Which was reduced to a single dimension.
- This reduction was done using the flatten method in TensorFlow.
- The reduction was done for better absorption of data by neurons in the network.
- After the flatten, there was an output layer of 7 neurons which was defined because we had seven emotions to classify.
- The combination generated a Fully Connected Dense Layer.



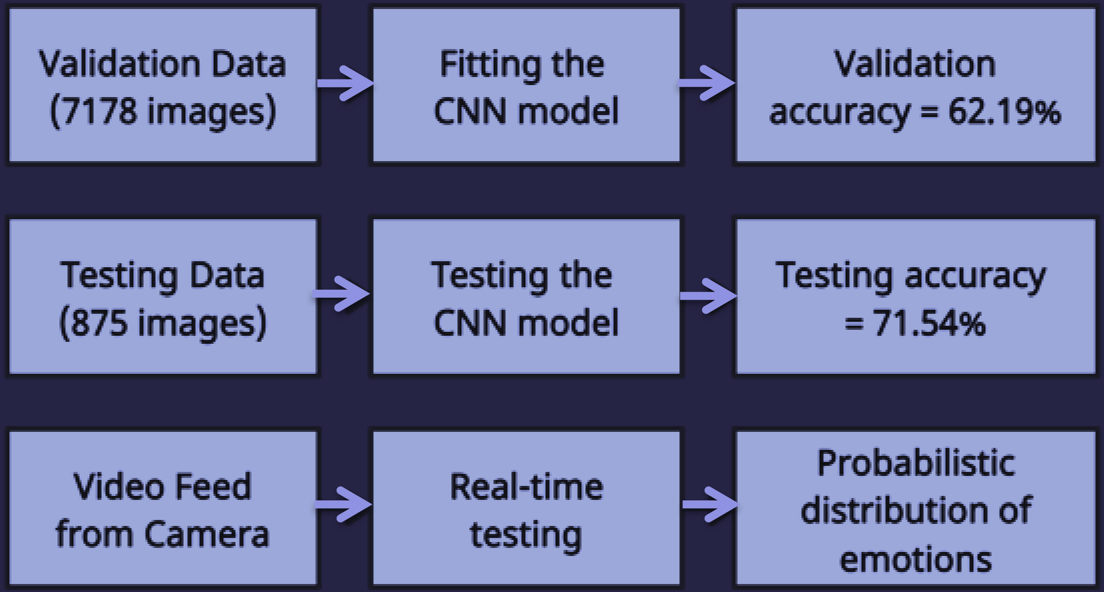
METHOD



Input Layer
Hidden Layer 1
2D Convolution
(Filter = 128,
Kernel = (2,2))
2D Pooling
(Kernel = (2,2))
Hidden Layer 2
2D Convolution
(Filter = 128,
Kernel = (2,2))
2D Pooling
(Kernel = (2,2))
Dropout
(Probability = 0.25)
Hidden Layer 3
Flatten
Dense
(Nodes = 1024)
Dropout
(Probability =
0.5)
Output layer

RESULTS

TESTING PROCESS



RESULTS

TESTING ACCURACY

Emotion	Accuracy
Disgust	64.8%
Happy	83.2%
Sad	74.4%
Anger	74.4%
Fear	49.6%
Neutral	72%
Surprise	82.4%

The average testing accuracy was 71.54%. The categorical cross-entropy was 1.22

RESULTS

CONFUSION MATRIX

	Angry	Disgust	Fear	Happy	Neutral	Sad	Surprise
Angry	93	0	13	0	6	5	7
Disgust	15	81	14	1	1	5	8
Fear	7	0	62	0	3	2	49
Happy	4	0	8	104	3	0	6
Neutral	9	0	6	5	90	3	10
Sad	6	0	14	1	7	93	4
Surprise	5	0	12	4	1	0	103

RESULTS

REAL-TIME TESTING

A total of 50 real-time experiments were done. In these experiments, the emotions - happy, surprise and neutral were detected with full confidence every time. Rest of the emotions, i.e. anger, sadness, disgust and fear were classified as roughly 70% of the experiments.

DISCUSSION

Novelty

Developed system is computationally inexpensive real-time embedded system

Advantages

Different types of emotions with male, femake faces of many age groups used in training

Accurate predictions of emotions in real-world situations

Comparison

Current systems are computationally complex and heavily dependent on huge and accurate datasets

Limitations

Difficulty in detecting emotions of sadness and fear

Difficulty in detecting faces in bad lighting conditions

CONCLUSION

- Implemented a Real-time facial expression based emotion categorization system
- It used convolutional neural network techniques to make accurate predictions on the input image
- Classified seven basic emotions, i.e. angry, disgust, fear, happy, neutral, sad, surprise with an accuracy of 71.54%
- The more easily distinguishable emotions were happy, surprised and neutral
- This system was deployed very conveniently on embedded systems like the Jetson Nano board along with a camera

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