Multimodal Emotion Classification using User's Speech & Facial Expression

Under the guidance of: **Prof. U S Tiwari**

Introduction

Emotions are one of the most basic features that distinguish human beings from the machines and robots. Humans express their emotions through various media like facial expressions, their actions and most importantly speech. To bring the artificial intelligence close to humans, it becomes necessary to be able to recognize as well as generate emotions by machines. One of a huge challenge is developing computers that can effectively simulate human interaction. A lot of research has been done in the past years in this field. This motivates us to develop a system which can efficiently determine the mental state of the user by studying the speech and facial expressions of the user.

Scope of Project Work

- **Call Center** conversation may be used to analyze behavioral study of call attendants with the customers which helps to improve quality of service of a call attendant.
- In **Aircraft** cockpits, speech recognition systems trained to recognize stressed speech are used for better performance and can be useful in detecting emergency situations.
- It is Useful for enhancing the naturalness in speech based **human machine interaction**

.

- Interactive movie, storytelling & **E-tutoring** applications would be more practical, if they can adapt themselves to listeners or students emotional states.
- **Home Automation** – Home Automation Systems capable of sensing emotion can avert risk of depression by changing ambient lighting, playing cheerful music, ordering favorite food items from nearby bakery.

Scope of Project Work

By doing this project, the followings are achieved:

a) Development of separate modules to detect the emotion of the person using Facial Expression and Speech Data

   i. **Module 1**: Emotion Classification using Facial Expressions

   ii. **Module 2**: Emotion Classification using Speech Data

b) Diffusing the results of speech and facial expression classifier to enhance the accuracy.

c) Using effective machine learning algorithms to achieve the above mentioned task.

d) Comparing the accuracies obtained by different methodologies and choosing the best one

The Data-Set

Audio Data

- **Source:** Surrey Audio-Visual Expressed Emotion (SAVEE)[3]
- **480** British English utterances recorded by 4 male actors 7 emotions—happy, angry, sad, disgusted, fearful, surprised, and neutral
- **Source: Recorded IIIT-A DATA**
- **853** audio clips by **82** actors (11 female, 71 male) expressing the 7 seven emotions.

All the audio clips are captured at a frequency of 44100 Hz. The length of each audio file is around **2.0 ~ 3.0 seconds** and are stored in wave (.wav) format. The total number of audio clips are **1333,** which are further divided into **988** for training and **345** for validating the model.

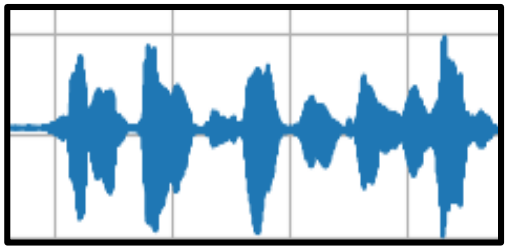
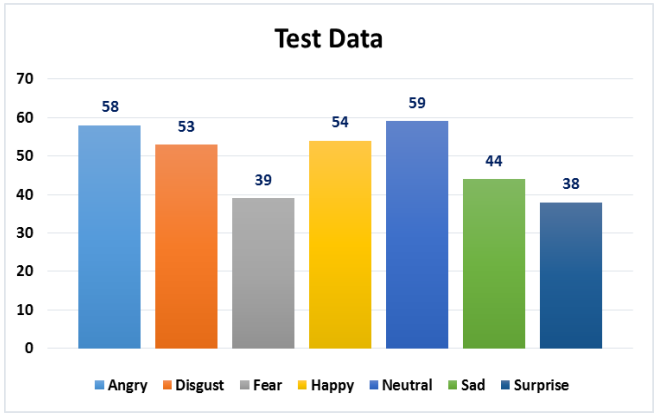


Fig. Recording for Dataset



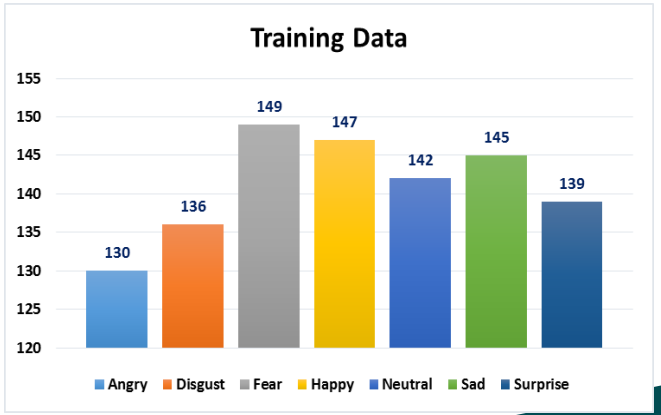
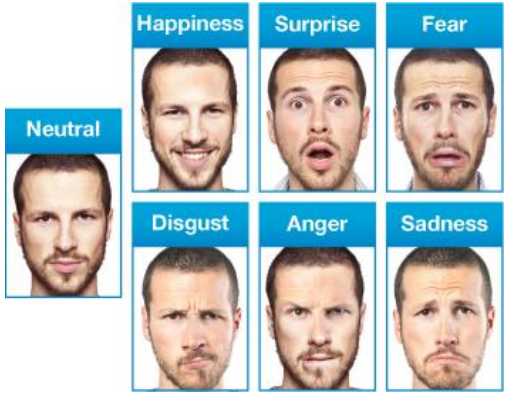
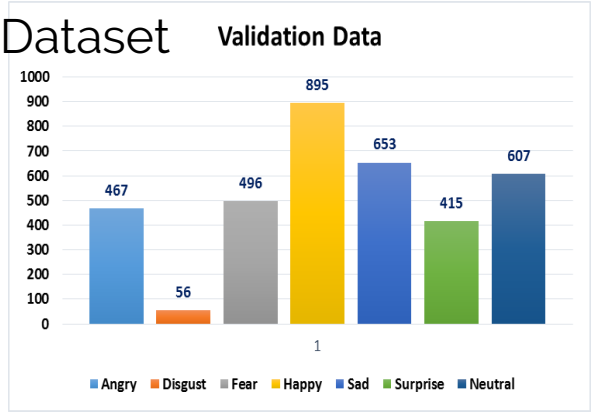


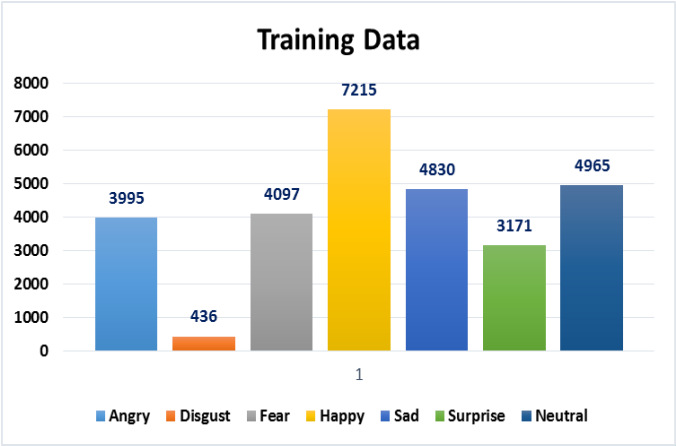
Image Data

- 32,298 grayscale images
- Each image of 48 x 48 pixel
- 28,709 Training + 3,589 validation
- 7 emotion classes
- Source: FER2013 Dataset

0=Angry
1=Disgust
2=Fear
3=Happy
4=Sad
5=Surprise
6=Neutral.

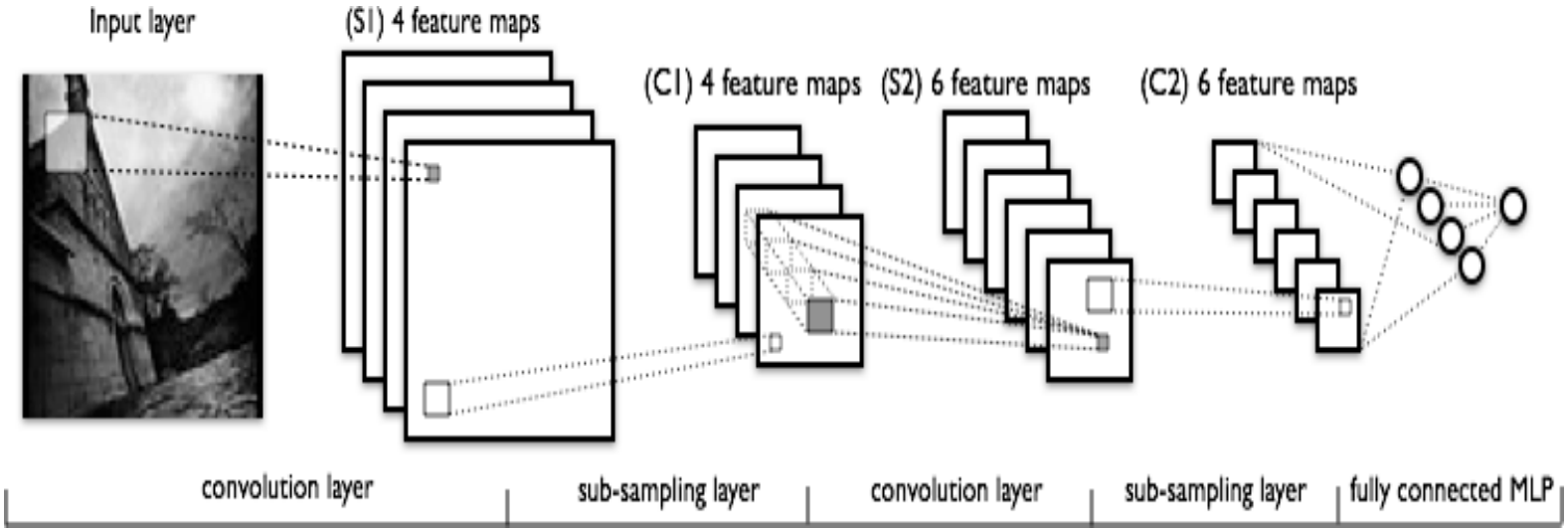




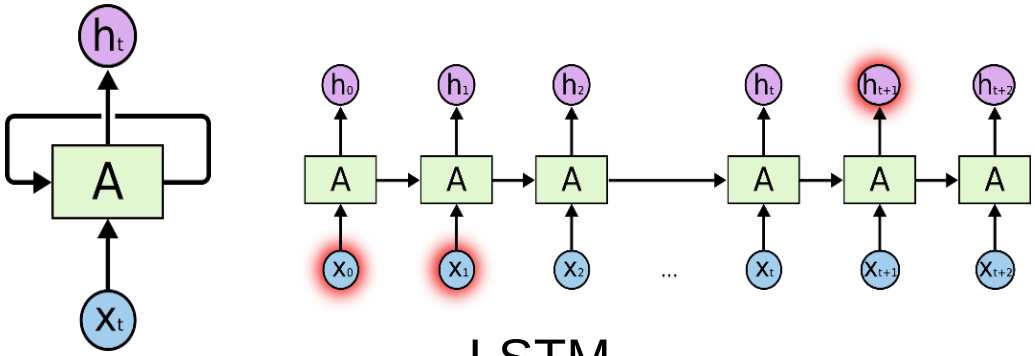


Approach: Deep Learning

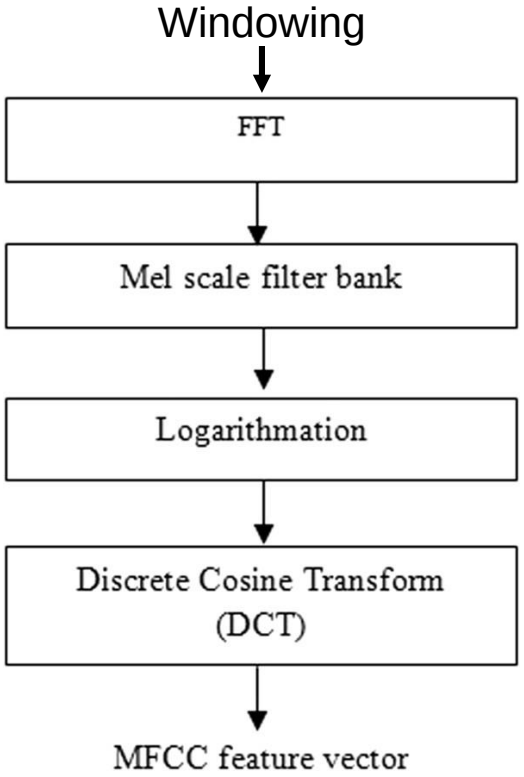
- **Convolutional Neural Network(CNN):** CNN take into consideration spatial information in an image
  - **Input Layer** will hold the raw pixel values of the image, in this case an image of width 32, height 32, and with three color channels R,G,B it would have dimensions 32 x 32 x 3.
  - **CONV Layer** will compute the output of neurons that are connected to local regions in the input, each computing a dot product between their weights and a small region they are connected to in the input volume. This may result in volume such as [32x32x12] if we decided to use 12 filters.
  - **RELU Layer** will apply an element wise activation function, such as the max(0,x) thresholding at zero. This leaves the size of the volume unchanged ([32x32x12]) and removes the negative intensities.
  - **POOL layer** will perform a down sampling operation along the spatial dimensions (width, height), resulting in volume such as [16x16x12] if we use a 2 x 2 pooling filter. Eg. 2 x 2 max pool filter.
  - **FC Layer**(i.e. fully-connected) layer will compute the class scores, resulting in volume of size [1x1x10], where each of the 10 numbers correspond to a class score, such as among the 10 categories.



Why CNN??- The basic need of CNN aroused for image recognitions problems as in case of images the no of parameters in input layer become large and in order to make the recognizing system efficient the number of hidden layers in the neural network are also large, due to which the effect to the weights of initial hidden layers is not much during back propagation. This increases the number of iterations needed to adjust the weights in order to obtain good accuracy from the system, thereby increasing the computation power.

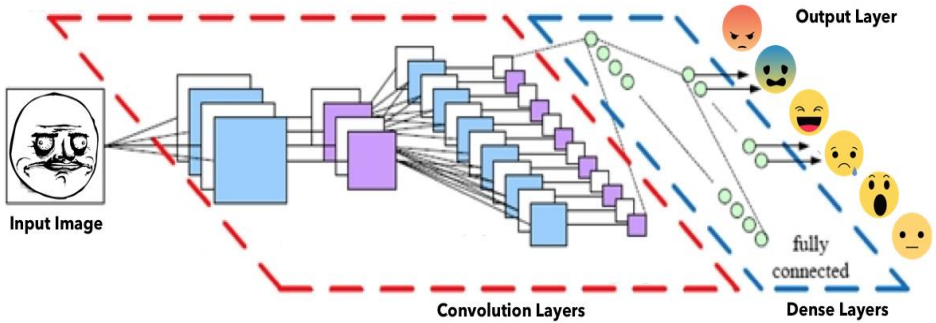

h_t
A
x_t
h_0 h_1 h_2 h_t h_{t+1} h_{t+2}
A A A A A A
x_0 x_1 x_2 ... x_t x_{t+1} x_{t+2}

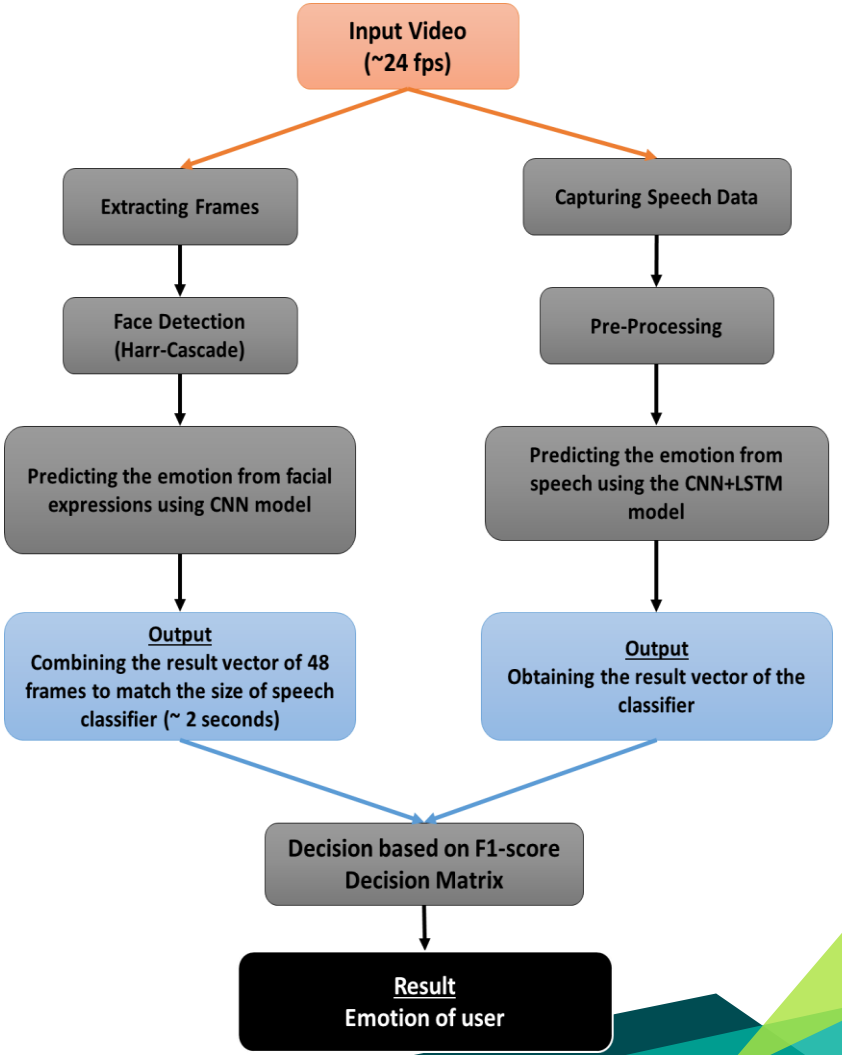
LSTM


Windowing
FFT
Mel scale filter bank
Logarithmation
Discrete Cosine Transform (DCT)
MFCC feature vector

MFCC

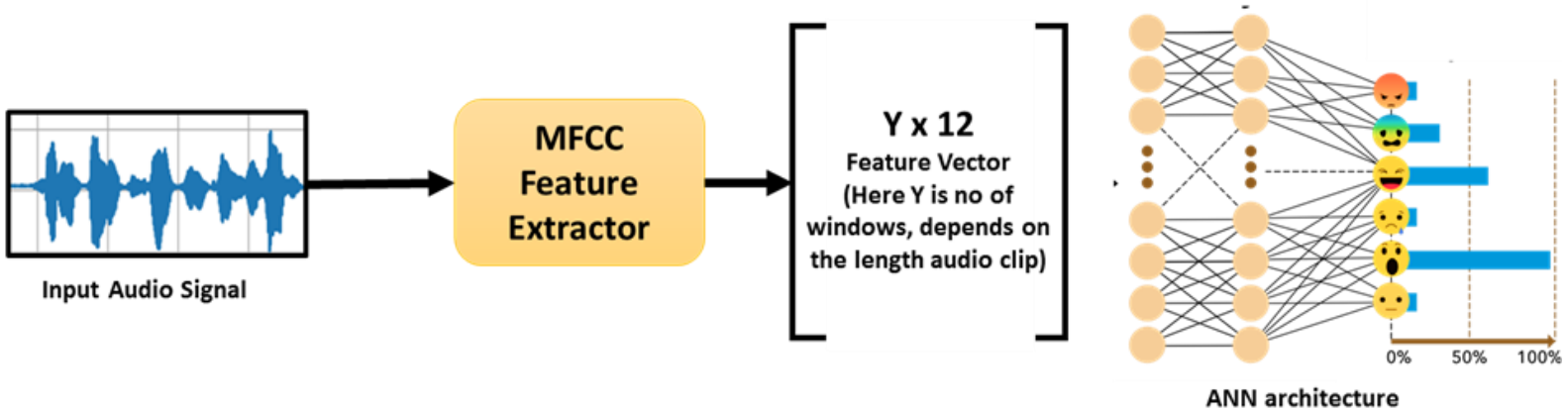
Methodology





Model 1: Using MFCC

Accuracy Obtained: **50.12%**



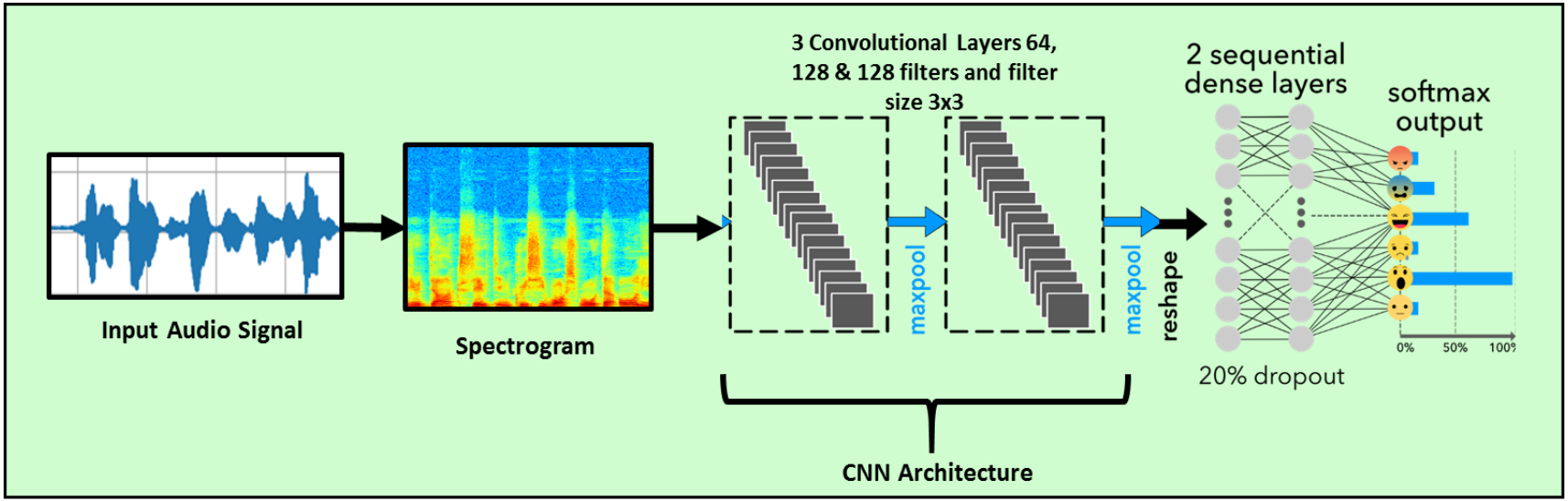
Emotion	Pitch	Intensity	Speaking rate	Voice quality
Anger	higher mean wider range abrupt changes	higher	slightly faster	breathy chest tone
Joy	higher mean wider range	higher	faster or slower	breathy blaring
Sadness	lower mean narrower range	lower	slower	resonant
Fear	higher mean wider range	normal	faster	irregular voicing
Disgust	lower mean wider range	lower	slower	grumbled chest tone

Variation of various acoustic variables

[5]R. Murray and J. L. Arnott, “Toward the simulation of emotion in synthetic speech: A review of the literature on human vocal emotion”

Model 2: CNN

Accuracy Obtained: **72.46%**

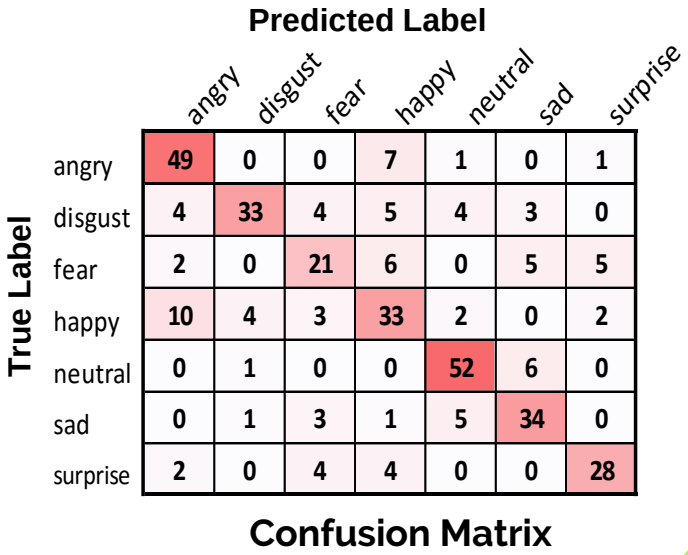


None

Layer (type)	Output Shape	Param #	Connected to
convolution2d_1 (Convolution2D)	(None, 64, 98, 433)	640	convolution2d_input_1[0][0]
batchnormalization_1 (BatchNorma	(None, 64, 98, 433)	256	convolution2d_1[0][0]
elu_1 (ELU)	(None, 64, 98, 433)	0	batchnormalization_1[0][0]
maxpooling2d_1 (MaxPooling2D)	(None, 64, 49, 216)	0	elu_1[0][0]
dropout_1 (Dropout)	(None, 64, 49, 216)	0	maxpooling2d_1[0][0]
convolution2d_2 (Convolution2D)	(None, 128, 51, 218)	73856	dropout_1[0][0]
batchnormalization_2 (BatchNorma	(None, 128, 51, 218)	512	convolution2d_2[0][0]
elu_2 (ELU)	(None, 128, 51, 218)	0	batchnormalization_2[0][0]
maxpooling2d_2 (MaxPooling2D)	(None, 128, 17, 72)	0	elu_2[0][0]
dropout_2 (Dropout)	(None, 128, 17, 72)	0	maxpooling2d_2[0][0]
convolution2d_3 (Convolution2D)	(None, 128, 19, 74)	147584	dropout_2[0][0]
batchnormalization_3 (BatchNorma	(None, 128, 19, 74)	512	convolution2d_3[0][0]
elu_3 (ELU)	(None, 128, 19, 74)	0	batchnormalization_3[0][0]
maxpooling2d_3 (MaxPooling2D)	(None, 128, 4, 18)	0	elu_3[0][0]
dropout_3 (Dropout)	(None, 128, 4, 18)	0	maxpooling2d_3[0][0]
flatten_1 (Flatten)	(None, 9216)	0	dropout_3[0][0]
output1 (Dense)	(None, 2048)	18876416	flatten_1[0][0]
dropout_4 (Dropout)	(None, 2048)	0	output1[0][0]
output2 (Dense)	(None, 1024)	2098176	dropout_4[0][0]
dense_1 (Dense)	(None, 7)	7175	output2[0][0]

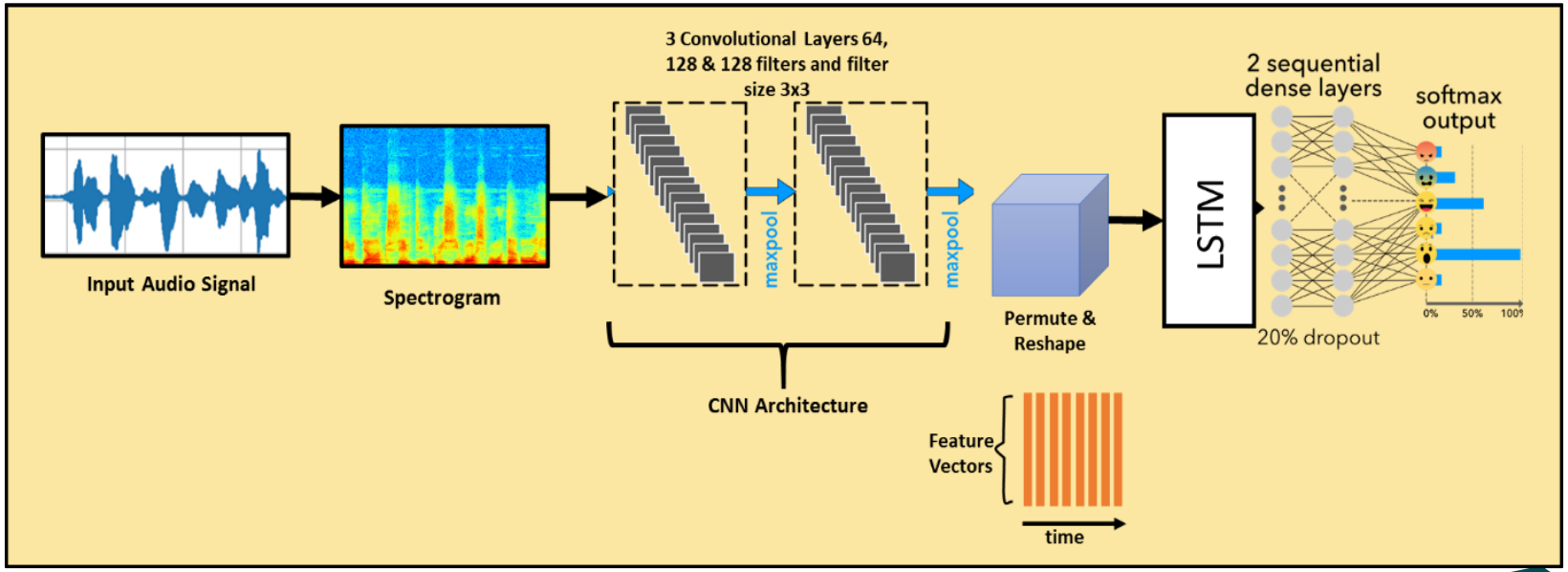
Total params: 21,205,127
Trainable params: 21,204,487
Non-trainable params: 640

```
Test score: 0.968174676273
Test accuracy: 0.724637680814
```



Model 3: CNN + LSTM

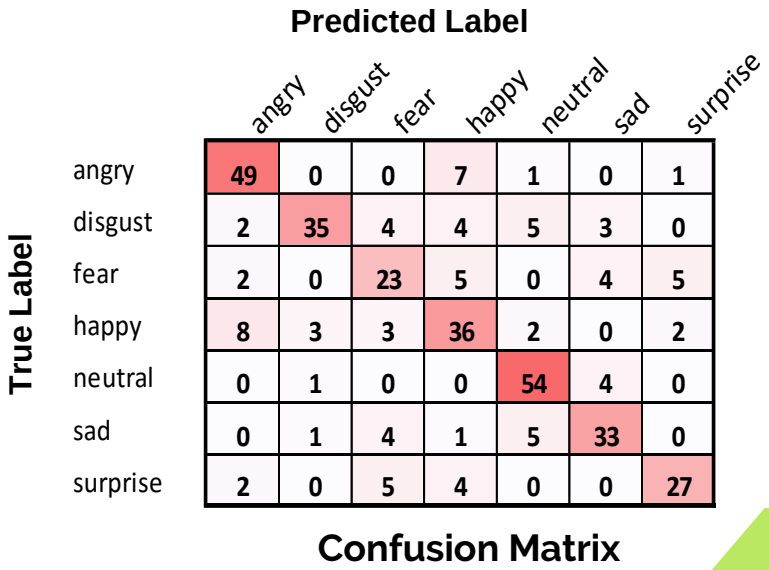
Accuracy Obtained: **74.49%**



elu_2 (ELU)	(None, 128, 51, 218)	0	batchnormalization_2[0][0]
maxpooling2d_2 (MaxPooling2D)	(None, 128, 17, 72)	0	elu_2[0][0]
dropout_2 (Dropout)	(None, 128, 17, 72)	0	maxpooling2d_2[0][0]
convolution2d_3 (Convolution2D)	(None, 128, 19, 74)	147584	dropout_2[0][0]
batchnormalization_3 (BatchNorma	(None, 128, 19, 74)	512	convolution2d_3[0][0]
elu_3 (ELU)	(None, 128, 19, 74)	0	batchnormalization_3[0][0]
maxpooling2d_3 (MaxPooling2D)	(None, 128, 4, 18)	0	elu_3[0][0]
dropout_3 (Dropout)	(None, 128, 4, 18)	0	maxpooling2d_3[0][0]
convolution2d_4 (Convolution2D)	(None, 128, 6, 20)	147584	dropout_3[0][0]
batchnormalization_4 (BatchNorma	(None, 128, 6, 20)	512	convolution2d_4[0][0]
elu_4 (ELU)	(None, 128, 6, 20)	0	batchnormalization_4[0][0]
maxpooling2d_4 (MaxPooling2D)	(None, 128, 1, 5)	0	elu_4[0][0]
dropout_4 (Dropout)	(None, 128, 1, 5)	0	maxpooling2d_4[0][0]
permute_1 (Permute)	(None, 5, 128, 1)	0	dropout_4[0][0]
reshape_1 (Reshape)	(None, 5, 128)	0	permute_1[0][0]
gru1 (LSTM)	(None, 5, 32)	20608	reshape_1[0][0]
gru2 (LSTM)	(None, 32)	8320	gru1[0][0]
output1 (Dense)	(None, 16)	528	gru2[0][0]
output2 (Dense)	(None, 16)	272	output1[0][0]
dense_1 (Dense)	(None, 7)	119	output2[0][0]

Total params: 401,303
Trainable params: 400,407
Non-trainable params: 896

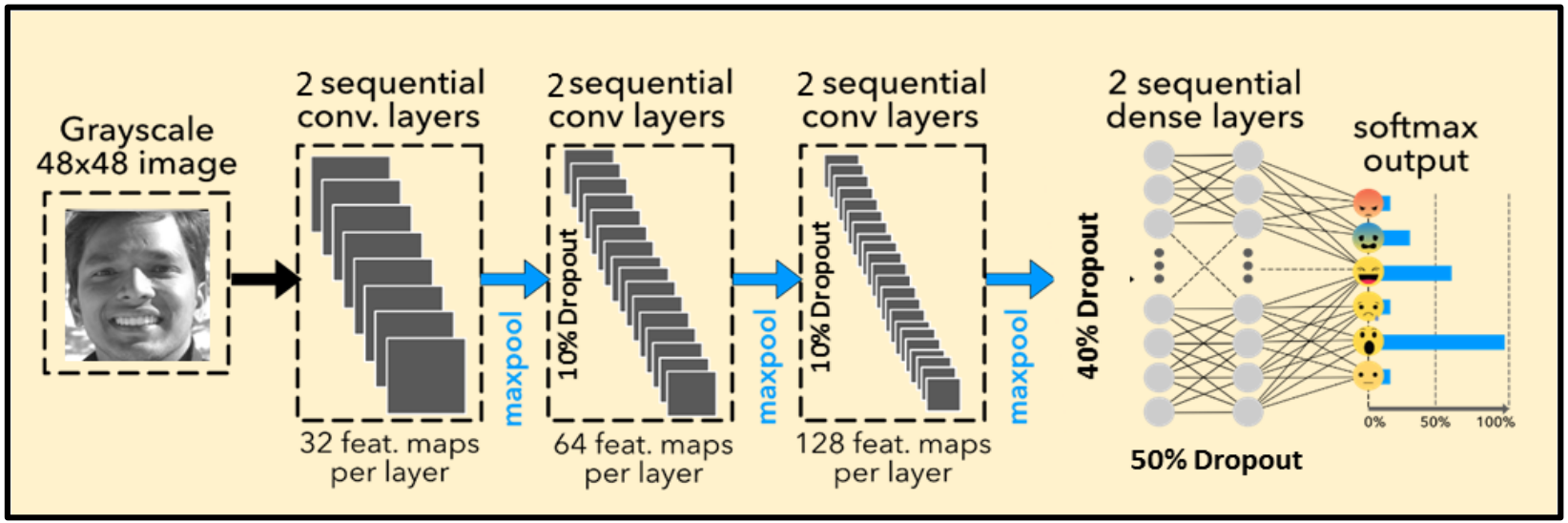
```
Test score: 0.9643366737591
Test accuracy: 0.7449871345
```



Confusion Matrix

Module 2: Facial Expression

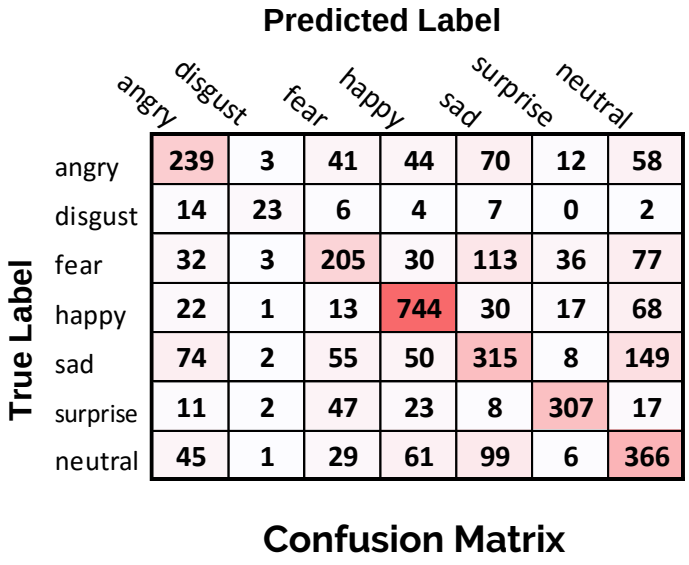
Accuracy Obtained: **61.27%**



Layer (type)	Output Shape	Param #	Connected to
convolution2d_1 (Convolution2D)	(None, 3, 50, 32)	13856	convolution2d_input_1[0][0]
convolution2d_2 (Convolution2D)	(None, 5, 52, 32)	9248	convolution2d_1[0][0]
maxpooling2d_1 (MaxPooling2D)	(None, 2, 26, 32)	0	convolution2d_2[0][0]
dropout_1 (Dropout)	(None, 2, 26, 32)	0	maxpooling2d_1[0][0]
convolution2d_3 (Convolution2D)	(None, 4, 28, 64)	18496	dropout_1[0][0]
convolution2d_4 (Convolution2D)	(None, 6, 30, 64)	36928	convolution2d_3[0][0]
maxpooling2d_2 (MaxPooling2D)	(None, 3, 15, 64)	0	convolution2d_4[0][0]
dropout_2 (Dropout)	(None, 3, 15, 64)	0	maxpooling2d_2[0][0]
convolution2d_5 (Convolution2D)	(None, 5, 17, 128)	73856	dropout_2[0][0]
convolution2d_6 (Convolution2D)	(None, 7, 19, 128)	147584	convolution2d_5[0][0]
maxpooling2d_3 (MaxPooling2D)	(None, 3, 9, 128)	0	convolution2d_6[0][0]
dropout_3 (Dropout)	(None, 3, 9, 128)	0	maxpooling2d_3[0][0]
flatten_1 (Flatten)	(None, 3456)	0	dropout_3[0][0]
dense_1 (Dense)	(None, 2048)	7079936	flatten_1[0][0]
dropout_4 (Dropout)	(None, 2048)	0	dense_1[0][0]
dense_2 (Dense)	(None, 7)	14343	dropout_4[0][0]

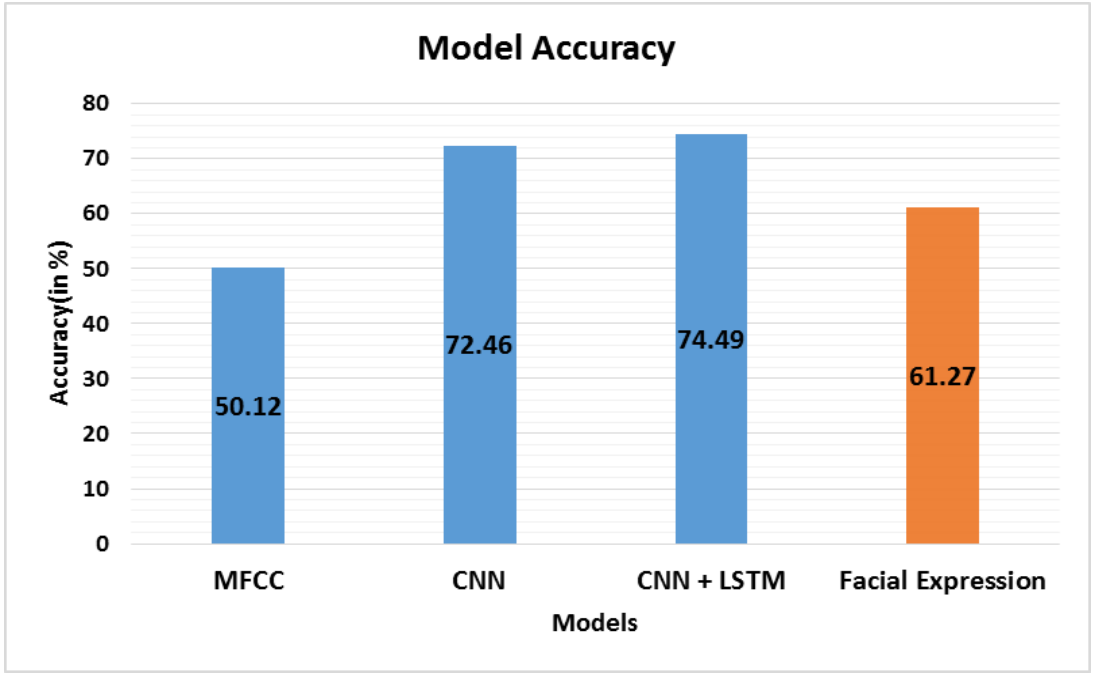
Total params: 7394247

```
Test score: 1.08653423576
Test accuracy: 0.612705489002
```



Confusion Matrix

Choosing the Best Model



Fusion Based on F-Scores

$$\text{Precision} = \frac{TP}{TP + FP}$$

TP=True Positive
FP=False Positive

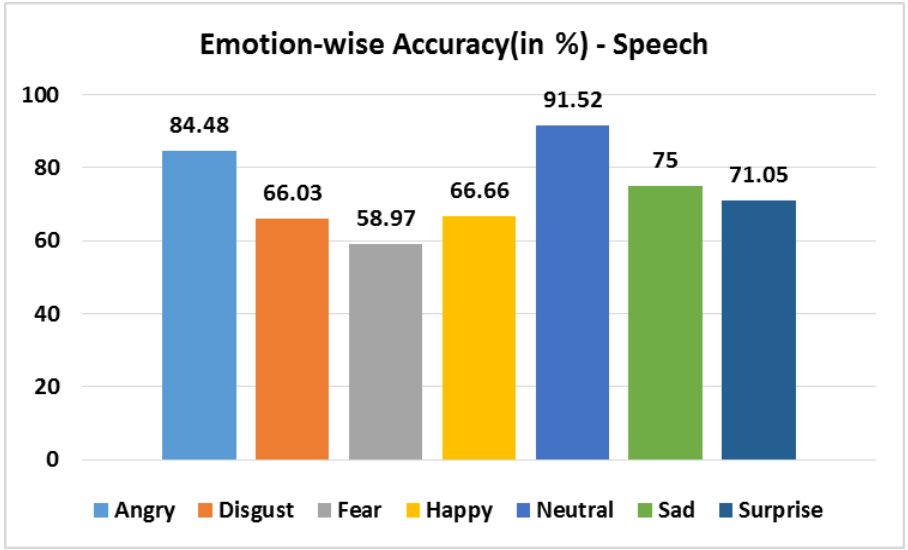
$$\text{Recall} = \frac{TP}{TP + FN}$$

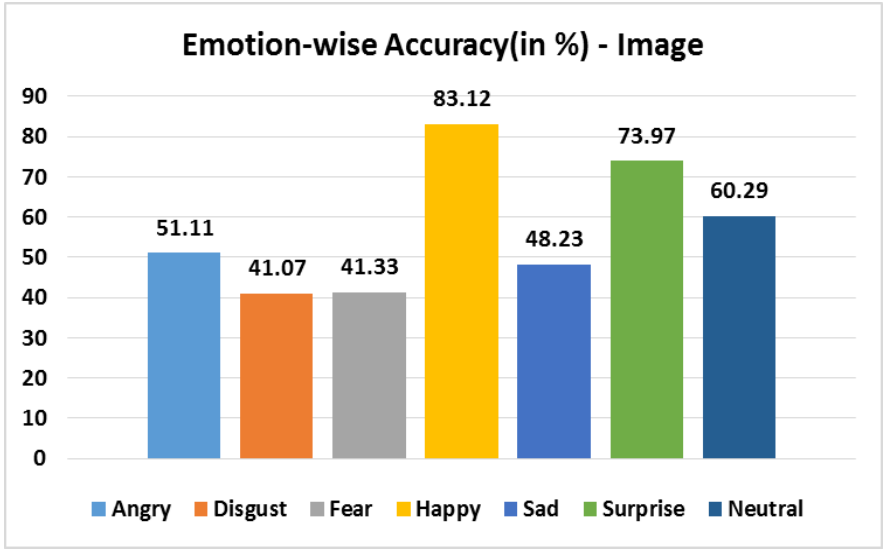
TP=True Positive
FN=False Negative

$$\text{F-Score} = \frac{2 * (\text{recall} * \text{precision})}{\text{recall} + \text{precision}}$$

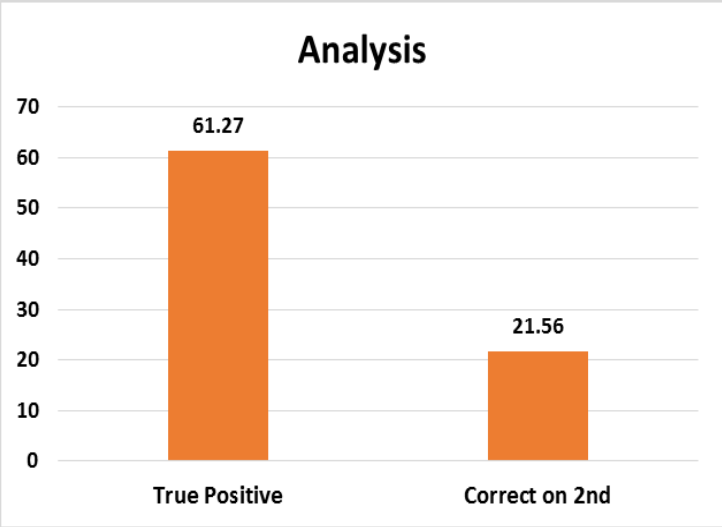
Emotions	Images	Speech
Angry	0.5308	0.9034
Disgust	0.5748	0.4864
Fear	0.4581	0.5194
Happy	0.8113	0.6024
Neutral	0.5302	0.7880
Sad	0.4765	0.75
Surprise	0.7623	0.6236

Analysis


Emotion-wise Accuracy(in %) - Speech
100
80
60
40
20
0
84.48
66.03
58.97
66.66
91.52
75
71.05
Angry
Disgust
Fear
Happy
Neutral
Sad
Surprise


Emotion-wise Accuracy(in %) - Image
90
80
70
60
50
40
30
20
10
0
51.11
41.07
41.33
83.12
48.23
73.97
60.29
Angry
Disgust
Fear
Happy
Sad
Surprise
Neutral

Dataset	*Accuracy*
SAVEE	60.19%
IIIT A	80.93%
SAVEE + IIIT A	74.49%



Dashboard

Public Leaderboard - Challenges in Representation Learning: Facial Expression Recognition Challenge

This leaderboard is calculated on approximately 50% of the test data.
The final results will be based on the other 50%, so the final standings may be different.

See someone using multiple accounts?
Let us know.

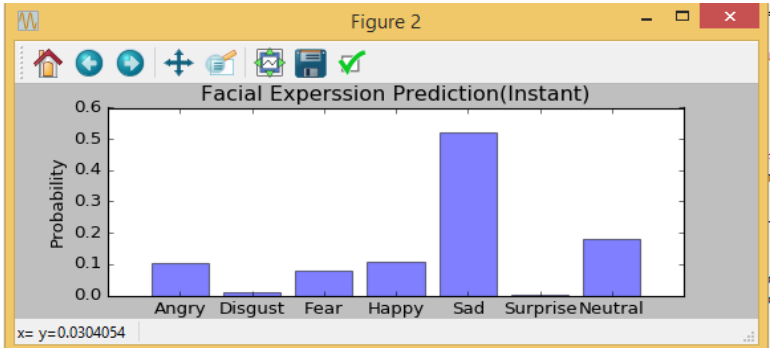
#	Δ1w	Team Name * In the money	Score	Entries	Last Submission UTC (Best – Last Submission)
1	new	RBM *	0.69769	5	Thu, 23 May 2013 16:12:26 (-43h)
2	new	Unsupervised	0.69072	8	Fri, 24 May 2013 18:32:35
3	new	Maxim Milakov	0.68153	7	Fri, 24 May 2013 20:07:41
4	new	Radu+Marius+Cristi	0.67317	6	Fri, 24 May 2013 14:35:49 (-2.4d)
5	new	Lor.Voldy	0.64558	2	Tue, 21 May 2013 19:29:59 (-0h)
6	new	Eric Cartman	0.64447	1	Tue, 21 May 2013 19:32:52
7	new	ryank	0.64057	2	Tue, 21 May 2013 21:49:50
8	new	Xavier Bouthillier	0.62775	1	Fri, 24 May 2013 11:23:46
9	new	sayit	0.61911	2	Wed, 22 May 2013 16:52:46 (-14.7h)
10	new	Alejandro Dubrovsky	0.61382	5	Fri, 24 May 2013 23:30:26
11	new	jaberg	0.60797	6	Fri, 24 May 2013 22:09:53 (-30.7h)
12	new	kg	0.59181	4	Thu, 23 May 2013 23:45:22 (-0h)
13	new	bulbuloglu	0.58958	8	Fri, 24 May 2013 12:35:42 (-15.3h)
14	new	Liu	0.58038	8	Fri, 24 May 2013 21:10:48 (-26.2h)

Kaggle Position(9th) with 61.27% accuracy for facial data

On testing the validation data, we analysed that **21.56% misclassified images have second most likely emotion as the correct label.**

Modules Developed

i. Emotion Classification using speech signal from audio file
ii. Emotion Classification using from microphone audio file
iii. Real Time Webcam Video Classification using Facial Expression
iv. Emotion Classification using fusion of speech and audio signals.



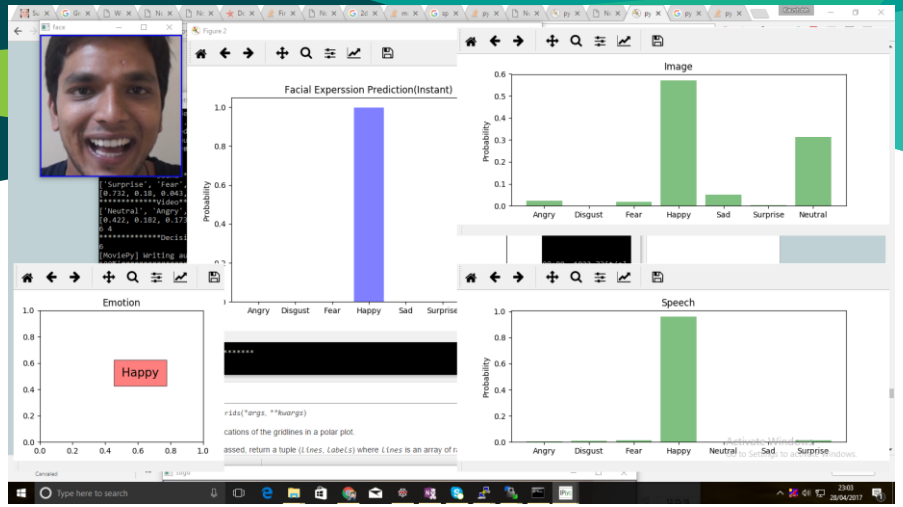
t1.py | test_audio_file.py | test_file.py | untitled0.py | untitled3.py | audio_video_file.py

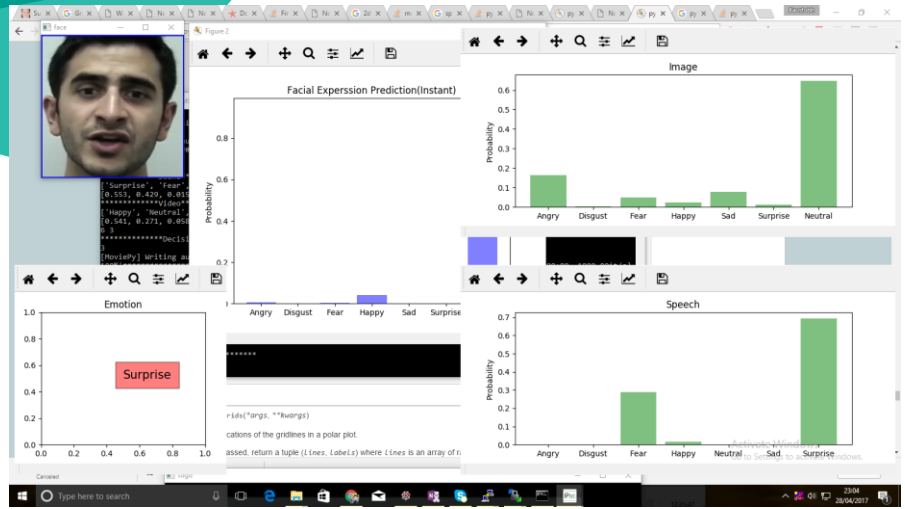
```
34
35 expressions = "Angry", "Disgust","Fear", "Happy","Sad", "Surprise", "Neutral"
36
37 def find_exp(score) :
38     yx = zip(score[0,:],expressions)
39     yx.sort(reverse=True)
40     y1 = np.empty([7], dtype='float32')
41     x1 = [x for y,x in yx]
42     y1 = [round(y,3) for y,x in yx]
43
44     return x1,y1
45
46
47
48
49 ################################
50 K.set_image_dim_ordering('th')
51
52 model= load_model('model_221.h5')
53 print ('Model Loaded....')
54
55 model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
56 model.load_weights('my_model_221.h5')
57 print ('Weights Loaded....')
58
59 ######################################
60
61
62
63 ##################VIDEO DATA
64
65
66 face_cascade = cv2.CascadeClassifier('haarcascade_frontalface_default.xml')
67 cap = cv2.VideoCapture('MAH01715.MP4')
68 ans = []
69 time = []
70 p = 0
71 i = 0
72 c = 0
73 t = 0
74 x_test = np.empty([1,1,48,48])
75 f = open('emotions.txt','w')
76 f.close()
77 while(cap.isOpened()):
78
79     ret, frame = cap.read()
80     #gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
       gray = frame;
```

Editor - C:\Users\Incarnation\Pictures\Screenshots\CNNandRNN_saving_Weights.py

test_file.py | untitled0.py | untitled3.py | audio_video_file.py | test_video_file.py | CNNandRNN_saving_Weights.py

```
58 #plt.imshow(X_train[5][0], interpolation='nearest')
59 #plt.show()
60
61
62 print("--------------test data----------")
63 print (X_test.shape)
64 print (Y_test.shape)
65 print (test_size)
66 print (test_rows)
67 print (test_cols)
68
69
70 X_train = X_train.astype("float32")
71 X_test = X_test.astype("float32")
72
73 Y_train = np_utils.to_categorical(Y_train,7)
74 num_classes = Y_train.shape[1]
75 Y_test = np_utils.to_categorical(Y_test,7)
76
77
78
79 print("############model###############")
80 channel_axis = 1
81 freq_axis = 2
82 time_axis = 3
83 np.random.seed(1337)  # for reproducibility
84 K.set_image_dim_ordering('th')
85
86
87 model = Sequential()
88
89 model.add(Convolution2D(64, 3, 3, border_mode='full', input_shape=(1, train_rows, train_cols)))
90 model.add(BatchNormalization(axis=channel_axis, mode=0))
91 model.add(ELU())
92 model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
93 model.add(Dropout(0.1))
94
95 model.add(Convolution2D(128, 3, 3, border_mode='full'))
96 model.add(BatchNormalization(axis=channel_axis, mode=0))
97 model.add(ELU())
98 model.add(MaxPooling2D(pool_size=(3, 3), strides=(3, 3)))
99 model.add(Dropout(0.1))
100
101 model.add(Convolution2D(128, 3, 3, border_mode='full'))
102 model.add(BatchNormalization(axis=channel_axis, mode=0))
103 model.add(ELU())
```


Facial Expression Prediction(Instant)
Image
Emotion
Happy
Speech
Angry Disgust Fear Happy Sad Surprise Neutral
Probability


Facial Expression Prediction(Instant)
Image
Emotion
Surprise
Speech
Angry Disgust Fear Happy Sad Surprise Neutral
Probability

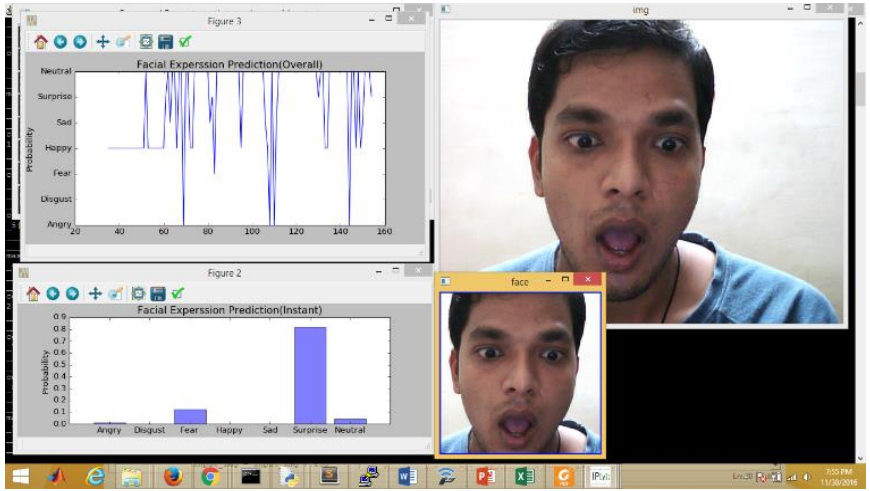


Figure 3
Facial Expression Prediction(Overall)
Figure 2
Facial Expression Prediction(Instant)
img
face
Neutral Surprise Sad Happy Fear Disgust Angry
Probability

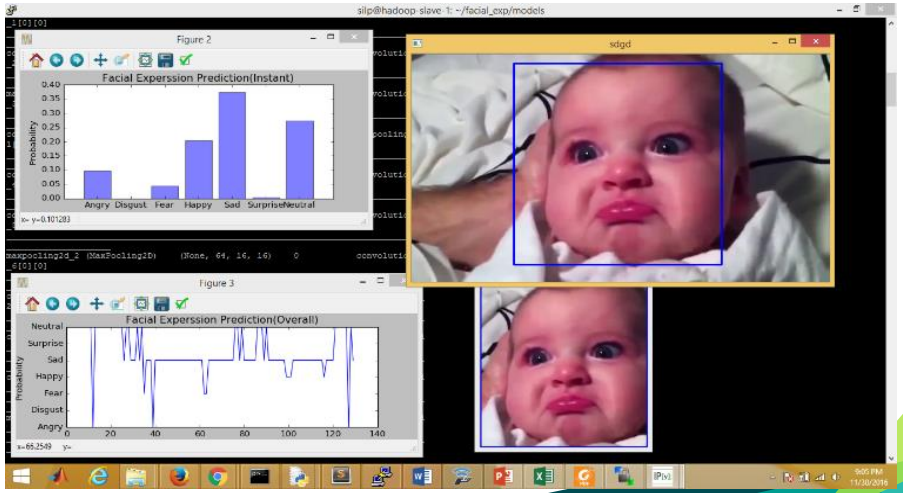


Figure 2
Facial Expression Prediction(Instant)
sdgd
Figure 3
Facial Expression Prediction(Overall)
Angry Disgust Fear Happy Sad Surprise Neutral
Probability


CyberLink PowerDirector Trial Version

Technical Requirements

- Nvidia GPU
- CUDA
- Python
- Anaconda
- Librosa
- pyAudioAnalysis
- Theano
- Kares
- PyCharm

Thank You!

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