

**SAVITRIBAI PHULE PUNE UNIVERSITY**

**A PROJECT REPORT ON**

**EXPRESSIVE ENGLISH  
TEXT-TO-SPEECH SYNTHESIS SYSTEM**

**SUBMITTED TOWARDS THE  
PARTIAL FULFILLMENT OF THE REQUIREMENTS OF**

**BACHELOR OF ENGINEERING (Computer Engineering)**

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**Expressive english text-to-speech synthesis system**

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## **Abstract**

Many English text-to-speech conversion are available like Adobe Acrobat reader, Jovie and KMouth. But their output is extremely monotonic and robotic in nature. This limits their ability to be used for reading emotion rich novels. We try to solve this problem by using Machine Learning, Natural Language Processing and Digital Signal Processing concepts. Our system first predicts the emotions present in the text and then according to the emotion the system tries to modify the audio output of the text. For emotion prediction, we use a trained emotion classifier, which has been trained on the emotion datasets which are available publicly. Also, there is another system based on Natural Language Processing approach which tries to identify the arrangement of the sentence and based on which emotion of the sentence is predicted. The voice synthesis is done by a trained Hidden Markov Model based synthesis system. Presently, we identify and incorporate most prominent emotions in the text viz. neutral, joy, surprise, sadness and angry.

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# CHAPTER 1

## SYNOPSIS

## 1.1 Project Title

Expressive English Text-to-speech synthesis system

## 1.2 Project Option

The project group members decided to opt for unsponsored in-house project. This led the members to find their own idea for the project.

## 1.3 Internal Guide

Dr. G. P. Potdar

## 1.4 Technical Keywords (As per ACM Keywords)

F: Theory Of Computation

F.2: ANALYSIS OF ALGORITHMS AND PROBLEM COMPLEXITY

F.2.1: Numerical Algorithms and Problems (G.1, G.4, I.1)

B. Computations on matrices

For TF-IDF representation, the feature vector of a particular sentence is represented as a sparse matrix using python scipy library. These matrices are then used for further calculations. In deep learning approach, the weights of a layer are internally represented using matrices. Various operations like convolution and element-wise addition are performed depending on the structure of the network.

I: Computing Methodologies

I.2: ARTIFICIAL INTELLIGENCE

I.2.7: Natural Language Processing

A. Text analysis

Text mining task of emotion detection is addressed in this project. It involves lexical analysis, part of speech tagging and term-weighting using TF-IDF. For deep learning, word

embeddings are used to map a word to a continuous vector space.

#### B. Speech recognition and synthesis

In this project we synthesize expressive speech from input text. Synthesized speech can be created by concatenating pieces of recorded speech that are stored in a database. Systems differ in the size of the stored speech units; a system that stores phones or diphones provides the largest output range, but may lack clarity. The two primary technologies generating synthetic speech waveforms are concatenative synthesis and formant synthesis. Concatenative synthesis is based on the concatenation (or stringing together) of segments of recorded speech. Formant synthesis does not use human speech samples at runtime. Instead, the synthesized speech output is created using additive synthesis and an acoustic model. Parameters such as fundamental frequency, voicing, and noise levels are varied over time to create a waveform of artificial speech. Many systems based on formant synthesis technology generate artificial, robotic-sounding speech that would never be mistaken for human speech. As our main motivation behind the project was to generate human-like speech we use concatenative synthesis method.

### I.5: PATTERN RECOGNITION

#### I.5.4: Applications

A. Signal Processing Signal Processing algorithms are used to perform operations on the neutral audio signal to synthesize expressive speech. Following are some of the functions performed: Speaking style and speaker identity adaptation supporting various voice conversion algorithms. Gaussian Mixture Model based voice conversion algorithms. Prosody transformation algorithms for voice conversion. Mean and standard deviation transformation of f0. Smoothing algorithms for voice conversion.

## 1.5 Problem Statement

Develop a software program that reads a text file containing English sentences such that the emotions in the sentences are reflected in the audio.

## 1.6 Abstract

Many English text-to-speech conversion are available like Adobe Acrobat reader, Jovie and KMouth. But their output is extremely monotonic and robotic in nature. This limits their ability to be used for reading emotion rich novels. We try to solve this problem by using Machine Learning, Natural Language Processing and Digital Signal Processing concepts. Our system first predicts the emotions present in the text and then according to the emotion the system tries to modify the audio output of the text. For emotion prediction, we use a trained emotion classifier, which has been trained on the emotion datasets which are available publicly. Also, there is another system based on Natural Language Processing approach which tries to identify the arrangement of the sentence and based on which emotion of the sentence is predicted. The voice synthesis is done by a trained Hidden Markov Model based synthesis system. Presently, we identify and incorporate most prominent emotions in the text viz. neutral, joy, surprise, sadness and angry.

## 1.7 Goals and Objectives

The goal of the project is to create a software system that will be able to identify emotions from english text and accordingly produce affective output. There are two objectives associated with our project. First objective is to identify emotion associated with each and every sentence of the text. And the second objective is to modify neutral speech to incorporate emotion associated with the text.

## 1.8 Relevant mathematics associated with the Project

Let  $S$  be the set denoting the system:

$$S = \{s, e, X, Y, F_{me}, DD, NDD, S_c, F_c\}$$

where,

$s$  = start state

= Classifier for the sentences is trained  
 e = end state  
 = System gives speech with emotions as output  
 X = set of input  
 = {text file}  
 Y = set of output  
 = {speech with emotions}  
 $F_{me}$  = set of functions  
 =  $\{F_{ip}, F_{ml}, F_{clas.}, F_{s/p}, F_{op}, F_1, F_2, F_3\}$   
 where,  
 $F_{ip}$  = Function to take input X  
 $F_{ml}$  = Function to train the classifier using Machine Learning  
 $F_{clas.}$  = Function to classify the input text  
 $F_{s/p}$  = Function to synthesize the audio using Hidden Markov Model  
 $F_{op}$  = Function to write the output speech file  
  
 $F_1$  = Get emotion using Naive Bayes Classifier

Naive Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes' theorem. As a general statement, we can state Bayes' theorem as follows

$$P(\omega_j|x) = \frac{p(x|\omega_j) \cdot P(\omega_j)}{p(x)} \quad (1.1)$$

The data is represented by  $\mathbf{x}$  and labels are represented by  $\omega_j$ .

$F_2$  = Get emotions using LSTM classifier  
 RNNs maintain a hidden vector  $\mathbf{h}$ , which is updated at time step  $t$  as follows:

$$\mathbf{h}_t = \tanh(\mathbf{W} * \mathbf{h}_{t-1} + \mathbf{I} * \mathbf{x}_t) \quad (1.2)$$

where  $\tanh$  is the hyperbolic tangent function,  $\mathbf{W}$  is the recurrent weight matrix and  $\mathbf{I}$  is a projection matrix. The hidden state  $\mathbf{h}$  is then used to make a prediction

$$\mathbf{y}_t = \text{softmax}(\mathbf{W} * \mathbf{h}_{t-1}) \quad (1.3)$$

where *softmax* provides a normalized probability distribution over the possible classes and  $\mathbf{W}$  is a weight matrix.



Training vanilla RNNs is known to be particularly difficult.

LSTMs address the problems commonly found in training RNNs by incorporating gating functions into their state dynamics . At each time step, an LSTM maintains a hidden vector  $\mathbf{h}$  and a memory vector  $\mathbf{m}$  responsible for controlling state updates and outputs. More concretely, we define the computation at time step  $t$  as follows :

$$\begin{aligned}
\mathbf{g}^u &= \sigma(\mathbf{W}^u * \mathbf{h}_{t-1} + \mathbf{I}^u * \mathbf{x}_t) \\
\mathbf{g}^f &= \sigma(\mathbf{W}^f * \mathbf{h}_{t-1} + \mathbf{I}^f * \mathbf{x}_t) \\
\mathbf{g}^o &= \sigma(\mathbf{W}^o * \mathbf{h}_{t-1} + \mathbf{I}^o * \mathbf{x}_t) \\
\mathbf{g}^c &= \tanh(\mathbf{W}^c * \mathbf{h}_{t-1} + \mathbf{I}^c * \mathbf{x}_t) \\
\mathbf{m}_t &= \mathbf{g}^f \odot + \mathbf{g}^u \odot \mathbf{g}^c \\
\mathbf{h}_t &= \tanh(\mathbf{g}^o \odot \mathbf{m}_{t-1})
\end{aligned} \tag{1.4}$$

$F_3$  = Function to generate audio using Hidden Markove Model The task is to compute in a best way, given the parameters of the model, the probability of a particular output sequence. This requires summation over all possible state sequences. The probability of observing a sequence:

$$Y = y(0), y(1), \dots, y(L - 1) \tag{1.5}$$

of length L is given by

$$P(Y) = \sum_X P(Y|X)P(X), \tag{1.6}$$

where the sum runs over all possible hidden-node sequences

$$X = x(0), x(1), \dots, x(L - 1) \tag{1.7}$$

here  $\sigma$  is the logistic sigmoid function,  $\mathbf{W}^u, \mathbf{W}^f, \mathbf{W}^o, \mathbf{W}^c$  are recurrent weight matrices and  $\mathbf{I}^u, \mathbf{I}^f, \mathbf{I}^o, \mathbf{I}^c$  are projection matrices.

DD = Deterministic Data

$$= \phi$$

NDD = Non Deterministic Data

$$= \{X\}$$

$S_c$  = Success case

$$= Y \text{ contains speech with emotions}$$

$F_c$  = Failure case

$$= \overline{S_c}$$

## **1.9 Names of Conferences / Journals where papers can be published**

1. Association for Computational Linguistics: Human Language Technologies.
2. The SIGNLL Conference on Computational Natural Language Learning.

## **1.10 Review of Conference/Journal Papers supporting Project idea**

1. Association for Computational Linguistics: Human Language Technologies conference is held to facilitate a platform for the researchers who work in Computational Linguistics. Research related to natural language understanding by the computer is published here. This is why, a research paper related to our topic can be published in this conference.
2. SIGNLL is a top-tier conference, yearly organized by SIGNLL (ACL's Special Interest Group on Natural Language Learning). The conference includes research papers from the field of Natural Language Processing which includes understanding of the natural language by computer and processing them. As our project deals with Natural Language Processing, this conference can be used as a platform to publish our research paper.

## 1.11 Plan of Project Execution

Task Name	Start	End	Days
Study of emotion classification algorithms	8/2	8/16	14
Collecting and cleaning datasets	8/18	8/30	14
Study of human audio features	9/1	9/8	7
Study of algorithms for modifying audio	9/9	10/4	25
Deciding implementation approach	10/6	11/10	35
Implementing classifier module	12/1	12/15	14
Implementing audio feature modification module	12/16	12/31	15
Performance improvement	1/2	1/14	12
Testing and deploying the project	1/15	1/30	15
Documentation and open source release of the project	2/1	2/26	25

# **CHAPTER 2**

## **TECHNICAL KEYWORDS**

## 2.1 Area of Project

The project titled "Expressive English text-to-speech synthesis system" belongs to the domains of Machine Learning, Natural Language Processing and Digital Signal Processing. Since, we are trying to predict the emotions from text, a machine learning classifier is used for that purpose. Also, there are some cases wherein we have to check the sentence structure of prediction of emotions. This is where we use Natural Language Processing. Digital Signal Processing is required to modify neutral speech audio into affective audio.

## 2.2 Technical Keywords

F: Theory Of Computation

F.2: ANALYSIS OF ALGORITHMS AND PROBLEM COMPLEXITY

F.2.1: Numerical Algorithms and Problems (G.1, G.4, I.1)

B: Computations on matrices

For TF-IDF representation, the feature vector of a particular sentence is represented as a sparse matrix using python scipy library. These matrices are then used for further calculations. In deep learning approach, the weights of a layer are internally represented using matrices. Various operations like convolution and element-wise addition are performed depending on the structure of the network.

I: Computing Methodologies

I.2: ARTIFICIAL INTELLIGENCE

I.2.7: Natural Language Processing

A: Text analysis

Text mining task of emotion detection is addressed in this project. It involves lexical analysis, part of speech tagging and term-weighting using TF-IDF. For deep learning, word embeddings are used to map a word to a continuous vector space.

B. Speech recognition and synthesis

In this project we synthesize expressive speech from input text. Synthesized speech can be created by concatenating

pieces of recorded speech that are stored in a database. Systems differ in the size of the stored speech units; a system that stores phones or diphones provides the largest output range, but may lack clarity. The two primary technologies generating synthetic speech waveforms are concatenative synthesis and formant synthesis. Concatenative synthesis is based on the concatenation (or stringing together) of segments of recorded speech. Formant synthesis does not use human speech samples at runtime. Instead, the synthesized speech output is created using additive synthesis and an acoustic model. Parameters such as fundamental frequency, voicing, and noise levels are varied over time to create a waveform of artificial speech. Many systems based on formant synthesis technology generate artificial, robotic-sounding speech that would never be mistaken for human speech. As our main motivation behind the project was to generate human-like speech we use concatenative synthesis method.

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# **CHAPTER 3**

## **INTRODUCTION**

### 3.1 Project Idea

To create a software program, which will take English language text as input and then will identify emotions of each and every sentence present in the text. It will try to speak the sentences such that the detected emotions are incorporated in the audio.

### 3.2 Motivation behind the Project

The project group members are avid readers. We usually read novels and articles from various different sources. When we tried to use Adobe PDF reader's inbuilt 'read-out-aloud' feature for listening to the novel, we realized that it was highly monotonous and robotic in nature. This type of text-to-speech is unsuitable for listening to novels which are quite rich with different types of emotions. We then used some other text-to-speech engines like IvonaTTS, Jovie and KMouth (of Okular PDF reader). But the results were similar as that of Adobe PDF reader. Then we tried some other text-to-speech engines like MaryTTS and PSOLA. They have some ability to handle emotional audio synthesis, but they lack emotion detection facility. This inspired us to build a system which will first try to identify emotion associated with English text and then try to speak the sentences with emotions associated with it.

### 3.3 Literature Survey

Emotion in speech synthesis is an important aspect as it makes the speech more natural sounding and may help to convey more information about context apart from just neutral speech [1]. The focus of this paper is the manipulation of a robotic voice signal for the purpose of adding emotional expression. In particular, its main aim was to design the emotion expressed by a robotic voice by manipulating specific acoustic parameters such as pitch, amplitude and speech rate. The three basic emotions considered were: anger, happiness and sadness.

There are two main aspects of our project i.e emotion classification and modification of neutral speech according to the identified emotion [1]. [2] extensively focuses on identifying emotions from English text. The authors have developed 2 classifiers, one Naive-Bayes and other is Max-entropy, for identification of emotions. Also, they have used Stanford Parser's Univer-



sal dependency for identifying sentence construction and then predicting the emotions. These three emotion prediction sub-systems then vote on the emotions they have retrieved and the emotion which gets maximum votes is selected as the overall emotion of the sentence. The approach for emotion classification used in [2] provided good results.

Researchers in [3] improve upon [2] by providing a simple and memory optimized way for classifying emotions using customized decision tree. They have modified the already existing Digg dataset and SemEval Affective Text-2007 by adding a new feature, emotion intensity. [4] provided us with a novel way of vector representation. It discusses emotion categorization using word embeddings is discussed on Chinese news corpus. Word embeddings can capture semantic context and can be used to infer similarity between words. This approach requires very little feature engineering and yields substantial success. This increases the efficiency of emotion prediction in [3].

The other main module of our system is modifying the neutral speech waveform according to the predicted emotion. We first worked with formant synthesis in which various parameters of speech like f0, intensity, pitch etc are modified to obtain desired emotion [6]. This paper presents algorithms that allows a robot to express its emotions by modulating the intonation of its voice. It describes a technique which allows to continuously control both the age of a synthetic voice and the quantity of emotions that are expressed.

A system for emotion detection and affective audio synthesis is presented in [6]. The formant synthesis technique did not provide satisfactory results for speech synthesis as discussed in [6] and [10]. All the papers before this dealt with a particular aspect of this project. This paper provides an integrated approach for classification of emotion and speech synthesis. It presents a Text-to-speech engine which identifies emotions from text using a Machine Learning classifier. Then a voice is synthesized using Hidden Markov Modelling technique [2]. The voice is modified using various emotions' characteristics classified using Self-Organizing Maps (SOM).

# **CHAPTER 4**

## **PROBLEM DEFINITION AND SCOPE**

## **4.1 Problem Statement**

Develop a software program that reads a text file containing English sentences such that the emotions in the sentences are reflected in the audio.

### **4.1.1 Goals and objectives**

The goal of the project is to create a software system that will be able to identify emotions from english text and accordingly produce affective output. There are two objectives associated with our project. First objective is to identify emotion associated with each and every sentence of the text. And the second objective is to modify neutral speech to incorporate emotion associated with the text.

### **4.1.2 Statement of scope**

The project aims at identifying 4 different emotions (happy, angry, sad and neutral) from the english text and producing speech that incorporates the emotions in the output. The input of the project is English text or English PDF file. The output of the project is speech signal with emotions of the text incorporated in it. Also, there are huge possibilities of construction a sentence with English language. Our scope is limited to identifying emotions of simple English sentences with arguably contains only one emotion. Only one negation is allowed in the sentence which can or cannot qualify the affective words in the sentence.

## **4.2 Major Constraints**

Large and accurate datasets for emotion classification using Machine Learning approaches are not available publicly because the researchers who create those datasets use university funding to crowdsource that job. We have used the datasets by requesting them for the same. So, dataset is extremely small by the standards required to train a highly accurate classifier.

Machine Learning performs lot of computations on the input data while training the model. Due to unavailability of faster computing devices, the classifier model training takes enormous amount of time.

Our system predicts only five different types of emotions namely, joy, sadness, surprise, anger and neutral due to the limitations posed by the dataset.

As most of the novels, storybooks and scripts use text or Portable Document Format (PDF), our system supports only the aforementioned formats for input.

The accent of the voice output of our system is US English. This is due to the dataset which we have used (CMU's Arctic voice dataset) to train the voice synthesis module.

## **4.3 Methodologies of Problem solving and efficiency issues**

### **4.3.1 Emotion classification**

In order to efficiently and accurately extract emotions from the input text, we extensively tried and used several techniques out of which the selected ones are discussed below.

#### **4.3.1.1 Natural Language Processing (NLP)**

This method involves understanding the English language, its subtleties, grammar, word synonyms, structure of sentences and efficiently processing each word so as to get the required output. This methodology uses Stanford Parser[15][16] to create an Universal Dependency tree. This helps us in identifying dependency of words on each other. Part-of-speech (POS) of each word is identified using Tree Tagger Tool[16]. Emotion of each word is identified using NRC lexicon[12] word set which contains about 14000 words tagged with their emotions. We have used the *python – nltk* package for the same.

#### **4.3.1.2 Long Short Term Memory (LSTM)**

A LSTM network is an artificial neural network that contains LSTM units instead of, or in addition to, other network units. A LSTM unit is a recurrent network unit that excels at remembering values for either long or short durations of time. The key to this ability is that it uses no activation function within its recurrent components. Thus, the stored value is not iteratively squashed over time, and the gradient or blame term does not tend to vanish when Backpropagation through time is applied to train it which helps in our

case. It efficiently identifies the structure of the sentences giving more accurate results than traditional neural networks for our dataset. We have used *sklearn* and *keras* python packages for training LSTM.

#### 4.3.1.3 Naive Bayes

Naive Bayes is a simple technique for constructing classifiers: models that assign class labels to problem instances, represented as vectors of feature values, where the class labels are drawn from some finite set. In our case the class labels were the emotions. It is not a single algorithm for training such classifiers, but a family of algorithms based on a common principle: all naive Bayes classifiers assume that the value of a particular feature is independent of the value of any other feature, given the class variable which can be assumed safely for our work since we are working on independent sentences without considering the context in which the sentence appears. We have used *sklearn* python package for this classifier.

### 4.3.2 Affective Speech Synthesis

In order to efficiently and accurately synthesize affective audio from emotion-tagged sentences, we extensively tried and used several techniques out of which the selected ones are discussed below.

#### 4.3.2.1 Hidden Markov Modelling (HMM)

A hidden Markov model (HMM) is a finite state machine which generates a sequence of discrete time observations. At each time unit, the HMM changes states at Markov process in accordance with a state transition probability, and then generates observational data  $\mathbf{o}$  in accordance with an output probability distribution of the current state. We have used HTS [11], a tool to create voice synthesis module using HMM technique. In our case, the state transition probabilities depend upon the change of phonemes for the given word. We have used *festival* and *MaryTTS* speech building modules for synthesizing the voice after training it with the arctic dataset provided by Carnegie Mellon University (CMU)[14].

#### 4.3.2.2 Digital Signal Processing (DSP)

HMM module generates speech in neutral affect, so in order to generate affective waveform from the neutral audio, we require signal processing modules that are provided by *MaryTTS* signal processing libraries[13] which are open source. These libraries include the latest research available in the

field of affective audio generation and it is continuously updated with the state-of-the-art techniques in DSP.

## **4.4 Outcomes**

We define outcomes as the changes, benefits, learning or other effects that happen as a result of our work. The break-through achieved by our project is that it is the first end-to-end system which takes English text as input and produces affective output. Our work is multi-disciplinary in the sense that it extensively includes concepts and techniques from domains such as Machine Learning, Deep Learning, Natural Language Processing, Digital Signal Processing and High Performance Computing to name a few.

## **4.5 Applications**

These days, the publisher not only publishes a printed version of the book but also releases an audio book. These audio books are generated by hiring voice actors in the recording studio where they read the entire book. Our project can work as an effective replacement for the process of audio book generation thereby saving both time and money of the publishers.

There are many PDF readers available which lack the emotional speech output producing capability for the novels and story books. These PDF readers can integrate our project by using an Application Programming Interface (API) and can effectively produce affective speech output.

Robots, these days, are now capable of speaking sentences in different languages. But their output is monotonous and devoid of any emotion. Our project's API can be used in the robots to eradicate this problem and thus, can help to make robots sound more human-like.

## 4.6 Hardware Resources Required

Our project requires following hardware resources to run smoothly and successfully

Sr. No.	Parameter	Min. Requirement	Justification
1	CPU Speed	1.0 GHz	Fast processor required for fast processing
2	RAM	4 GB	LSTM, Naive Bayes and NRC Lexicon model loading
3	Audio output device	-	To listen to output audio

Table 4.1: Hardware Requirements

## 4.7 Software Resources Required

Our project requires following software resources to run smoothly and successfully

Sr. No.	Parameter	Suggested	Justification
1	Any Linux distribution	Ubuntu 16.04	Easy dependency installation
2	Python	Python 2.7	Stable and large community support against python 3.0
3	MaryTTS	MaryTTS 5.2	Advanced and stable signal processing functionalities
4	NLTK	NLTK 3.2.2	Provides English processing tools
5	Scikit-learn	Scikit-learn 0.18.1	Provides machine learning algorithms

Table 4.2: Software Requirements



# **CHAPTER 5**

## **PROJECT PLAN**

## 5.1 Project Estimates

### 5.1.1 Reconciled Estimates

#### 5.1.1.1 Cost Estimate

Our project falls in organic class of software product.

For organic:

$$\begin{aligned}\text{Effort} &= 2.4 * (\text{KLOC})^{1.05} \\ &= 4.969271 \text{ PM}\end{aligned}$$

Where,

KLOC is the estimated size of the software expressed in kilo lines of code

$$\begin{aligned}\text{Duration} &= 2.5 * (\text{Effort})^{0.38} \\ &= 4.5976 \text{ Months}\end{aligned}$$

#### 5.1.1.2 Time Estimates

Learning about the tools, technologies and theory associated with our project which includes literature survey, Machine Learning, Deep Learning and Linguistic characteristics of Human speech took about 5 months.

Time required to implement the software system was about 2 months.

### 5.1.2 Project Resources

We have identified following three types of resources required for the successful completion of our project within the stipulated time period.

#### 5.1.2.1 Human Resources

1. Internal Guide: Dr. Girish P. Potdar
2. Group members:
  - i Pranjali Bhor
  - ii Vaibhav Chaudhari
  - iii Prathamesh Dharangutte
  - iv Murtaza Raja

### 5.1.2.2 Hardware Resources

The following hardware resources were required during the incubation phase of our project

Sr. No.	Parameter	Required	Justification
1	CPU Speed	2.0 GHz	Faster computation for training classifier
2	RAM	8 GB	LSTM and Naive Bayes matrices temporary storage
3	Nvidia GPU	GTX 860m	LSTM is neural network which requires GPU power to get trained
4	Audio output device	-	To test the audio output

Table 5.1: Hardware Requirements during incubation

### 5.1.2.3 Software Resources

Following are the software resources required by our project while in its incubation phase

Sr. No.	Parameter	Suggested	Justification
1	Any Linux distribution	Ubuntu 16.04	Easy dependency installation
2	Python	Python 2.7	Stable and large community support against python 3.0
3	MaryTTS	MaryTTS 5.2	Advanced and stable signal processing functionalities
4	NLTK	NLTK 3.2.2	Provides English processing tools
5	Scikit-learn	Scikit-learn 0.18.1	Provides machine learning algorithms
6	Nvidia CUDA	CUDA 8.0	Provides drivers for running code on Nvidia GPU
7	CudNN	CudNN v5.0	Required to run Neural Network training algorithms on Nvidia GPU

Table 5.2: Software Requirements during incubation

## 5.2 Risk Management w.r.t. NP Hard analysis

### 5.2.1 Risk Identification

For risks identification, review of scope document, requirements specifications and schedule is done. Answers to questionnaire revealed some risks. Each risk is categorized as per the categories mentioned in Pressman. Please refer table 5.3 for all the risks

### 5.2.2 Risk Analysis

The risks for the Project can be analyzed within the constraints of time and quality

ID	Risk Description	Probability	Impact		
			Schedule	Quality	Overall
1	Risk 1	Medium	Low	Medium	Medium
2	Risk 2	Low	Low	Medium	Medium
2	Risk 3	Medium	Medium	Medium	Medium

Table 5.3: Risk Table

Probability	Value	Description
High	Probability of occurrence is	$> 75\%$
Medium	Probability of occurrence is	$26 - 75\%$
Low	Probability of occurrence is	$< 25\%$

Table 5.4: Risk Probability definitions

Impact	Value	Description
Very high	> 10%	Schedule impact or Unacceptable quality
High	5 – 10%	Schedule impact or Some parts of the project have low quality
Medium	< 5%	Schedule impact or Barely noticeable degradation in quality Low Impact on schedule or Quality can be incorporated

Table 5.5: Risk Impact definitions

### 5.2.3 Overview of Risk Mitigation, Monitoring, Management

Following are the details for each risk.

Risk ID	1
Risk Description	If some of the words in the sentence are unknown to the classifier then the emotion of the sentence may not be identified correctly.
Category	Post-deployment
Source	Input text
Probability	Medium
Impact	Medium
Response	Mitigate
Strategy	Give only one emotion for the entire sentence
Risk Status	Identified

Risk ID	2
Risk Description	If all the words in the sentence are unknown to the classifier, then the sentence cannot be labelled.
Category	Post-deployment
Source	Input text
Probability	Low
Impact	Medium
Response	Mitigate
Strategy	Making classifier using larger dataset
Risk Status	Identified

Risk ID	3
Risk Description	A sentence might contain more than one emotion which might make it difficult to process its audio.
Category	Development
Source	Classifier label
Probability	Medium
Impact	Medium
Response	Accept
Strategy	Processing audio using available technique
Risk Status	Identified

## 5.3 Project Schedule

### 5.3.1 Project task set

Task 1: Learning and understanding the basics of machine learning and digital signal processing techniques.

Task 2: Generating a large dataset for emotion identification.

Task 3: Implementing and comparing various techniques available for speech processing and selecting the suitable one.

Task 4: Creating a classifier that classifies the emotions in english text with reasonable accuracy.

Task 5: Creating a speech signal processing module.

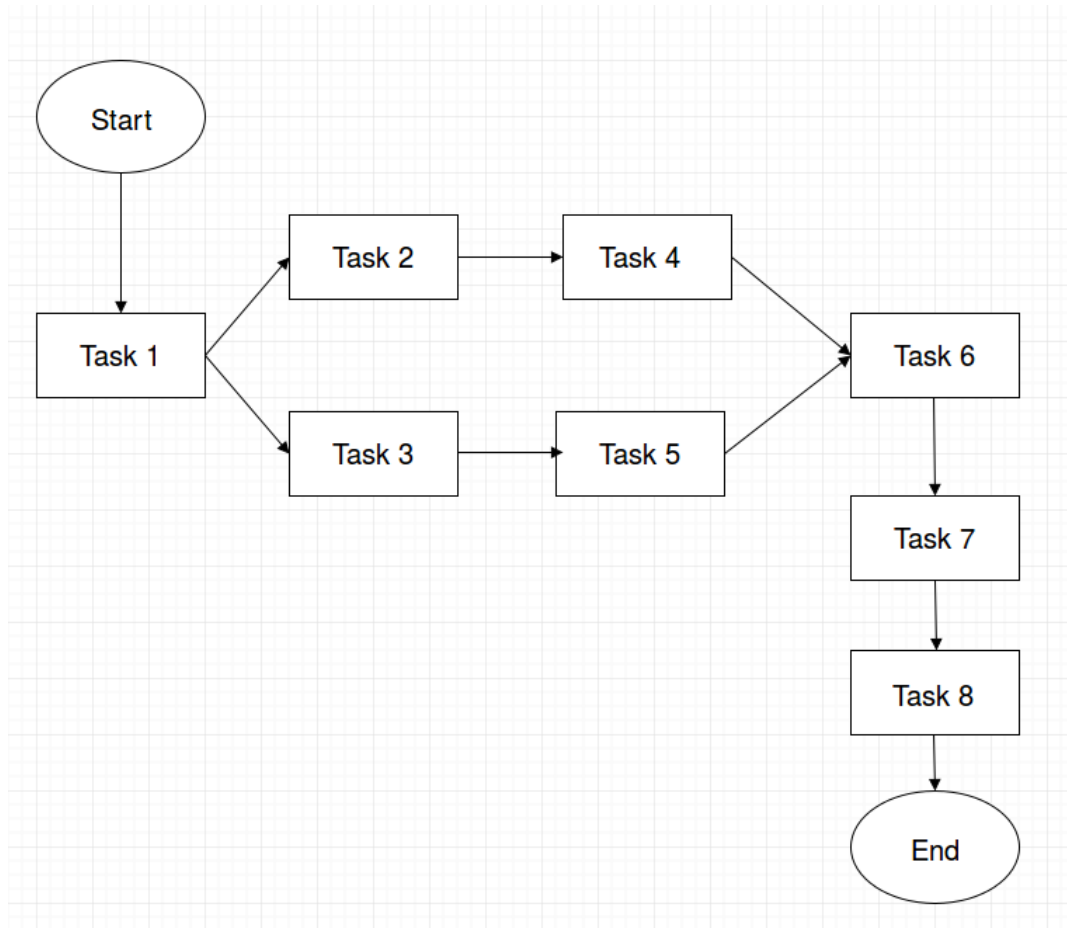
Task 6: Combining speech signal processing module and classifier module to complete the system.

Task 7: Testing and fixing of bugs in the system.

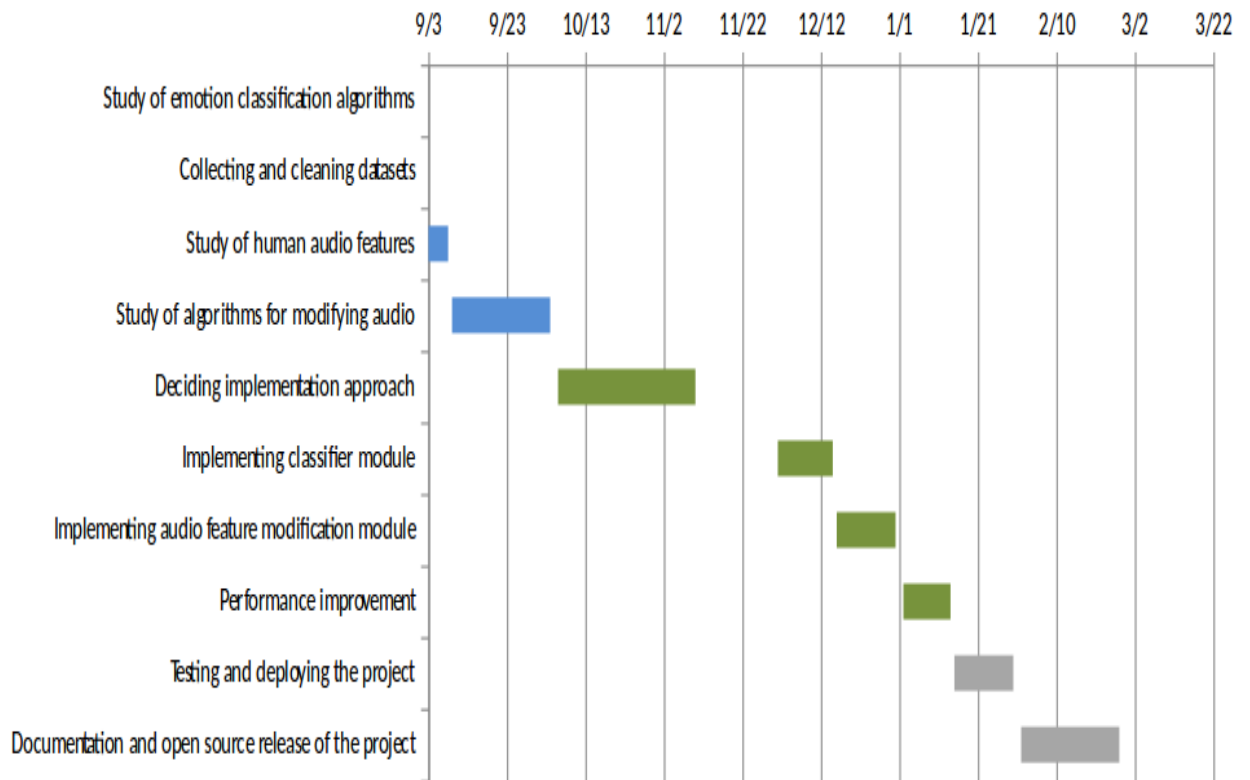
Task 8: Documentation and open source release of the project.



### 5.3.2 Task network



### 5.3.3 Timeline Chart



## 5.4 Team Organization

### 5.4.1 Team structure

The team structure for the project is identified. Roles are defined.

Pranjal Bhor: Multi-threaded execution of the system and NLP emotion classifier developer.

Vaibhav Chaudhari: Speech Synthesis System and signal processing developer.

Prathamesh Dharangutte: Developer of Machine Learning based emotion classifier.

Murtaza Raja: UI and NLP based emotion classifier developer.

### **5.4.2 Management reporting and communication**

#### E-mail

It was used to communicate structural and design changes in the software to be developed.

#### Whatsapp

It was used to communicate in-short the work progress and status reporting

#### Verbal communication

It was used for extensive discussion about the strategy, implementation and future to-do things about the project.

**CHAPTER 6**

**SOFTWARE REQUIREMENT  
SPECIFICATION**

## 6.1 Introduction

### 6.1.1 Purpose and Scope of Document

The purpose of this document is to present a detailed description of emotion labelling and speech signal processing mechanisms with a text-to-speech engine. It will explain the purpose and features of the system, the interfaces of the system, what the system will do, and how the system will react to external stimuli. This document is intended for both the users and the developers of the system. This software system is designed to enhance the emotional aspect of the neutral text-to-speech engine. The system can be used by the PDF readers, audio books generating studios and video games companies to automate the reading of the english text.

### 6.1.2 Overview of responsibilities of Developer

There are certain responsibilities which have to be taken care of by the developers of this project. First and foremost is to accurately define the scope and goals of the project. According to the scope, project design is made. Project plan of development is made. Each developer holds certain responsibility of specific module development. The module development should contain novel approach to the problem encountered. Different types of testing are to be carried out on the final product made.

## 6.2 Usage Scenario

This section provides various usage scenarios for the system to be developed.

### 6.2.1 5.2.1 User profiles

**User:** User is the actor who uses the system. That is, user gives input to the system and gets the system's output.

**Developer:** Developer is the actor who is responsible for designing, developing and maintaining the software system.

**Researcher:** Researcher is responsible for formulating new features for the system, which are not currently available.

Sr No.	Use Case	Description	Actors	Assumptions
1	English text input	The input file contains only the english text	User	The input is english text file
1	Non english text input	The input file contains non-english sentences	User	The input file contains english text

Table 6.1: Use Cases

### 6.2.2 Use-cases

### 6.2.3 Use Case View

Use Case Diagram. Example is given below

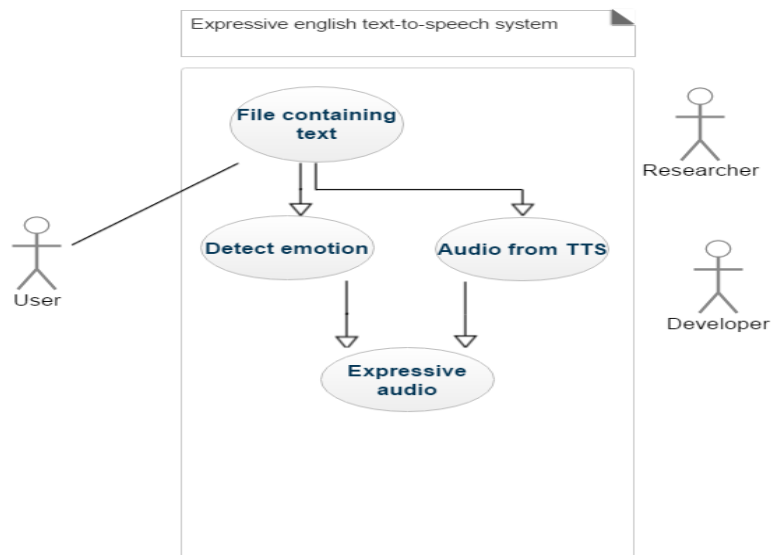


Figure 6.1: Use case diagram

## 6.3 Data Model and Description

### 6.3.1 Data Description

There are multiple types of data in the system. The machine learning classifier is a trained model which contains all the data on which it was trained along with its relationships with the output. The input data to the system consists of English text or PDF file. This data is to be loaded in memory in-order to work on it. Each and every sentence from the input file is to be classified into one of the 5 emotions. This also requires a data structure. The output of the system is audio data.

### 6.3.2 Data objects and Relationships

The input to the system is English text or PDF file. The data that will be manipulated by the system is Neutral audio speech.

## 6.4 Functional Model and Description

### 6.4.1 Data Flow Diagram

#### 6.4.1.1 Level 0 Data Flow Diagram

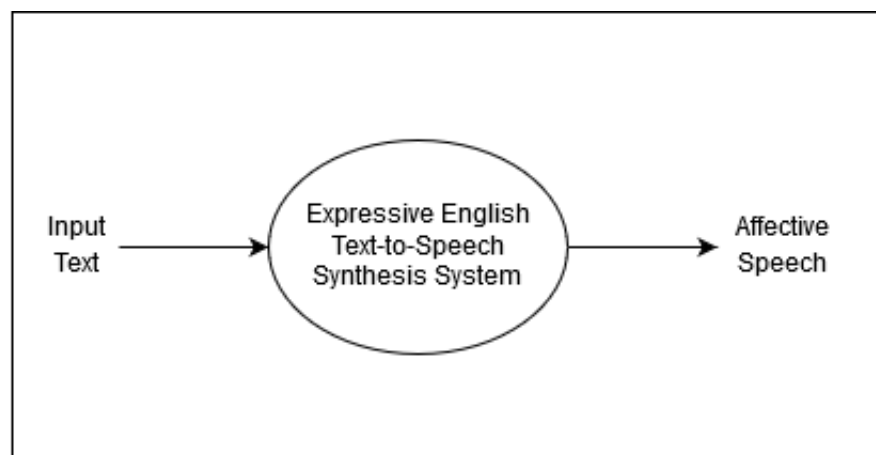


Figure 6.2: Level 0 Data flow diagram

#### 6.4.1.2 Level 1 Data Flow Diagram

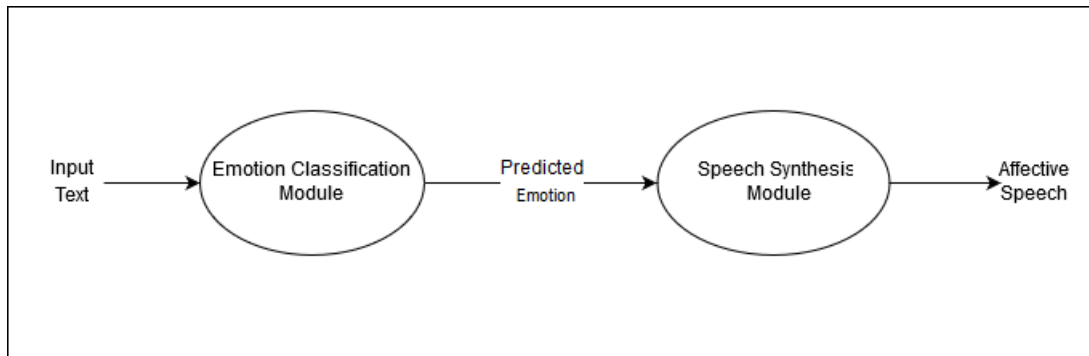


Figure 6.3: Level 1 Data flow diagram

#### 6.4.1.3 Level 2 Data Flow Diagrams

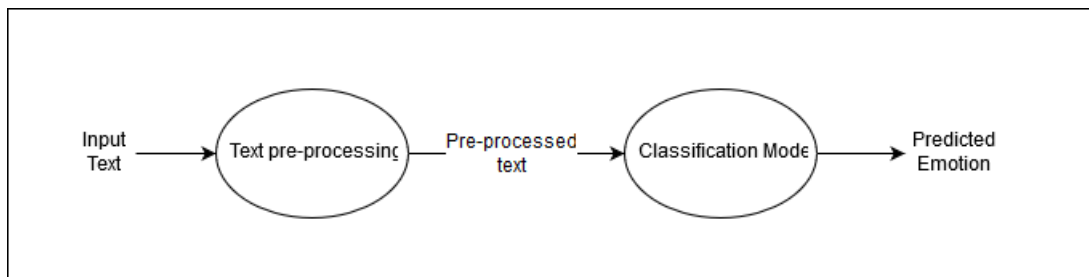


Figure 6.4: Level 2 Data flow diagram - Emotion Classification



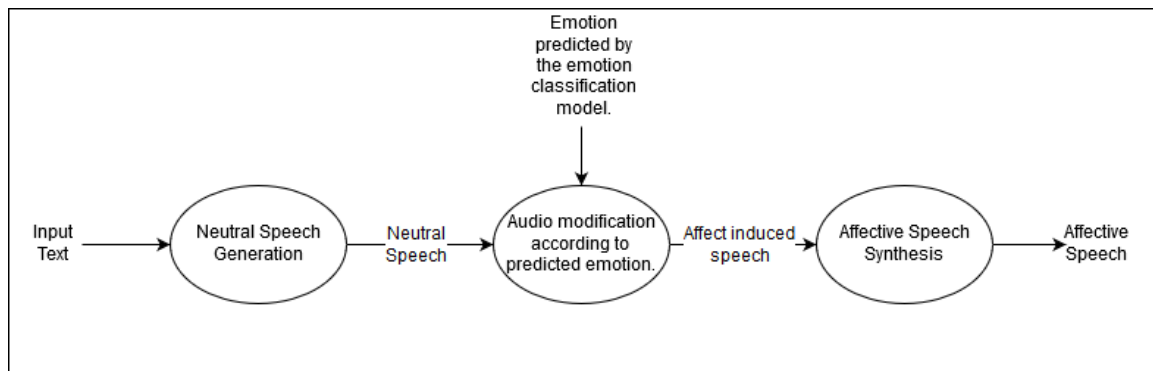


Figure 6.5: Level 2 Data flow diagram - Speech Synthesis

#### 6.4.1.4 Level 3 Data Flow Diagrams

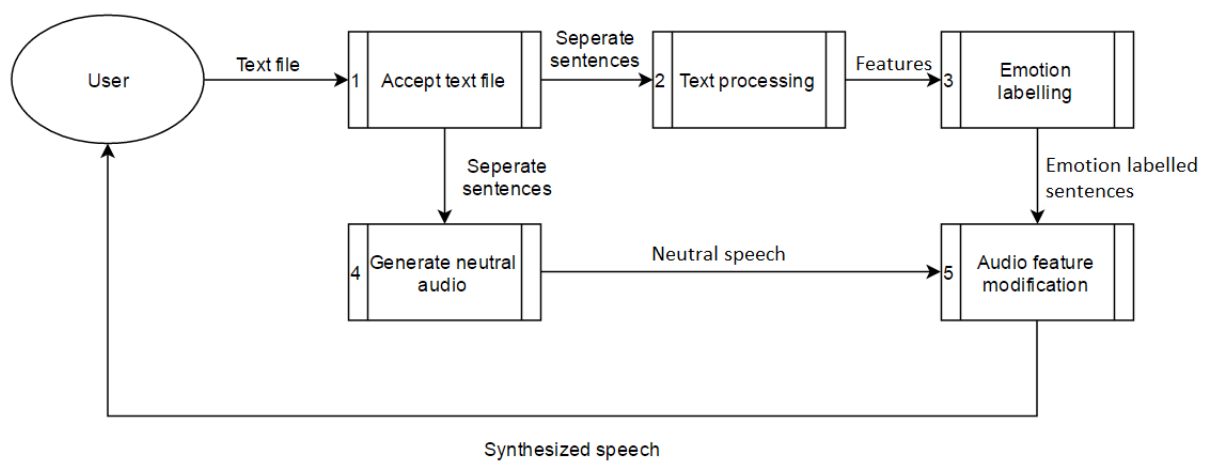


Figure 6.6: Level 3 Data flow diagram

### 6.4.2 Activity Diagram:

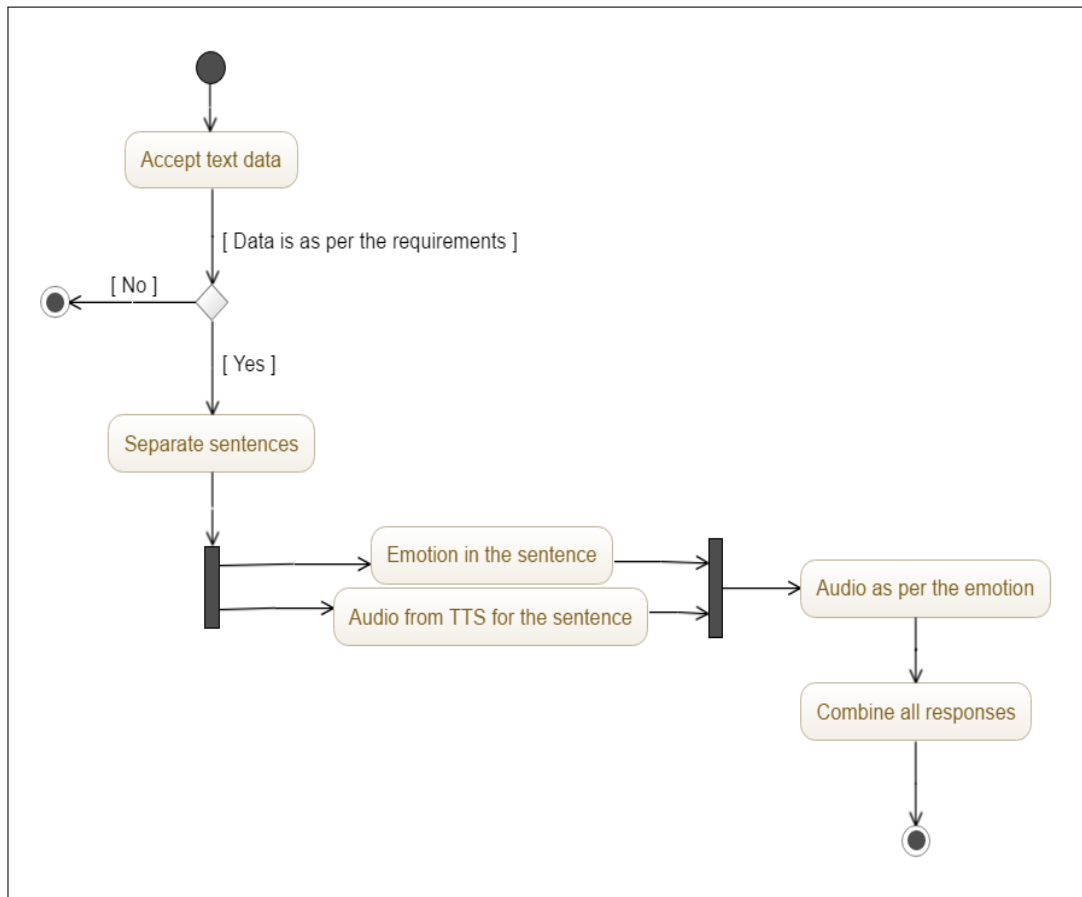


Figure 6.7: Activity diagram

### 6.4.3 Non Functional Requirements:

#### Interface Requirements

The Graphical User Interface of the project should contain facility to select an English text or PDF file. It should also contain a mechanism to display the emotions of each and every sentence in the text file. There should be a media player type mechanism present in the system which the user can use to listen and seek the audio in-window. It can also contain facility to pause and stop the audio playing.

## Performance Requirements

The system should be as fast as possible. The file loading and emotion detection phase should be extremely fast. Each sentence can be considered independently and so can be processed through multi-threading. Similar goes for the audio generation. Every sentence's audio can be generated independently of other sentences.

## Software quality attributes

The software should be available all the time whenever user needs it. For a standalone software, it should be able to run whenever invoked. A web based application should have up-time of more than 99%. The software should be reliable and should not give erratic or unwanted behaviour. It should be as modular as possible so that modifiability of the software can be improved.

### **6.4.4 Design Constraints**

There are no design constraints which will impact the subsystem. The software contains simple GUI as mentioned above and implementing that constraints the project developers in no significant way.

### **6.4.5 Software Interface Description**

The software interface contains a mechanism through which an user will be able to load a file and can take an audio file of the input as the output. In the future, an Application Programming Interface (API) can be provided for the developers' use which will directly communicate with the commercially hosted servers.

#### 6.4.6 State Diagram:

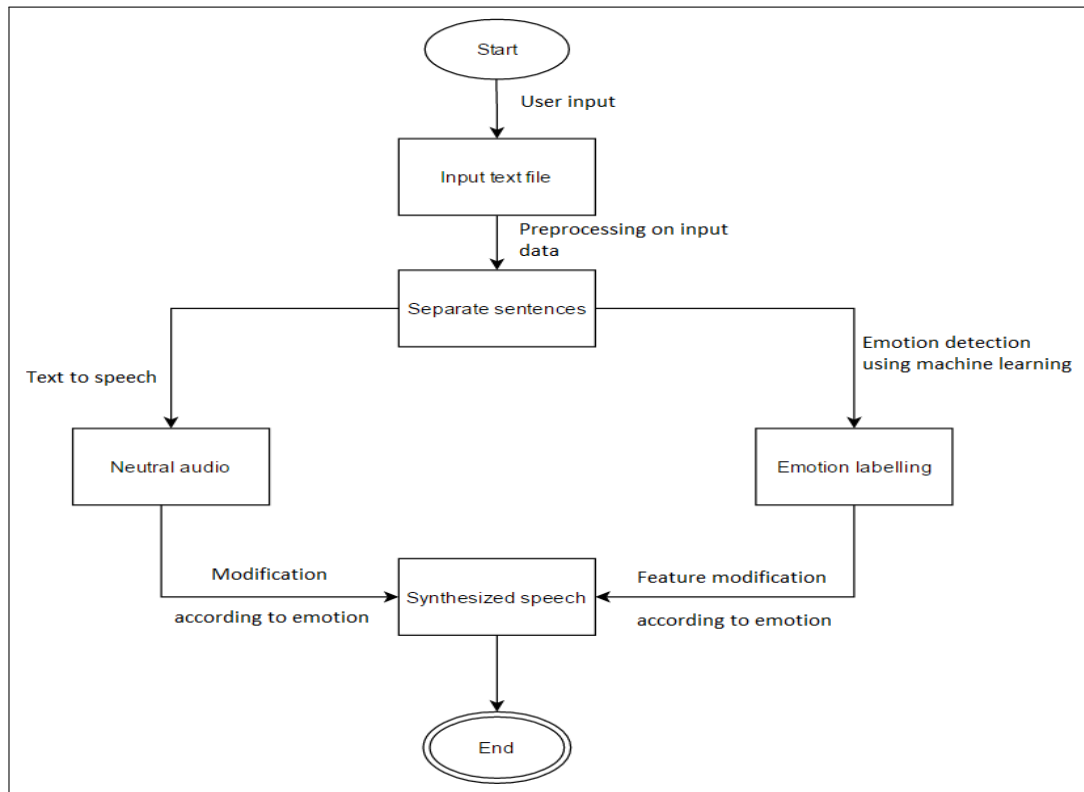


Figure 6.8: State transition diagram

**CHAPTER 7**

**DETAILED DESIGN DOCUMENT**  
**USING APPENDIX A AND B**

## 7.1 Introduction

Architecture design gives an overview of the software system. The architecture consists of an Emotion Detection and Signal Processing (EDSP) engine. The EDSP engine consists of an emotion classifier which includes Navie Bayes and Long Short Term Memory (LSTM) classifiers. It also includes Text-to-Speech generation engine and signal processing engine which modifies the neutral voice output into affective voice output.

## 7.2 Architectural Design

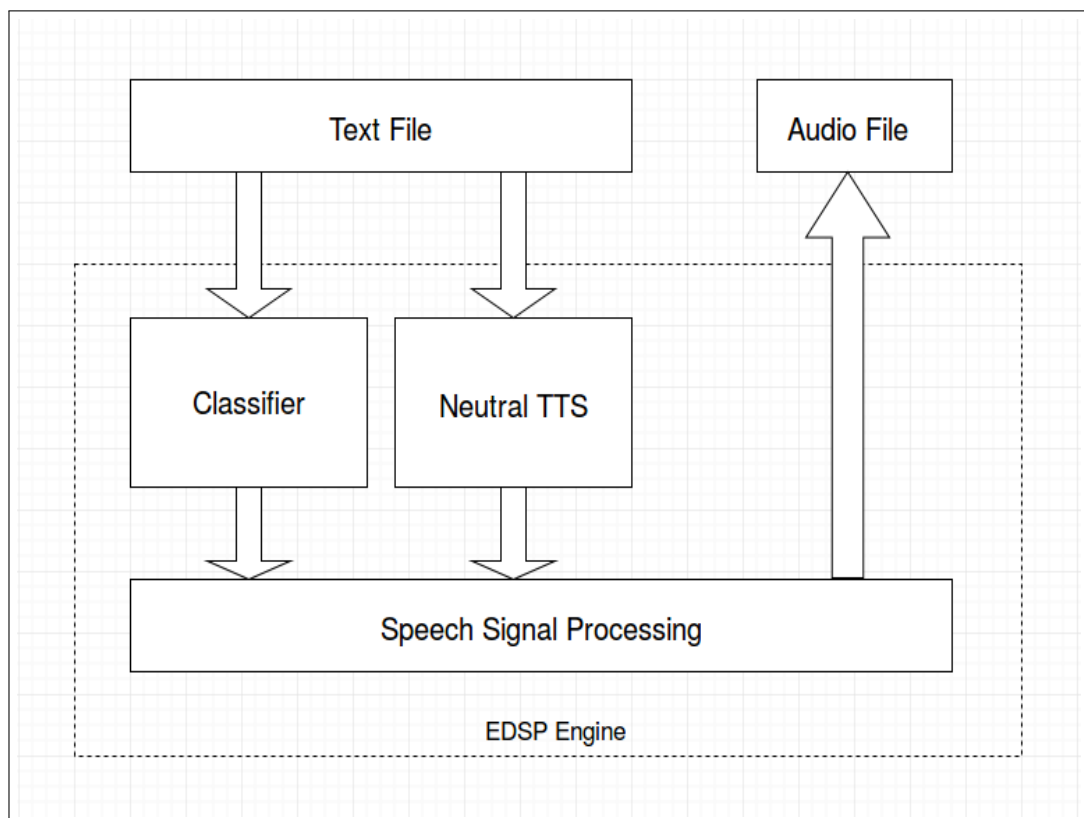


Figure 7.1: Architecture diagram

## **7.3 Data design (using Appendices A and B)**

The internal and global software data structures have been presented below.

### **7.3.1 Internal software data structure**

Multi-dimensional arrays

This data structure is used to store the machine learning classifier data. The classifier learns the data and maps it with the output. This mapping is stored in multi-dimensional arrays.

Dictionary

The input file contains many sentences. The emotions of these sentences are found out and they are stored in a dictionary where sentence is the key and its emotion is the value. Tree

The system uses Stanford Parser to find out which phrases are qualified by specific words. The parser generates a parse tree out of the input English sentence.

### **7.3.2 Global data structure**

There is no global data structure in the system. All the data structures are used internally by respective components.

### **7.3.3 Database description**

Input data is stored in plain English text files or PDF files. Internally there is no use of database for handling of any types of tasks. The audio output is stored in .wav file format.

## 7.4 Component Design

### 7.4.1 Class Diagram

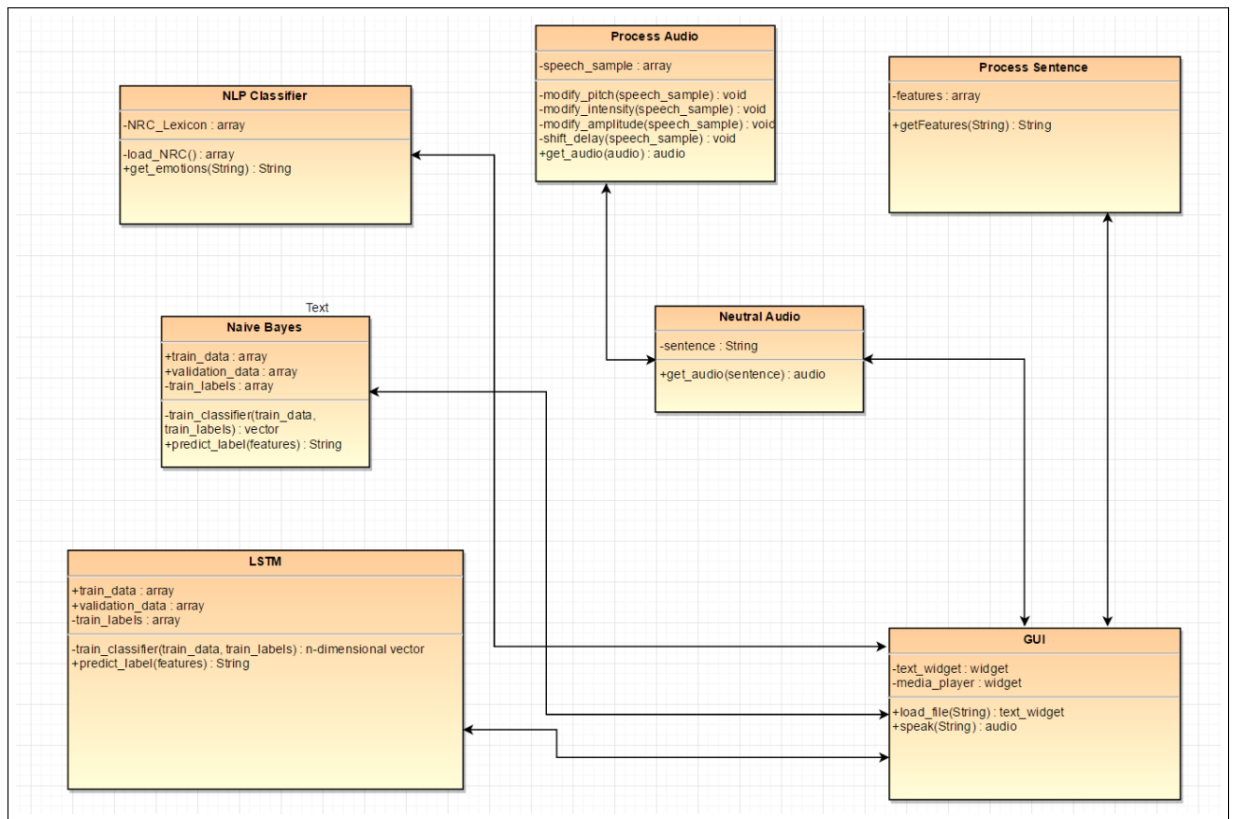


Figure 7.2: Class Diagram



# **CHAPTER 8**

## **PROJECT IMPLEMENTATION**

## 8.1 Introduction

Our system consists of a simple GUI wherein user has to load his text/PDF file containing English sentences. As soon as the file is loaded, each sentence from the file gets tagged with its most probable emotion. After clicking on speak button, affective audio for the sentences is generated and stored as a .wav file which is automatically played in the GUI. The user can control the audio file playing using a small media player provided.

## 8.2 Tools and Technologies Used

Python 2.7 Programming language

Python provides excellent libraries to automate most of the trivial work for system design. The members of the project group were already experienced in Python 2.7 and that is why we chose this as primary language for system implementation.

MaryTTS signal processing engine

MaryTTS is a research based Text-to-speech engine which supports many different languages including English. It has its own signal processing engine which modifies the neutral audio according to the input parameters given. This engine helps us to get emotional audio by modifying neutral audio.

Festival

It is a Hidden Markov Modelling (HMM) tool for building synthetic voice. As HMM is another form of machine learning, it requires training data in the form of voice audio and its text. As we want to have our own text-to-speech engine, we had to build our own voice which is why festival is used.

NLTK and SCIKIT libraries

NLTK contains many functions which carry out trivial tasks efficiently like stop words removal and tokenizing the words. It is also used to traverse on the parse tree generated by Stanford Parser. SCIKIT provides machine learning algorithms. We use the implementation of machine learning algorithms provided by SCIKIT python.

## 8.3 Methodologies/Algorithm Details

### 8.3.1 Algorithms

#### 8.3.1.1 Overall System Algorithm

---

**Algorithm 1** Overall system algorithm

---

```
1: procedure GENERATE_AUDIO(sentence)
2:   naive_emotion  $\leftarrow$  GET_EMOTION_FROM_NAIVE(sentence)
3:   lstm_emotion  $\leftarrow$  GET_EMOTION_FROM_LSTM(sentence)
4:   nlp_emotion  $\leftarrow$  GET_EMOTION_FROM_NLP(sentence)
5:   final_emotion  $\leftarrow$  MOST_VOTED_EMOTION(naive_emotion, lstm_emotion, nlp_emotion)
6:   neutral_audio  $\leftarrow$  HMM_AUDIO_SYNTHESIS(sentence)
7:   affective_audio  $\leftarrow$  SIGNALPROC(sentence, emotion)
8:   return save_audio(affective_audio)
9: end procedure

1: procedure SENTENCE_HANDLER(sentence)
2:   final_audio =  $\phi$ 
3:   for each sentence in text do
4:     temp_audio  $\leftarrow$  GENERATE_AUDIO(sentence)
5:     final_audio  $\leftarrow$  final_audio  $\cup$  temp_audio
6:   end for
7: end procedure
```

---

#### 8.3.1.2 Naive Baye's Classification Algorithm

---

**Algorithm 2** Naive Baye's Classification Algorithm

---

```
1: procedure GET_EMOTION_FROM_NAIVE(sentence)
2:   classifier  $\leftarrow$  load_naive_classifier()
3:   emotion  $\leftarrow$  classifier.classify(sentence)
4:   return emotion
5: end procedure
```

---

### 8.3.1.3 Get emotion from LSTM

---

**Algorithm 3** Get emotion from LSTM

---

```
1: procedure GET_EMOTION_FROM_LSTM(sentence)
2:   classifier  $\leftarrow$  load_lstm_classifier()
3:   emotion  $\leftarrow$  classifier.classify(sentence)
4:   return emotion
5: end procedure
```

---

### 8.3.1.4 HMM Audio Synthesis

---

**Algorithm 4** HMM Audio Synthesis Algorithm

---

```
1: procedure HMM_AUDIO_SYNTHESIS(sentence)
2:   linguistic_specification = get_linguistic_specification(sentence)
3:   final_hmm_sequence =  $\phi$ 
4:   for all representation  $\in$  linguistic_specification do
5:     hmm_sequence  $\leftarrow$  generate_hmm(representation)
6:     final_hmm_sequence  $\leftarrow$  final_hmm_sequence  $\cup$  hmm_sequence
7:   end for
8:   voice_output  $\leftarrow$  generate_voice_from_hmm(final_hmm)
9:   return voice
10: end procedure
```

---

### 8.3.1.5 Get emotion from NLP module

---

**Algorithm 5** Get emotion from NLP module

---

```
1: procedure GET_EMOTION_FROM_NLP(sentence)
2:   split sentence on spaces and store in word_list
3:   word_list  $\leftarrow$  lemmatize(word_list)
4:   word_dictionary  $\leftarrow \phi$ 
5:   for each word in word_list do
6:     word_emotion  $\leftarrow$  NRCclassifier(word)
7:     word_dictionary[word]  $\leftarrow$  word_emotion
8:   end for
```

---

---

**Algorithm 5** Get emotion from NLP module (continued)

---

```
9:   emotion_dictionary  $\leftarrow$  {'neutral':0,'joy':0,'sadness':0,'surprise':0,'anger':0}
10:   dependency_tree = StanfordParser(sentence)
11:   get_index  $\leftarrow$  0
12:   Indices  $\leftarrow \phi$ 
13:   for each word in word_dictionary do
14:     emotion_dictionary[word_dictionary[word]] += 20
15:     get_index  $\leftarrow$  find_max_qualified_word(dependency_tree)
16:     for  $i = 0$  and  $i \leq \text{length}(\text{dependency\_tree})$  do
17:       if dependency_tree[i].description is 'amod' or 'advmod' then
18:         if dependency_tree[i].head = get_index then
19:           if dependency_tree[i].form in strong_qual_words then
20:             emotion_dictionary[word_dictionary[word]] += 100
21:           else if dependency_tree[i].form in avg_qual_words then
22:             emotion_dictionary[word_dictionary[word]] += 50
23:           end if
24:         end if
25:       end if
26:     end for
27:     Indices  $\leftarrow$  Indices  $\cup$  get_index
28:   end for
29:   answer_emotion  $\leftarrow$  get_max_valued_emotion(emotion_dictionary)
30:   if negation present in the sentence then
31:     if the negation word qualifies an index in Indices then
32:       if max_emotion_value  $\neq$  20 then
33:         answer_emotion  $\leftarrow$  'neutral'
34:       else if max_emotion_value == 20 then
35:         if answer_emotion == 'joy' then
36:           answer_emotion  $\leftarrow$  'sadness'
37:         else if answer_emotion == 'sadness' then
38:           answer_emotion  $\leftarrow$  'joy'
39:         else
40:           answer_emotion  $\leftarrow$  'neutral'
41:         end if
42:       end if
43:     end if
44:   end if
45:   return emotion
46: end procedure
```

---

## **8.4 Verification and Validation for Acceptance**

Many different sentences denoting various emotions like joy, sadness, surprise, angry and neutral were given to the system. The system predicted the emotions and the people who tested the system agreed on the satisfactory level of the output. The corresponding audio generated was also approved by the users who tested the system. This provided verification as well as validation for the project and it got acceptance.

# **CHAPTER 9**

## **SOFTWARE TESTING**

## **9.1 Type of Testing Used**

Since our project focuses mainly on two important tasks - Classification of sentences based on emotions using machine learning (A) and conversion of monotonic speech into expressive speech (B), we have analyzed different testing strategies based on the aforementioned tasks.

### **9.1.1 Unit testing**

This testing was very valuable for our project since we were able to independently test the emotion identification module and the speech synthesis module with good results. We essentially decoupled the two subsystems and tested them.

#### **9.1.1.1 Classification module**

This subsystem was tested by providing some sentences rich with five emotions - joy, sadness, anger, surprise and neutral. With an accuracy of about 80%, it produced the results accordingly. It labelled more sentences as neutral because the database was biased toward it.

#### **9.1.1.2 Speech synthesis module**

For voice synthesis and digital signal processing unit, same sentences were given as input. The affective audio generated by the unit was perceived to contain the emotion tagged as reported by the test users. The sentences which depicted anger as the emotion, were spoken a bit fast by the system.

### **9.1.2 Integration testing**

Having tested the individual subsystems, the emotion prediction and voice synthesis modules were then integrated. A sentence was passed to the input function of the system. The emotion classifier correctly identified the emotion tag of the sentence and then using this emotion tag, the affective audio was generated.

#### **9.1.2.1 Multithreading fix**

It was discovered during testing that a single MaryTTS engine does not handle simultaneous requests and is not thread safe. Therefore, we spawned multiple instances of the engine and then fired simultaneous requests to them.



### **9.1.3 Validation testing**

Since the ideas presented through this project are still in research phase, a usable product is a feat that cannot be achieved provided the current technology in this field. Still, we tried to test this software, targeting the audio book publishers as our client.

#### **9.1.3.1 Emotional speech as output**

This software provides the affective audio for emotions - joy, sadness, anger, surprise and neutral for the input provided by the user.

#### **9.1.3.2 Input characteristics**

Since majority of text is either available as .txt or as .pdf, this software has the ability to process both of them.

### **9.1.4 Performance and load testing**

We used load testing to test the system under various loads. The workstation on which testing was performed consisted of a 2.5 GHz quad-core machine with 8 GB of main memory running Ubuntu operating system.

### **9.1.5 GUI testing**

We made a very simple GUI in the beginning but soon found out that it is not user friendly and does not have a native-look-and-feel. Then we made another GUI which solved the problems of the previous one and offered better functionality in terms of audio playing and emotion selection.

#### **9.1.5.1 Emotion selection**

A drop down menu was associated with each and every sentence that represented the emotion of the sentence. The user has the ability to change this according to his or her preference.

#### **9.1.5.2 Audio playback**

A media player like functionality was added to the GUI so that the user can play, pause, stop, seek and change the volume of the audio being played.

### 9.1.5.3 Scrollable interface

If the number of sentences exceeded the minimum which can fit on the screen, the windows automatically provides scroll bars that can be used to navigate between the sentences.

## 9.2 Test Cases and Results

### 9.2.1 Unit testing

#### 9.2.1.1 Classifier module

No.	Input	Expected Output	Actual Output
1.	I am very delighted	joy	joy
2.	My dog died	sadness	sadness
3.	Oh my God, I got that!	surprise	surprise
4.	I am very angry at that behaviour	anger	anger
5.	Those were tough times for me	neutral	neutral
6.	I am not happy	sadness	sadness
7.	I am not very sad	neutral	neutral

Table 9.1: Test cases for classifier module

### 9.2.1.2 Speech synthesis module

No.	Input emotion	Expected Output	Actual Output
1.	joy	speaks in an overall pleasant way	as expected
2.	sadness	the pitch drops and tempo decreases	as expected
3.	surprise	the pitch increases, some words stressed	as expected
4.	anger	speaks a bit fast	speaks very fast
5.	neutral	speaks normally	as expected

Table 9.2: Test cases for speech synthesis module

### 9.2.2 Integration testing

No.	Input	Expected Output	Actual Output
1.	affective sentence	emotional speech generated	as expected
2.	neutral sentence	neutral speech generated	as expected
3.	text file with various sentences	proper affective audio generated corresponding to emotions	as expected
4.	pdf file with various sentences	proper affective audio generated corresponding to emotions	as expected

Table 9.3: Test cases for integration testing

### 9.2.3 Validation testing

No.	Feature	Implemented	Details
1.	produces affective voice on emotional text input	yes	can process 5 emotions
2.	handles text files	yes	can process .txt and .pdf
3.	automatically tags sentences with emotions	yes	currently 80% accurate
4.	support for other languages	no	future scope, data set limitations
5.	support for other accents	yes	training data to be provided

Table 9.4: Test cases for validation testing

### 9.2.4 Performance and load testing

No.	Input	Time taken to execute
1.	5-10 sentences.	2-3 seconds.
2.	1 page.	About 15 seconds.
3.	10-15 pages.	About 3 minutes.
4.	A novel of about 300 pages.	About 1 hour 5 minutes.
5.	3-4 instances of our software running at the same time.	Sometimes system gets hung up.

Table 9.5: Test cases for load testing

### 9.2.5 GUI testing

No.	Case	Expected Output	Actual Output
1.	loading files	.txt and .pdf files loaded	as expected
2.	changing emotion of a sentence	drop down updated	as expected
3.	sentences overflow the viewport	proper scroll bars are added accrdingly	as expected
4.	audio playing capability	play, pause, stop, seek, volume	as expected
5.	performing computational intensive task	show progress to user	no progress shown

Table 9.6: Test cases for GUI testing

# CHAPTER 10

## RESULTS

## 10.1 Screenshots

The welcome screen of our system looks as shown in Figure 10.1. It is a simple screen with some information about our project and the team members. It contains a only one button to load the English text file or PDF file.

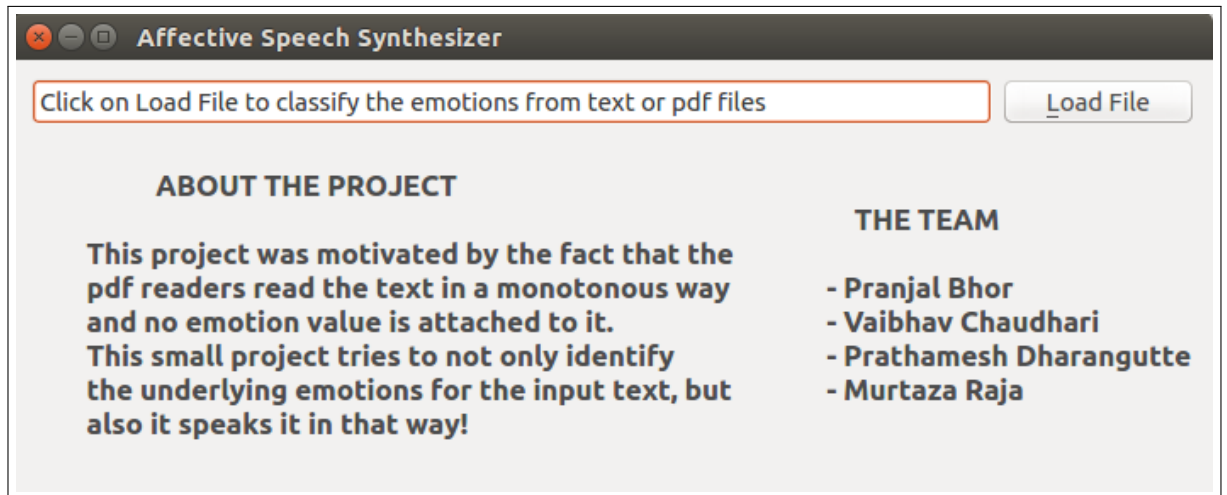


Figure 10.1: Intro screen

When the file has been loaded in the interface, the emotions from each sentence are predicted and displayed in the GUI. The interface expands itself and adds new components to handle the sentences and their emotions. The size of the GUI increases because of this. Also, there is a selectable dropdown against each sentence which can be used by the user to change the emotion of the sentece if he/she is not satisfied by what is given by our classifier. This GUI is shown in Figure 10.2.

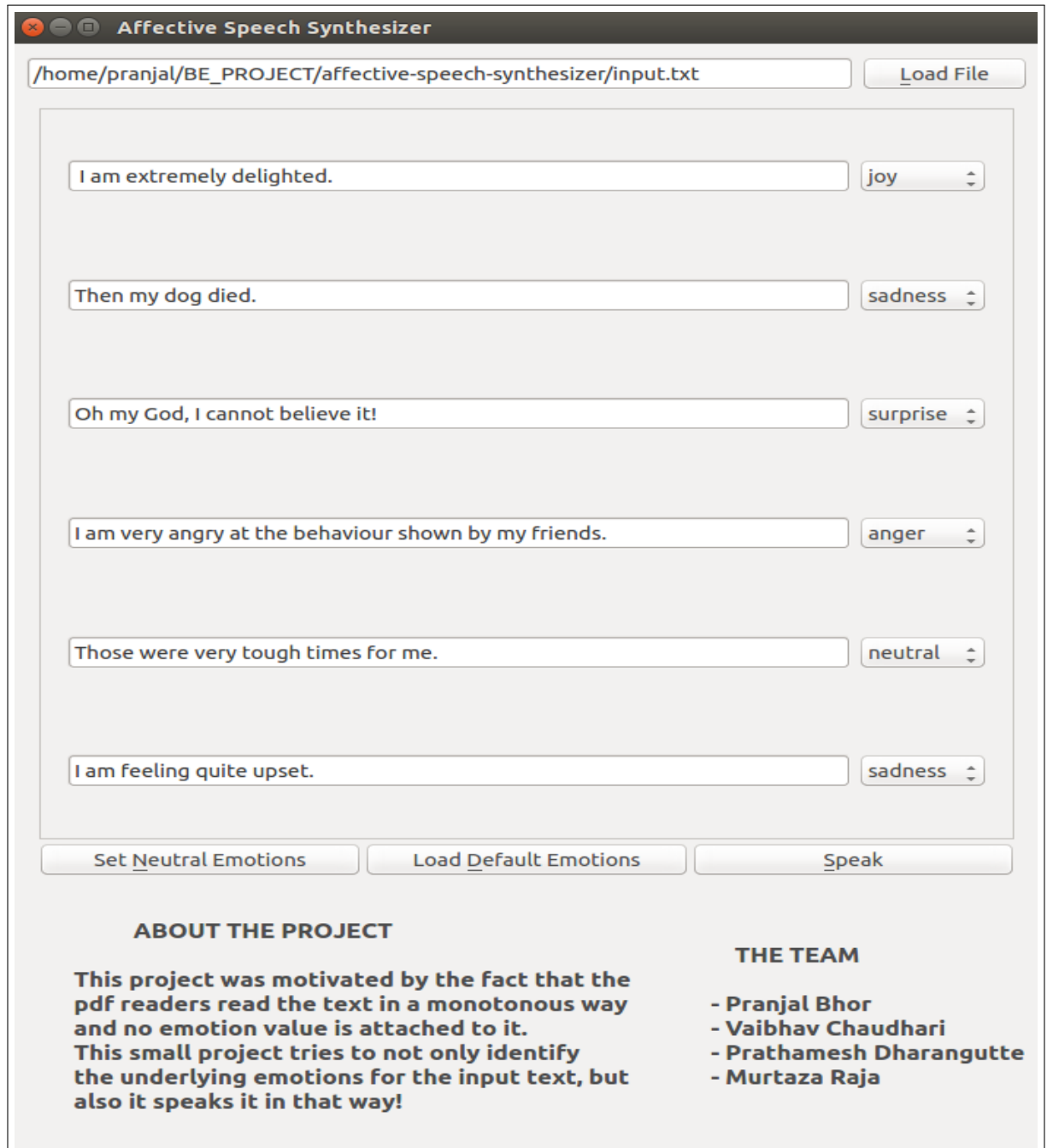


Figure 10.2: Emotion prediction screen



After the emotions are predicted from the sentences, the user clicks on speak button. Then the affective audio of each and every sentence is generated and is automatically played by the software. A new component of media player is loaded for that purpose. The user can pause and stop the audio, can increase or decrease the volume and can even seek the slider to whatever position he wants.

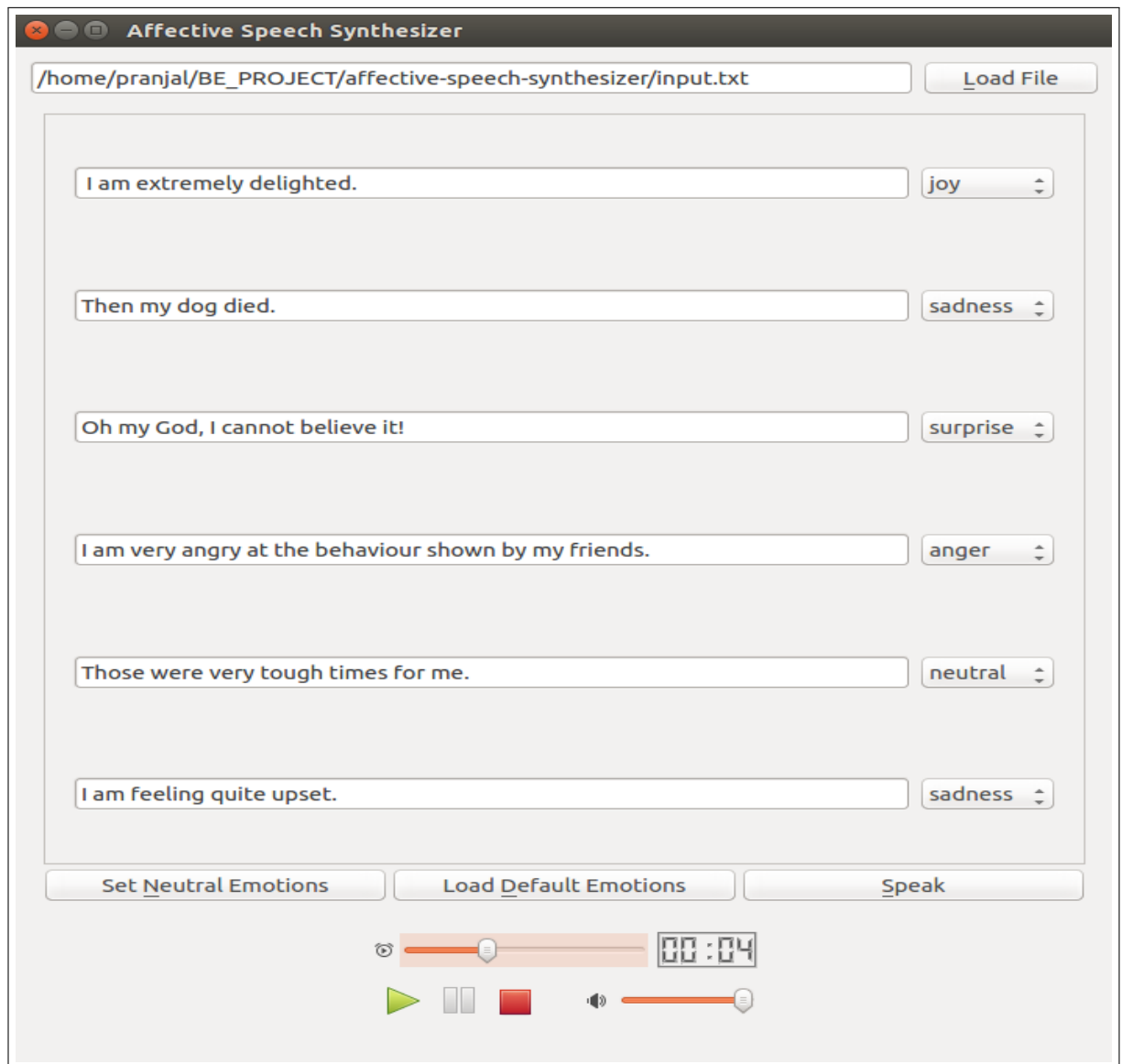


Figure 10.3: Affective audio playing screen

## 10.2 Accuracy of the Predictions

### 10.2.1 Theory of Precision, recall and F1-score

Precision ( $P$ ) is defined as the number of true positives ( $T_p$ ) over the number of true positives plus the number of false positives ( $F_p$ ).

$$\mathbf{P} = \frac{\mathbf{T}_p}{\mathbf{T}_p + \mathbf{F}_p} \quad (10.1)$$

Recall ( $R$ ) is defined as the number of true positives ( $T_p$ ) over the number of true positives plus the number of false negatives ( $F_n$ ).

$$\mathbf{R} = \frac{\mathbf{T}_p}{\mathbf{T}_p + \mathbf{F}_n} \quad (10.2)$$

These quantities are also related to the ( $F_1$ ) score, which is defined as the harmonic mean of precision and recall.

$$\mathbf{F}_1 = 2 * \frac{\mathbf{P} * \mathbf{R}}{\mathbf{P} + \mathbf{R}} \quad (10.3)$$

The respective precision, recall and F1 scores of the classifiers used in our project are shown in the figures below.

### 10.2.2 Precision, recall and F1 score for Naive Bayes Classifier

The accuracy score is 77.76%

Predicted	anger	joy	neutral	sadness	surprise
Actual					
anger	190	33	85	32	7
joy	19	218	148	19	10
neutral	27	34	1890	31	3
sadness	38	30	99	190	7
surprise	4	15	70	4	12
	precision		recall	f1-score	support
anger		0.68	0.55	0.61	347
joy		0.66	0.53	0.59	414
neutral		0.82	0.95	0.88	1985
sadness		0.69	0.52	0.59	364
surprise		0.31	0.11	0.17	105
avg / total		0.76	0.78	0.76	3215

Figure 10.4: Precision, recall and F1 of Naive Bayes

### 10.2.3 Precision, recall and F1 score for LSTM classifier

The accuracy score is 82.08%

Predicted	anger	joy	neutral	sadness	surprise
Actual					
anger	231	22	29	46	10
joy	24	262	33	34	21
neutral	48	82	1886	42	41
sadness	39	34	32	236	9
surprise	5	14	5	6	24
	precision		recall	f1-score	support
anger		0.67	0.68	0.67	338
joy		0.63	0.70	0.66	374
neutral		0.95	0.90	0.92	2099
sadness		0.65	0.67	0.66	350
surprise		0.23	0.44	0.30	54
avg / total		0.84	0.82	0.83	3215

Figure 10.5: Pprecision, recall and F1 of LSTM

#### 10.2.4 Accuracy score of NLP classifier

The accuracy score is 45.06%					
Predicted	anger	joy	neutral	sadness	surprise
Actual					
anger	128	41	138	27	6
joy	34	207	154	20	7
neutral	285	499	1023	171	31
sadness	81	66	113	85	4
surprise	20	25	36	9	6

Figure 10.6: Accuracy result of NLP classifier

**CHAPTER 11**

**DEPLOYMENT AND  
MAINTENANCE**

## 11.1 Installation and un-installation

The program is a runnable python script. It does not require installation like a traditional software. But some dependencies have to be installed to run the software. The steps are as follows:

1. Install project dependencies which includes: marytts-5.2, python 2.7, NLTK library, StanfordParser library, textract library, PyQT 4 and Phonon PyQT 4.
2. Download project source code
3. Execute 'run\_mary\_server.sh' script
4. Execute 'qtmain.py' script

As there is no traditional installation associated with the system. The following steps are enough to remove the project from the system:

1. Remove project dependencies which were installed in the installation steps.
2. Delete the project source code

**CHAPTER 12**

**CONCLUSION AND FUTURE  
SCOPE**

We developed a software that converts input text to its appropriate expressive speech. Two main modules namely emotion classifier and speech synthesis are present in our system. For emotion classification we worked with various techniques like Naive Bayes Classifier, SVM and LSTM. We observed that each technique has its ups and downs and there is no clear winner. Each technique is well suited for certain constructs of a sentence but may not work so well with other constructs. The accuracy of emotion classification is also an important aspect in this process. The accuracy of our Naive Bayes Classifier is about 78% and LSTM classifier is about 81%. One major requirement for the accurate prediction is the availability of a large, well formed and diverse dataset with high attribute accuracy. Improving the quality of the available dataset in the future and increasing the training examples will certainly improve the accuracy of emotion prediction.

Currently our system classifies the input text into only 5 emotions viz. joy, sadness, anger, surprise and neutral. But there are many subtleties in English language like sarcasm which cannot be correctly classified by present algorithms. The future work can include creating dataset and algorithms to identify more than above mentioned 5 emotions which can include fear, anger and disgust.

In our project we consider only one sentence at a time. The context of a paragraph or section is not taken into consideration. Also, the association or dependency of the speaker with the text is not considered. The future work can be done in this direction so as to identify the context of the paragraph and associativity of the speaker with the words he or she is speaking. This will certainly make the system Artificially Intelligent in audio generation.

At present our system only supports English language and only American accent due to the limitation of the audio dataset. In the future, dataset of Indian voice actors can be created and the Hidden Markov Model can be trained on it so as to create the voice with Indian accent. Similarly, audio can be recorded in any Indian regional language and its model can be trained so that the system can support languages other than English.

Furthermore, we generate expressive speech for joy, anger, sadness, surprise and neutral emotions but we do not consider their intensities. The future work can be directed in the direction of modifying neutral speech into expressive speech along with varying intensity depending on the context in which it is written.



One of the import limitations of our project includes that we consider only one dominant emotion in the sentence containing multiple emotions. An algorithm for the same can be developed in the future for synthesizing speech with multiple emotions such that all the emotions are perfectly incorporated in the audio.

The audio of the emotion anger produced by the system is not upto the mark of identification by a human listener. This is the limitation can be overcome in future by improving the anger audio synthesis parameters of MaryTTS engines.

# **CHAPTER 13**

## **REFERENCES**

# ANNEXURE A

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**ANNEXURE B**

**LABORATORY ASSIGNMENTS ON  
PROJECT ANALYSIS OF  
ALGORITHMIC DESIGN**

### Assignment

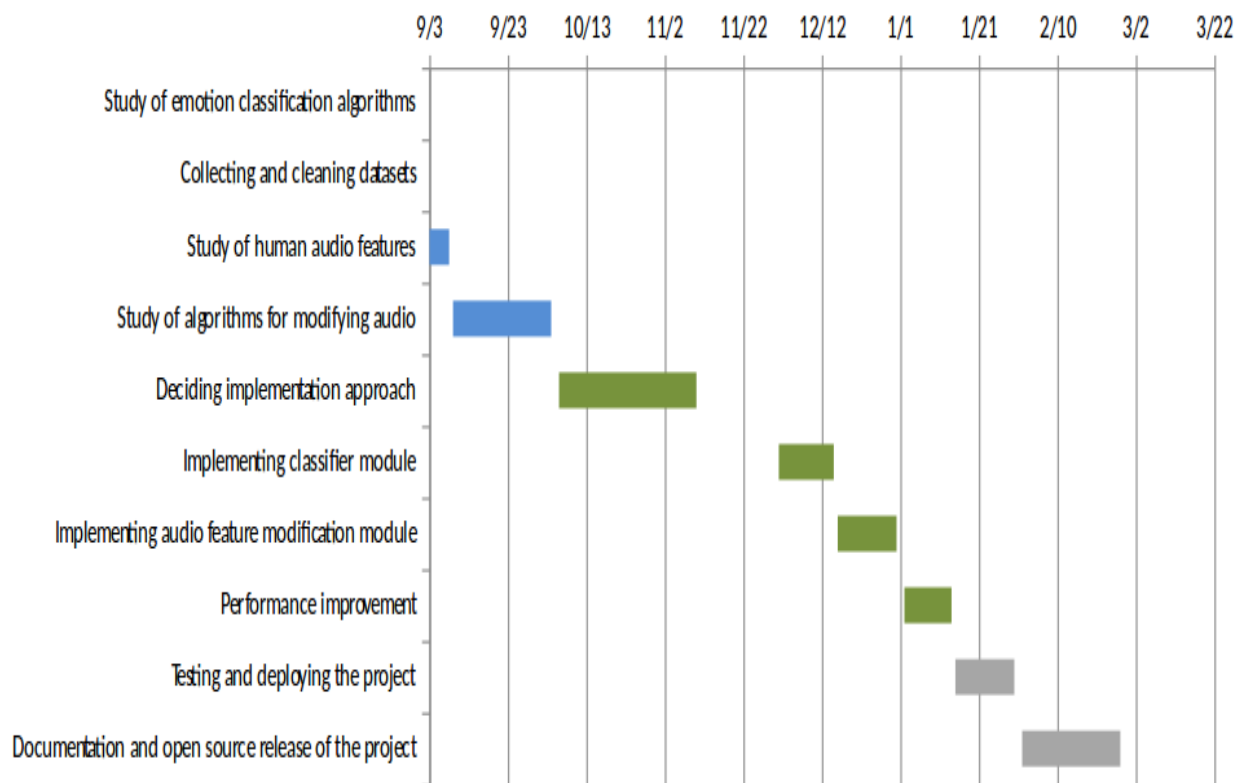
To develop the problem under consideration and justify feasibility using concepts of knowledge canvas and IDEA Matrix.

I	D	E	A
Increase Accuracy	Drive Interaction	Educate Machine	Accelerate Processing
Improve Efficiency	Deliver Results	Evaluate Predictions	Associate Knowledge
Ignore Risks	Decrease Errors	Eliminate Inaccuracy	Avoid Failure

Table B.1: IDEA Matrix

**ANNEXURE C**  
**PROJECT PLANNER**





**ANNEXURE D**  
**PLAGIARISM REPORT**

## Plagiarism report

# PLAGIARISMA

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speech according to the emotion in the text which will resemble closely to the human speech. Our project, in general, attempts to create an emotion based text-to-speech conversion system, and in particular, tries to solve the problem of speech distinction between angry and happy emotions which has not been reasonably addressed in the past.

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**ANNEXURE E**  
**TERM-II PROJECT LABORATORY**  
**ASSIGNMENTS**

## Assignment 1

Title:

Review of design and necessary corrective actions taking into consideration the feedback report of Term I assessment, and other competitions/conferences participated like IIT, Central Universities, University Conferences or equivalent centers of excellence etc.

Earlier state of the project:

Simple sentences could be easily tagged with their emotions. But when some qualifying word comes, the emotion identification failed. It gave erratic results.

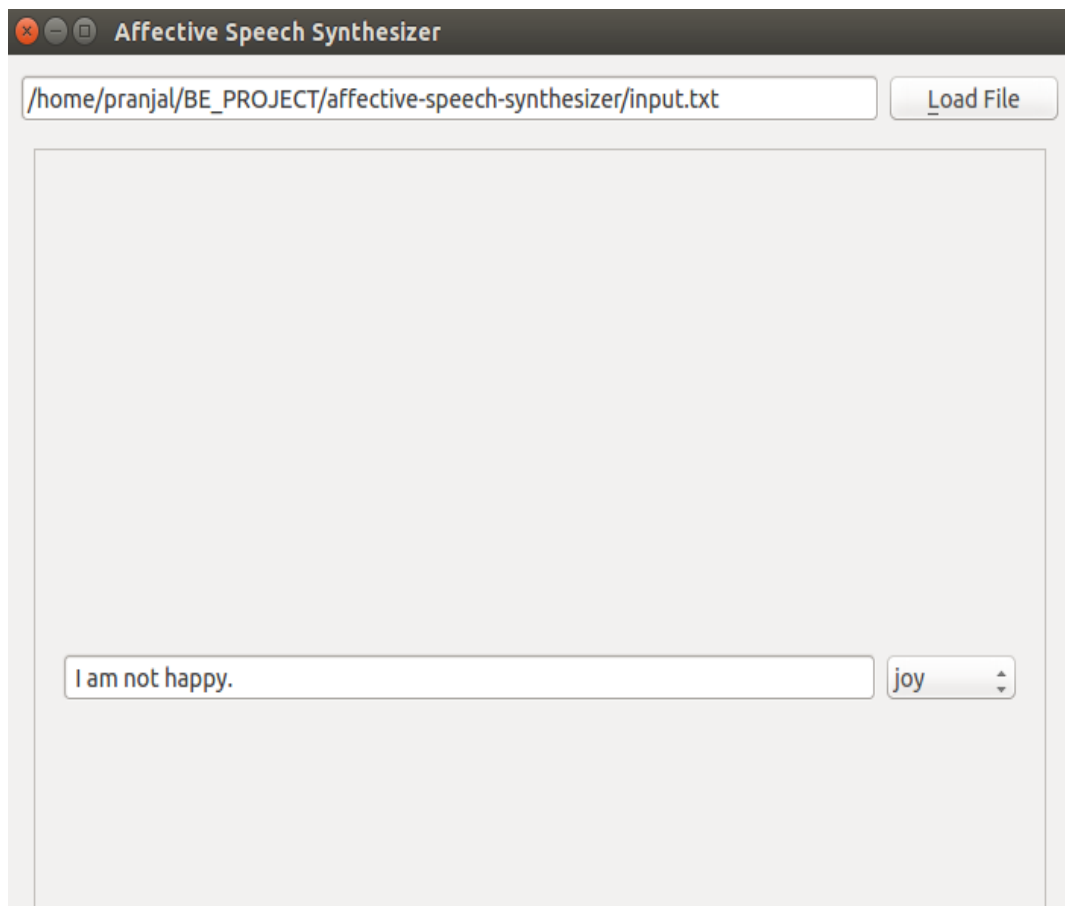


Figure E.1: I am not happy wrongly classified as joy

After Corrective actions:  
Sentences containing not and qualifiers like very, extremely are handled.

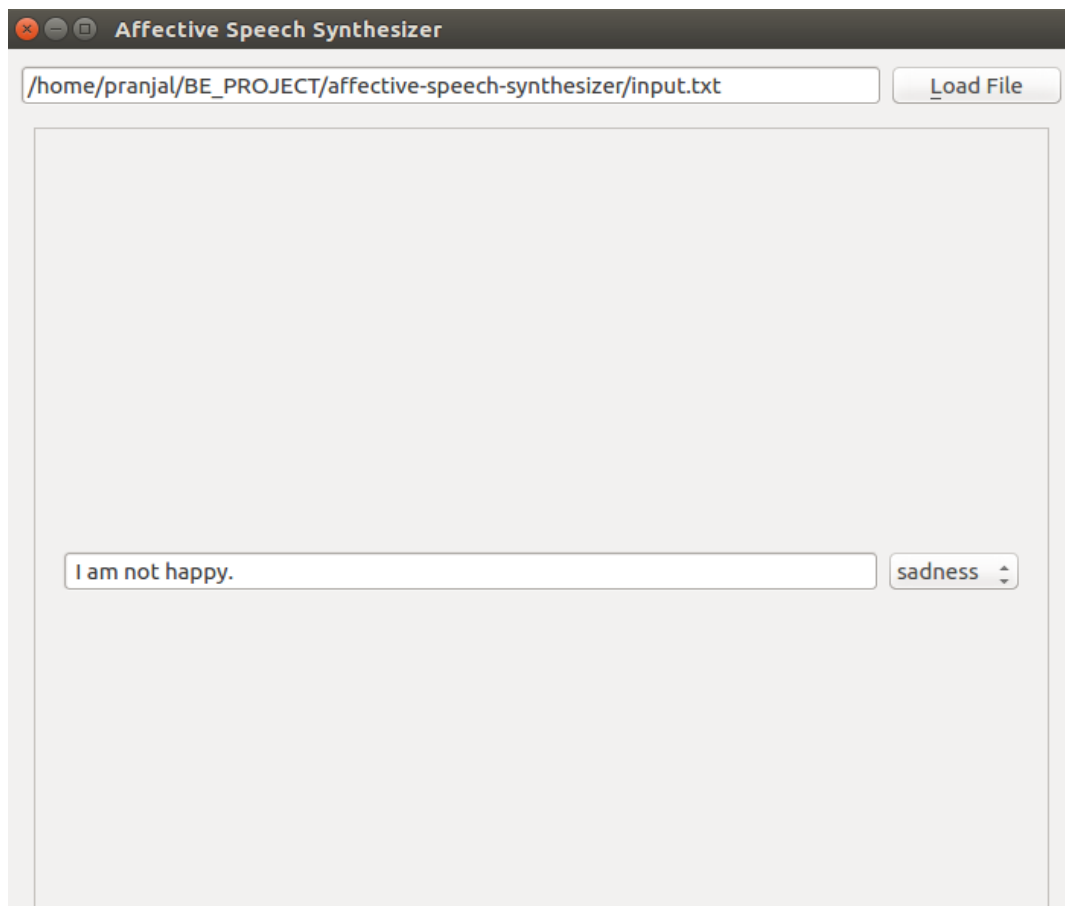


Figure E.2: I am not happy correctly classified as sadness

## Assignment 2

Title:

Project workstation selection, installations along with setup and installation report preparations.

Workstation Selection:

Platform Linux platform is suitable because most of the dependencies of our software can be easily setup in it.

Number of cores in the machine Multi-core system is preferable because our software exploits multithreading for faster execution.

Dependencies:

1. marytts-5.2
2. python 2.7
3. NLTK library
4. Stanford Parser library
5. textract library
6. PyQT 4
7. Phonon PyQT 4

Installation:

1. Install project dependencies which includes: marytts-5.2, python 2.7, NLTK library, StanfordParser library, textract library, PyQT 4 and Phonon PyQT 4.
2. Download project source code
3. Execute 'run mary server.sh' script
4. Execute 'qtmain.py' script

### Assignment 3

Title:

Programming of the project functions, interfaces and GUI (if any) as per 1 st Term term-work submission using corrective actions recommended in Term-I assessment of Term-work.

Project GUI as per 1st Term term-work:

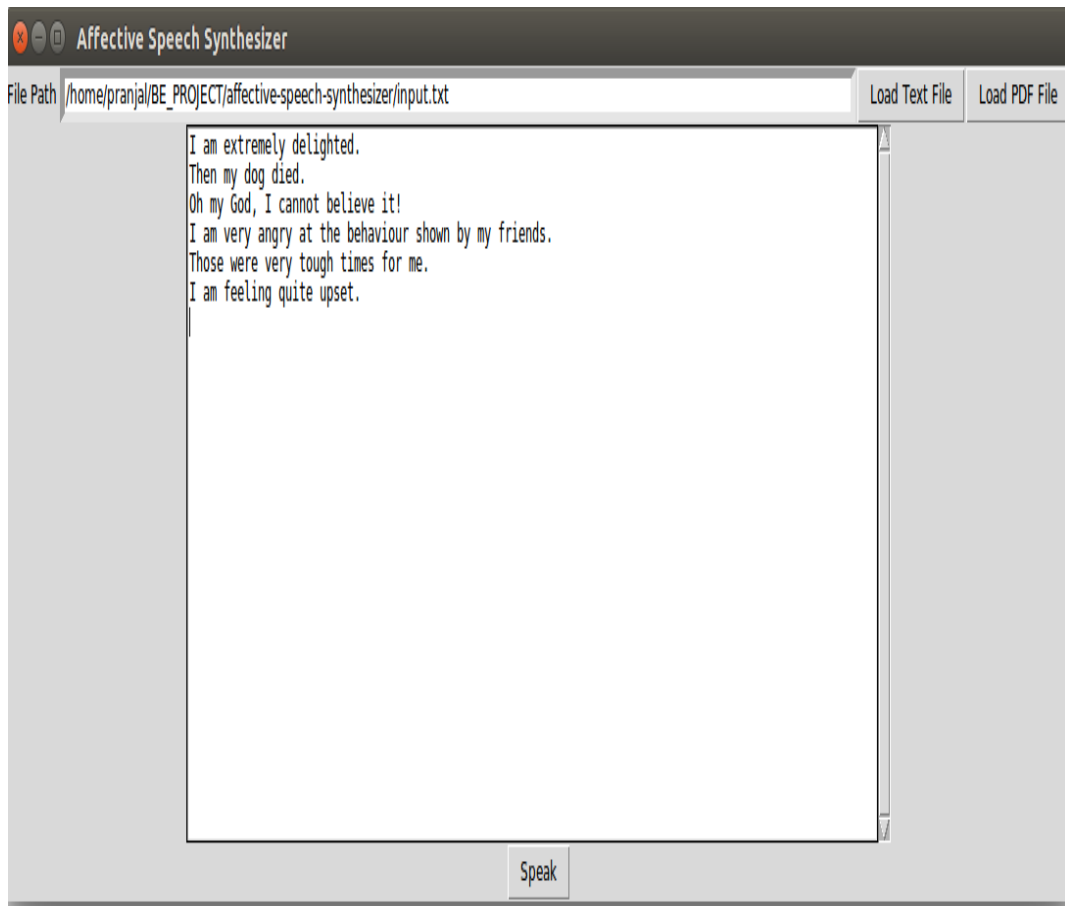


Figure E.3: Naive GUI made using python TKinter



Project GUI after corrective actions suggested by project guide:

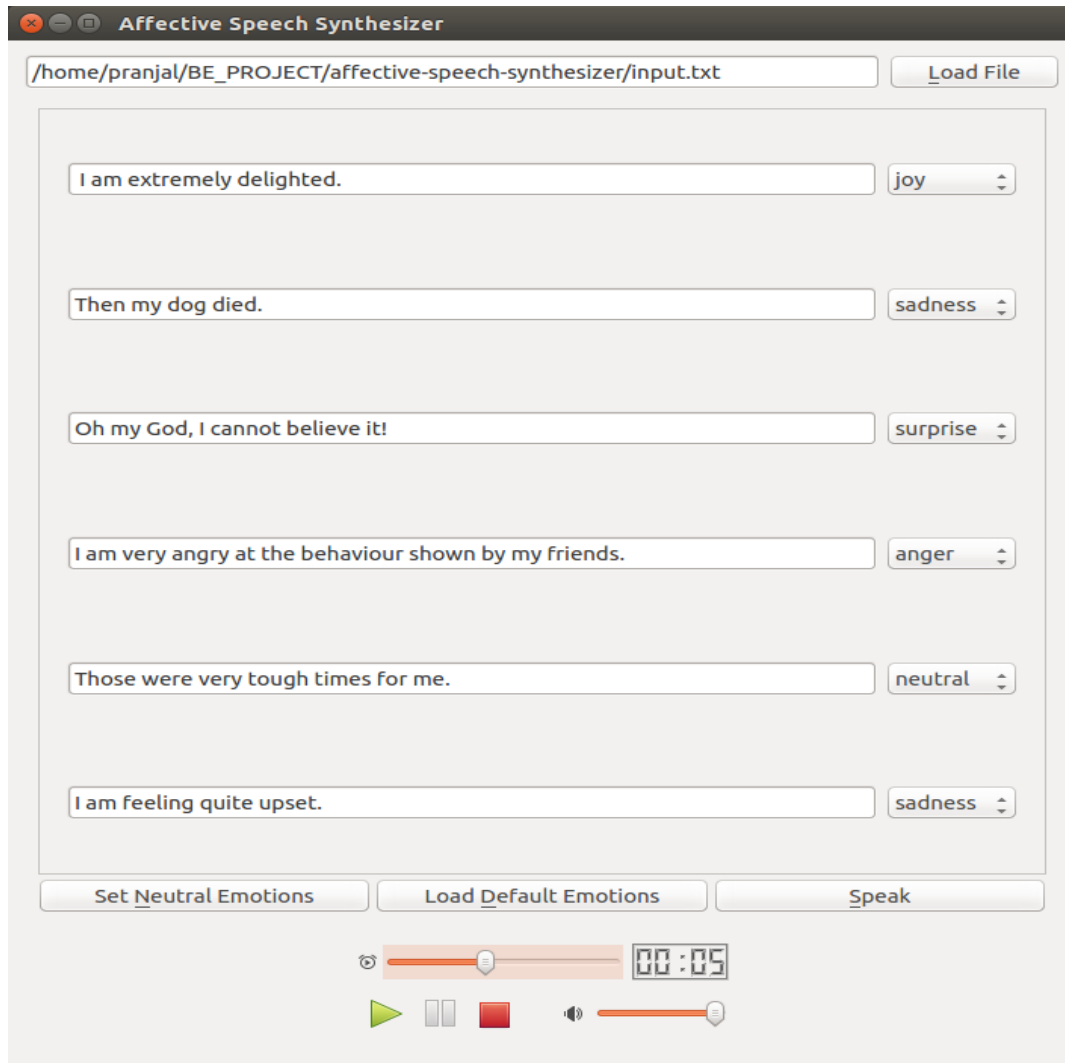


Figure E.4: Improved GUI with native look-and-feel

## Assignment 4

### E.1 Title

Test tool selection and testing of various test cases for the project performed and generate various testing result charts, graphs etc. including reliability testing.

### E.2 Type of Testing Used

Since our project focuses mainly on two important tasks Classification of sentences based on emotions using machine learning (A) and conversion of monotonic speech into expressive speech (B), we have analyzed different testing strategies based on the aforementioned tasks.

#### E.2.1 Unit testing

This testing was very valuable for our project since we were able to independently test the emotion identification module and the speech synthesis module with good results. We essentially decoupled the two subsystems and tested them.

##### E.2.1.1 Classification module

This subsystem was tested by providing some sentences rich with five emotions - joy, sadness, anger, surprise and neutral. With an accuracy of about 80%, it produced the results accordingly. It labelled more sentences as neutral because the database was biased toward it.

##### E.2.1.2 Speech synthesis module

For voice synthesis and digital signal processing unit, same sentences were given as input. The affective audio generated by the unit was perceived to contain the emotion tagged as reported by the test users. The sentences which depicted anger as the emotion, were spoken a bit fast by the system.

#### E.2.2 Integration testing

Having tested the individual subsystems, the emotion prediction and voice synthesis modules were then integrated. A sentence was passed to the input

function of the system. The emotion classifier correctly identified the emotion tag of the sentence and then using this emotion tag, the affective audio was generated.

#### **E.2.2.1 Multithreading fix**

It was discovered during testing that a single MaryTTS engine does not handle simultaneous requests and is not thread safe. Therefore, we spawned multiple instances of the engine and then fired simultaneous requests to them.

### **E.2.3 Validation testing**

Since the ideas presented through this project are still in research phase, a usable product is a feat that cannot be achieved provided the current technology in this field. Still, we tried to test this software, targeting the audio book publishers as our client.

#### **E.2.3.1 Emotional speech as output**

This software provides the affective audio for emotions - joy, sadness, anger, surprise and neutral for the input provided by the user.

#### **E.2.3.2 Input characteristics**

Since majority of text is either available as .txt or as .pdf, this software has the ability to process both of them.

### **E.2.4 Performance and load testing**

We used load testing to test the system under various loads. The workstation on which testing was performed consisted of a 2.5 GHz quad-core machine with 8 GB of main memory running Ubuntu operating system.

### **E.2.5 GUI testing**

We made a very simple GUI in the beginning but soon found out that it is not user friendly and does not have a native-look-and-feel. Then we made another GUI which solved the problems of the previous one and offered better functionality in terms of audio playing and emotion selection.

#### **E.2.5.1 Emotion selection**

A drop down menu was associated with each and every sentence that represented the emotion of the sentence. The user has the ability to change this according to his or her preference.

#### **E.2.5.2 Audio playback**

A media player like functionality was added to the GUI so that the user can play, pause, stop, seek and change the volume of the audio being played.

#### **E.2.5.3 Scrollable interface**

If the number of sentences exceeded the minimum which can fit on the screen, the windows automatically provides scroll bars that can be used to navigate between the sentences.

## E.3 Test Cases and Results

### E.3.1 Unit testing

#### E.3.1.1 Classifier module

No.	Input	Expected Output	Actual Output
1.	I am very delighted	joy	joy
2.	My dog died	sadness	sadness
3.	Oh my God, I got that!	surprise	surprise
4.	I am very angry at that behaviour	anger	anger
5.	Those were tough times for me	neutral	neutral
6.	I am not happy	sadness	sadness
7.	I am not very sad	neutral	neutral

Table E.1: Test cases for classifier module

### E.3.1.2 Speech synthesis module

No.	Input emotion	Expected Output	Actual Output
1.	joy	speaks in an overall pleasant way	as expected
2.	sadness	the pitch drops and tempo decreases	as expected
3.	surprise	the pitch increases, some words stressed	as expected
4.	anger	speaks a bit fast	speaks very fast
5.	neutral	speaks normally	as expected

Table E.2: Test cases for speech synthesis module

### E.3.2 Integration testing

No.	Input	Expected Output	Actual Output
1.	affective sentence	emotional speech generated	as expected
2.	neutral sentence	neutral speech generated	as expected
3.	text file with various sentences	proper affective audio generated corresponding to emotions	as expected
4.	pdf file with various sentences	proper affective audio generated corresponding to emotions	as expected

Table E.3: Test cases for integration testing

### E.3.3 Validation testing

No.	Feature	Implemented	Details
1.	produces affective voice on emotional text input	yes	can process 5 emotions
2.	handles text files	yes	can process .txt and .pdf
3.	automatically tags sentences with emotions	yes	currently 80% accurate
4.	support for other languages	no	future scope, data set limitations
5.	support for other accents	yes	training data to be provided

Table E.4: Test cases for validation testing

### E.3.4 Performance and load testing

No.	Input	Time taken to execute
1.	5-10 sentences.	2-3 seconds.
2.	1 page.	About 15 seconds.
3.	10-15 pages.	About 3 minutes.
4.	A novel of about 300 pages.	About 1 hour 5 minutes.
5.	3-4 instances of our software running at the same time.	Sometimes system gets hung up.

Table E.5: Test cases for load testing

### E.3.5 GUI testing

No.	Case	Expected Output	Actual Output
1.	loading files	.txt and .pdf files loaded	as expected
2.	changing emotion of a sentence	drop down updated	as expected
3.	sentences overflow the viewport	proper scroll bars are added accordingly	as expected
4.	audio playing capability	play, pause, stop, seek, volume	as expected
5.	performing computational intensive task	show progress to user	no progress shown

Table E.6: Test cases for GUI testing

#### Emotion Classification testing

Input	Expected Output	Actual Output
I am very delighted	joy	joy
My dog died	sadness	sadness
Oh my God, I got that!	surprise	surprise
I am very angry at that behaviour	anger	anger
Those were tough times for me	neutral	neutral
I am not happy	sadness	sadness
I am not very sad	neutral	neutral

Testing output audio quality:

For voice synthesis and digital signal processing unit, same sentences were given as input. The affective audio generated by the unit was



perceived to contain the emotion tagged as reported by the test users.

#### Reliability Testing:

Load testing - We used load testing to test the system under various loads. The workstation on which testing was performed consisted of a 2.5 GHz quad-core machine with 8 GB of main memory and Ubuntu platform.

To this system varying loads were provided to check performance of the system.

Input	Time taken to execute
5-10 sentences.	2-3 seconds.
1 page.	About 15 seconds.
10-15 pages.	About 3 minutes.
A novel of about 300 pages.	About 1 hour 5 minutes.
3-4 instances of our software running at the same time.	Sometimes system gets hung up.

**ANNEXURE F**  
**INFORMATION OF PROJECT**  
**GROUP MEMBERS**



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