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**Sentence-Level Emotion Apprehension Through Facial Expression & speech verification Analysis**

**Thesis**

**Submitted By**

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| **Declaration** |

We declare that this thesis is our original work and has not been submitted in any form for another degree or diploma at any university or other institute of tertiary education. Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references is given.

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| **Approval** |

The thesis titled “Sentence-Level Emotion Apprehension Through Facial Expression & speech verification Analysis” has been submitted to the following respected members of the board of examiners of the department of computer science in partial fulfilment of the requirements for the degree of Bachelor of Science in Computer Science on (18 February, 2021) and has been accepted as satisfactory.

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| **Abstract** |

The importance of Emotional state apprehension is widely perceived in social interaction and social intelligence. This analysis has been an active research topic since 19th century [10]. In human-to-human communication, the understanding of facial expressions forms a communication carrier that offers vital data about the mental, emotional, and even physical state of the persons in conversation [10]. Inevitably user emotional state plays an important role not only in human associations with other people but also in the way a user uses computers. As emotional state of a person may determine consistency, task solving, and decision-making skills [12]. Through this study, facial expression analysis refers to computer systems that attempt to automatically predict user emotional state by analysing and recognizing facial motions and facial feature changes from visual information. Though Interpretation is aided by circumstances, body gesture, voice, individual diversity, and cultural factors as well as by facial arrangement and timing [6]. In this study, facial expression analysis methods will be conducted to analyse the facial actions notwithstanding of context, culture, gender, and so on.

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| **Chapter 1: Introduction** |

**1.1 Background of the study**

This region includes a comprehensive survey on the approaches previously used to detect the emotion of a sentence. It can be seen that Dipankar Das and Shivaji Bandyopadhyay [4] operate a machine learning approach using Conditional Random Field (CRF). Their method is a two-step method where the first step is to create an emotion for each word in a sentence using WordNet’s Affect List and the next step is to find the authoritative sentiment of each sentence using weight points of each word in the sentence. The first step uses CRF for word-level commentary which searches for words in the sentence that are present in the Affect list and returns phrase tagging of emotions. The next step is performed by applying these word-level emotions to achieve the overall sentence level emotion based on weight scores of each word in a sentence. This paper produces a high accuracy of 87.65%, it is limited by the Synonyms set (SynSet) in the Affect list. This model failed to consider words that do not exist in the said list. The scholars in Paper [5] do an experimental analysis of different approaches to tackle the problem of sentence-level emotion tagging. They use five approaches, which include four knowledge-based ideas and one corpus-based idea. The first approach in knowledge-based ideas, WordNet-Affect Presence, deals with interpreting the disturbances in a text simply based on the residence of words from the Word-Net Affect lexicon. wherein the second approach, Latent Sentiment Analysis (LSA), the LSA similarity between the given text and each emotion is determined and each emotion is defined as a vector of the word expressing that particular emotion. In the third method, its synonyms from the WordNet SynSet are used. Ultimately, the fourth scheme, LSA all emotion words, serves the preceding set by combining the words in all the SynSets identified with a given sentiment, as found in WordNet Affect List. Besides, the corpus-based procedure used in this paper [5] uses a machine-learning classifier, Naive Bayes that is trained on Blog Posts to incorporate emotion in a labeled data set. This approach is more practical and has been employed similarly in our model. In paper [6], the authors discuss a design to find emotion labels using two methods: keyword spotting and lexical affinity. Certain methods use the existing lexical corpus to find words about a distinct emotion of the stated collection of emotions. In paper [6] negation was not considered. words like not, neither, and never, which can give the polarizing emotion of the sentence. it tags an emotion to sentence based on the context preferably than the word level emotion weights. This process assigns an emotion to the sentence by weighing the relation between the different words and emotions present in it. the ANEW list (Bradley and Lang 1999) is advised, and if found, its purpose is obtained.

**1.2 Statement of the problem**

The market for emotion-detection technology is worth approximately $21.6bn, and its value is prognosticated to more than double by 2024, relinquishing $56bn. Businesses can purchase systems to help them vet job applicants, analyse advertisements for their sentimental impression and test criminal defendants for signs of fraud [19]. The facial expression identification system was introduced in 1978 by Suwa et. al [10]. manifested an attempt to automatically interpret facial expressions by tracking the motion of 20 recognized points on an image series in 1978. The influence of the facial expression system is broadly acknowledged in social interaction and social intelligence. Facial expression analysis includes both estimations of facial motion and recognition of expression.

Paul Ekman and Friesen carrying out more in-depth Darwin studies have concluded that there are six transcultural and prototypic emotional expressions [7]. These basic expressions are happiness, anger, sadness, surprise, disgust, and fear. Some authors consider the neutral face as a seventh expression [7]. It is known that facial expression changes through a set or subset of prototypic emotional expressions. Given the huge influence, Ekman’s work possessed on the science of emotion, his opinions are pervasive in emotion-detection technology, informing many algorithms, including those sold by Microsoft, IBM and Amazon.

Ekman’s study is questionable not just because it underplays the importance of developmental differences, but also because it considers that there is a relationship between someone’s facial expression and their emotional state. Researchers have since discovered the exact opposite: a recent study by the Ohio State University implied that facial appearances are often unpredictable signs of emotion.

**1.3 Goals and Objective**

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| **Chapter 2: Literature Review** |

In the Emotion detection research field, several domains contribute like machine learning, natural language, neuroscience, etc. In previous researches, facial expression, voice features, or textual data are used separately to classify emotions. Emotion can be classified into several static classifications like happiness, sadness, disgust, anger, fear, and surprise. It can be further improved by combining the image, voice, and textual data. This combination of data gives further improved results

**2.1 Convolutional Neural Network:**

Like every other classification problem, the emotion recognition problem requires an algorithm to complete feature extraction and categorical classification. In order to classify an emotion, we need to extract certain features from data and build a model that can classify the input based on the feature. The procedure can be outlined as follows:

**1. Data Pre-processing:**

The data pre-processing is to standardize the data. The typical way is to set the mean of the data to 0 and to also divide the data by the standard deviation.

**2. Feature Extraction:**

The typical conventional method is to detect the face and extract the Action Units from the face, and certain emotions contain the combination of AUs code as features.

**3. Model Construction:**

The conventional classifier can be either a supervised or unsupervised algorithm. A typical example of a supervised algorithm is Support Vector Machine, and the examples of the unsupervised algorithm include Principal Component Analysis (PCA) and Linear Discriminant Analysis algorithm include Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA)

**4. Label or Result Generation:**

The typical way to generate a label or result is to find which decision boundary has the minimum Euclidean distance from the data.

**2.2 The issues with conventional method:**

Defining a facial expression can sometimes be difficult as representative of a certain emotion, even for humans. Research shows that different people recognize different emotions for the same facial expression. And it’s even harder for AI. A lot of factors make emotion recognition tricky. We can divide these factors as follows: technical and psychological.

**2.3 Technical challenges:**

Emotion recognition shares a lot of challenges with detecting moving objects in the video: identifying an object, continuous detection, incomplete or unpredictable actions, etc. Let’s have a look at the most widespread challenges of implementing an ER solution and also, ways of overcoming them.

An emotion recognition solution scans faces for eyebrows, eyes, noses, mouths, chins, and other facial features. Sometimes, this detection is complicated due to:

**The distance between features**: The software “remembers” the average distance between landmarks and looks for them only within this range.

**Feature size**: ER solutions struggle with detecting uncommon features, like unusually thin or pale lips, narrow eyes, etc.

**Skin color:** In some cases, a solution may misclassify a feature due to skin color.

To improve the accuracy level of feature identification, some researchers implement a part-based model that divides facial landmarks into several parts according to the physical structure of the face. Then this model feeds these parts into the network with relevant labels.

**2.3.1 Data:**

For any machine learning/deep learning algorithms, ER solutions require a lot of training data. This data has videos of various frame rates, various angles, various backgrounds, people of different genders and nationalities, etc.

**Training Dataset:**

The training data (fer2013) consists of 48x48 pixel grayscale images of faces. The faces have been automatically registered so that the face is more or less centered and occupies about the same amount of space in each image.

**Test Dataset:**

For the Test Dataset we have used CMU-MOSEI multimodal Dataset. We had to pre-process the video file according to our needs.

**2.3.2 Face occlusion and lighting issues:**

Occlusion due to changes in the pose is a common issue for motion detection in video, especially when working with unprepared data. A popular method for overcoming it is by using a formalization technique that detects facial features in the video, creates relevant landmarks, and extrapolates them to a 3D model of a human face.

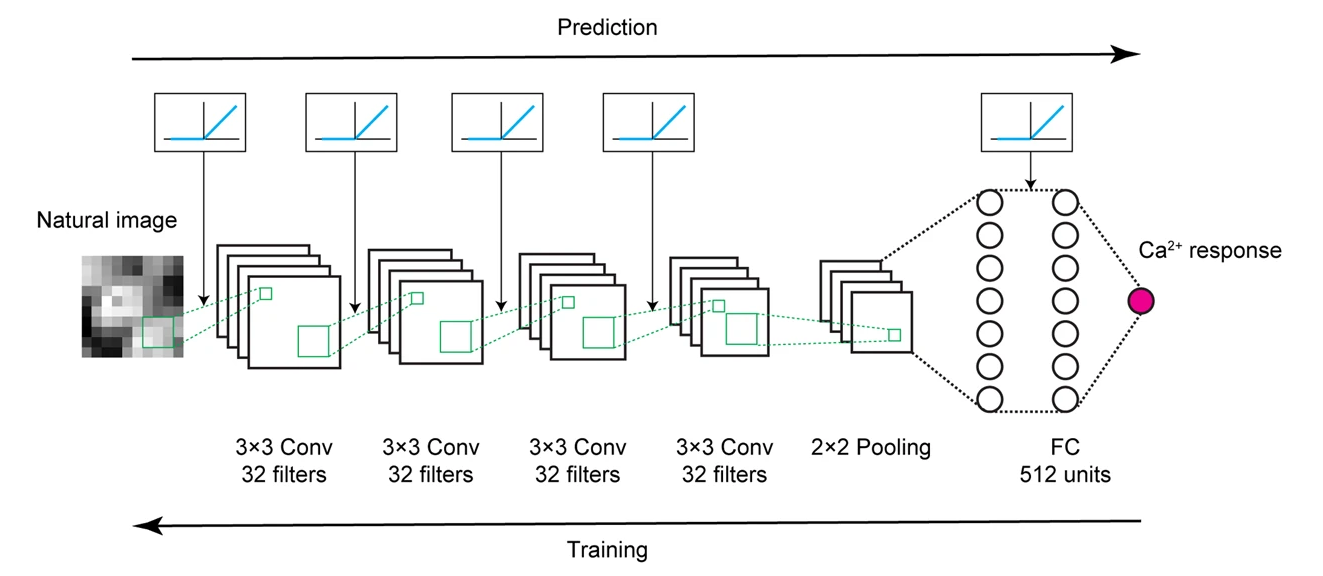
Generally, to increase the recognition rate, developers implement illumination normalization algorithms.

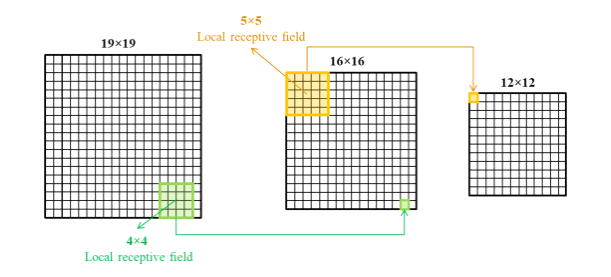
There are also some unconventional approaches. This layer is not sensitive to illumination changes and adds records of skin temperature changes that may indicate emotions.

**2.3.3 Recognizing incomplete emotions:**

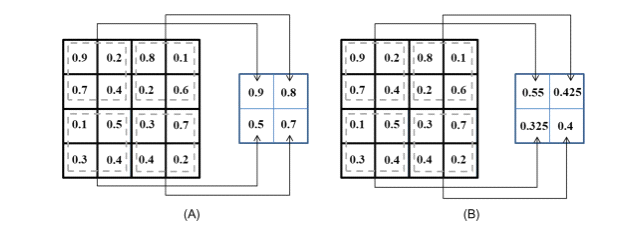
Most algorithms focus on recognizing the high-intensity expression. This leads to an inaccurate recognition of emotion when analyzing people from cultures with traditions of emotional suppression.

**2.4 Introduction to CNN:**

The structure of CNNs consisted of mainly 3 substructures, which include: convolutional layers, pooling layers, fully connected layers.

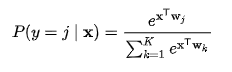
Convolutional layers are made from several feature maps. A new feature map is created by sliding a local receptive field over the input. The convolution can be used in various kinds of data such as images, text. Like in the image, an area of pixels is convolved, and in the text, a group of characters/words are convolved. Each neuron in the layers is not connected to all of the nodes (neurons) in the previous layer but is just connected to nodes in a special region known as the local receptive field.

These layers were generated to simplify the information. These layers are also called the subsampling layer. Pooling operations can be performed in various types such as geometric average, harmonic average, maximum pooling. Max-pooling and average-pooling are the most prevalent processes for pooling. The pooling layers are necessary to reduce the computational time.



Fully connected layers are the final layers in the CNN structure, placed after a sequence of convolution and pooling layers. These layers provide the feature vector for the input data, which can be used for some machine learning tasks such as classification, prediction. The last layer of fully connected layers is known as the SoftMax classifier.





The max-pooling layer performs the task to down sample the image or feature map, thereby reducing the computation and directing the next layers to focus on more detailed features. In conclusion, these 3 types of layers construct the uniqueness of the convolution block.

In addition to the convolutional block, the fully connected layers will serve as a classifier. Each unit of the layer contains the weight matrix, and through the linear transformation and activation function, the output becomes the input of the next layers of units [9]. In contrast to a traditional linear transformation, the activation function ReLU (shown as equation 4) will act in the same way as the convolutional layers to make the system more easily distinguish the feature.

Output = max (input, 0)

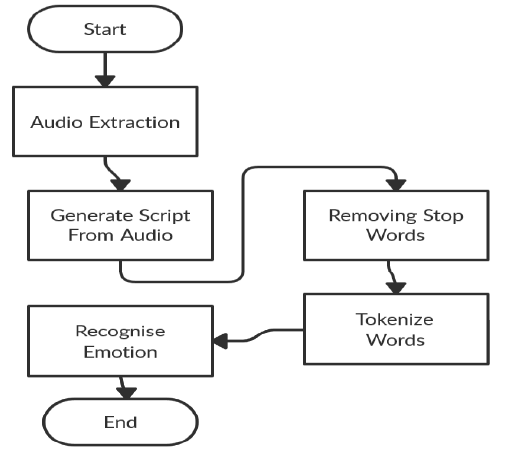
In addition, the last layer is normally a SoftMax classifier, and the result is typically the one with maximum probability in multinomial distribution.

classI ∼ Multinomial(φi)

label = arg max.

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| **Chapter 3: Methodology** |

**3.1 Work Flow:**



**3.2 Video Processing:**

The first step is to process the video and break the video into two part

**3.2.1 Video to Frame:**

First we extract frame from mp4 video which is located in Google drive. For extracting frame from video we imported scikit-image, opencv-python library. First challenge is to have consistent data. Main rules in the dataset creation were:

* light conditions: records during the day
* video quality at least 640 width or above
* removed any cover with titles
* Face must be in the middle

Then we make each frame grayscale and resize it to 640. After that we stored every frame in Google Drive.

Algorithm:

count = 0

success = True

vidcap = cv2.VideoCapture(videofile)

while success:

    if (count%one\_frame\_each == 0):# checks frame number and keeps one\_frame\_each

        success,image = vidcap.read() # reads next frame

        image\_gray = rgb2gray(image)  # grayscale image

        if image.shape[1]>640:     # if image width > 640, resize it

          tmp = resize(image\_gray, (math.floor(640 / image\_gray.shap e[1] \* image\_gray.shape[0]), 640),mode='constant')

        plt.imsave("%s/%s%d.png" % (OUTPUT\_FRAMES\_PATH,frame\_name, count), tmp, cmap= plt.cm.gray) # saves images to frame folder

        print ('\*', end="")

        if count>=100:   #limits frames to 100

          break

    else:

        success,image = vidcap.read()# reads next frame

    count += 1

**3.2.2 Video to Audio:**

Initially, we Have extracted audio from Video using MoviePy. MoviePy can edit all the several popular audio and video forms, including GIF, and runs on Windows/Mac/Linux, with Python 2.7+ and 3.

**3.2.3 Reducing Noise:**

The default feature given by speech\_recognition which is adjust\_for\_ambient\_noise was used to reduce the noise of the audio.

**3.2.4 Audio to Text:**

we have used and compared multiple voice recognition technology to achieve the best outcome. The technologies include google Text to speech, Microsoft Bing Speech, Wit, SoundHound for generating the script. On a given audio file, Google, Wit had shown similar results which are about 45% of the whole audio was extracted correctly where Bing showed comparatively better output about 61% of the whole transcript correctly. But finally, Soundhound was our API of choice for recognizing speech which is 80%+.

**3.3 Model Creation:**

For creating the model we use the Sequential API from keras library. Our Model contains four Convolutional Layers, two dense layer and one hidden layer.

Convolutional Layers:  
First Convolutional layer has 64 filters, size is 3x3, output matrix and input matrix are same. Second layer contains 128 filter, third layer contains 256 filters and last layer contains 512 filters. Other parameters were same.

Model is given bellow:

def createModel():

model = Sequential()  
model.add(Conv2D(64, (3, 3), padding='same', input\_shape=(48,48,1)))

model.add(BatchNormalization())

model.add(Activation('relu'))

model.add(MaxPooling2D(pool\_size=(2, 2), strides=None, padding='same'))

model.add(Dropout(0.25))

model.add(Conv2D(128, (3, 3), padding='same'))

model.add(BatchNormalization())

model.add(Activation('relu'))

model.add(MaxPooling2D(pool\_size=(2, 2), strides=None, padding='same'))

model.add(Dropout(0.25))

model.add(Conv2D(256, (3, 3), padding='same'))

model.add(BatchNormalization())

model.add(Activation('relu'))

model.add(MaxPooling2D(pool\_size=(2, 2), strides=None, padding='same'))

model.add(Dropout(0.25))

model.add(Conv2D(512, (3, 3), padding='same'))

model.add(BatchNormalization())

model.add(Activation('relu'))

model.add(MaxPooling2D(pool\_size=(2, 2), strides=None, padding='same'))

model.add(Dropout(0.25))

model.add(Flatten())

model.add(Dense(512))

model.add(BatchNormalization())

model.add(Activation('relu'))

model.add(Dropout(0.25))

model.add(Dense(256))

model.add(BatchNormalization())

model.add(Activation('relu'))

model.add(Dropout(0.25))

model.add(Dense(7))

model.add(Activation('softmax'))

return model

model = createModel()

**3.4 Training:**

In case of Recognition from the Video frames, the task is to categorize each face based on the emotion shown in the facial expression into one of seven categories (0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise, 6=Neutral). The training set consists of 28,709 examples and the public test set consists of 3,589 examples.

In case of Audio Recognition, the task is to categorize each word based on the meaning into one of five categories on the scale 0 to 1. Which are: Angry, fear, Happy, Sad and Surprise.

We train the model for 30 epoch and batch size of 8. Which game the model to have 71.5% accuracy.

**3.5 Emotion Recognition from Images:**

For recognizing the images that were saved during video to frame conversion need to have some modification to fit into the model.

**3.5.1 Image Processing:**

Firstly we need to detect the faces from the images. For face detection we use python keras.preprocessing library. Then the images were converter to have 48x48 shape.

**3.5.2 Prediction:**

**3.6 Emotion Recognition from Audio:**

**3.6.1 Removing Stop words:**

Words that are super common and doesn't carry that much of a meaning, they just connect the important words of a sentence are called stop-words. These should be removed too optimize and reduce valuable processing time. Here We have user NLTK (Naturak Language Toolkit) to Remove stopwords from the Extracted Context. Thus, the prescience is that by removing these words, one can focus on the words that carry more prominence in a sentence or carry more information about the overall corpus.

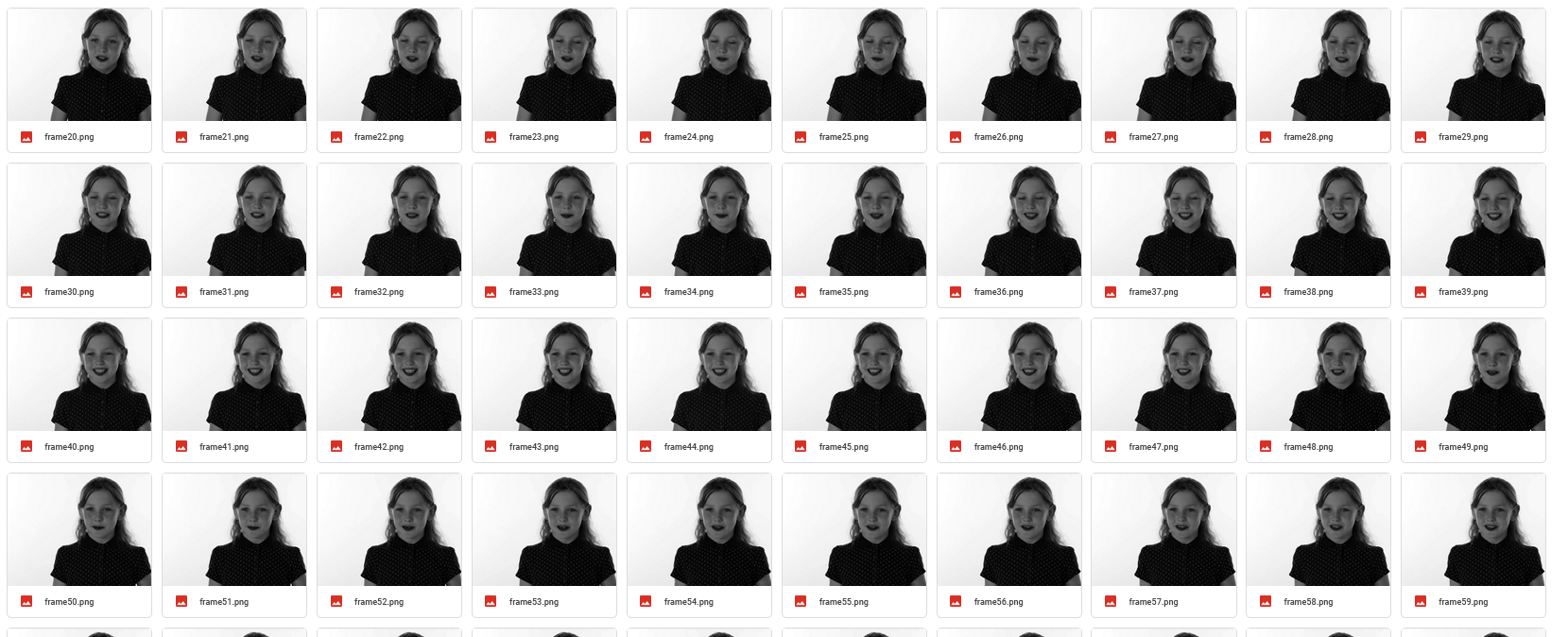
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his', 'himself', 'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them', 'their', 'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll", 'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during', 'before', 'after', 'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 'such', 'no', 'nor', 'not', 'only', 'own', 'same', 'so', 'than', 'too', 'very', 's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll', 'm', 'o', 're', 've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn', "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'weren', "weren't", 'won', "won't", 'wouldn', "wouldn't"]

**3.6.1 Prediction:**

We have used Text2Emotion python package to recognize the Emotion from the processed text extracted from the given video. Text2Emotion is a python package which automatically process texts, tokenize and extracts the emotions (Angry, fear, Happy, Sad and Surprise)

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| **Result & Discussion** |

The Video we used, was compiled into frames of every second and text was extracted from video.



100 Frames were taken throughout the whole video. Then The frames were resized into 48x48 grayscale image which was required according to our test Dataset.

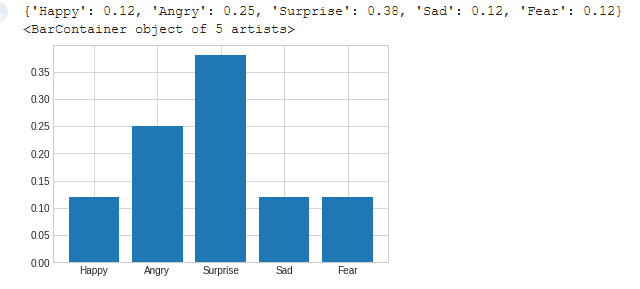
Using SoundHound Speech recognition Api support the recognized audio file was later transcripted into a text as,

“ what's the best thing about a gypsie on her period when you finger her you get here palm red for free biggest slut in history miss pac-man for twenty five cents that is a pap smear called a pap smear because girls wouldn't do if it was called scrape the short side and while what do you call a cheap circumcision difference between a walrus and a lesbian.”

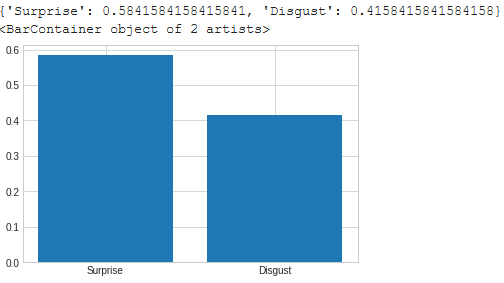
After Removing stop words from the raw transcript it changed significantly into,

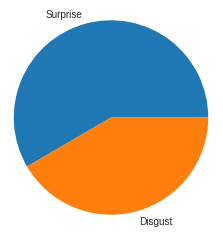
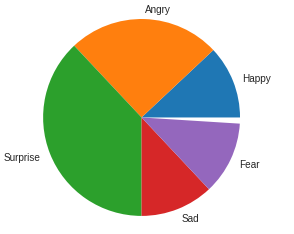
“ what's best thing gypsie period finger get palm red free biggest slut history miss pac-man twenty five cents pap smear called pap smear girls called scrape short side call cheap circumcision difference walrus lesbian “

Thus, Our text is ready for processing. Tokenization was automatically done through the process of Text2Emotion as its own feature.



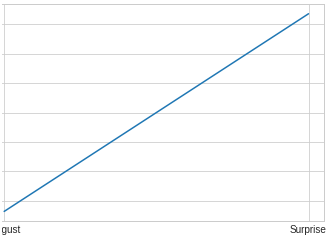
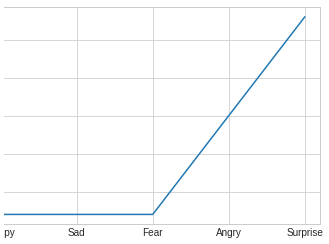
The Above image shows the Result Found from the extracted context from the video. On the Other hand, from the video recognition we get,



A comparision PiChart of these two recognition is given below,  

Then we Merged Both result Dictionaries into one final dictionary given priority to the image recognized result. Which gives us a final picture of the recognition.

{'Happy': 0.12, 'Angry': 0.25, 'Surprise': 0.5841584158415841, 'Sad': 0.12, 'Fear': 0.12, 'Disgust': 0.4158415841584158}

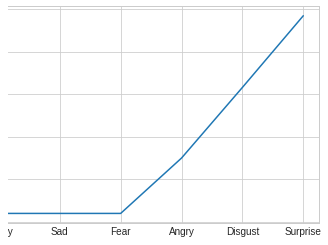


Fig: Merged\_Final\_Result

|  |
| --- |
| **Future Work** |

The Video we used

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