CHAPTER 4
THE PROPOSED SYSTEM DESIGN, IMPLEMENTATION, AND PERFORMANCE EVALUATION

This chapter discusses system design and detailed work flow of the proposed speech based children gender classification system. And also the discussion about the experimental implementation and the performance evaluations of the proposed system are discussed. The proposed system is implemented using the Python programming language. The speech signals are digitised at a sample frequency rate 44.1 kHz. In this experiment, spoken sentences in Myanmar language are used as input and the system outputs the gender of the speaker.

4.1. System Design of the Proposed System

The proposed system consists of four main components, namely, dataset preparation, preprocessing, feature extraction and classification. For dataset preparation, voice of children is needed and so children’s speech is recorded repeatedly in a quiet place. And then speech features are extracted from recording files to create a speech features dataset. The second stage is preprocessing of the speech signal. In machine learning and data mining, preprocessing makes input data easier to work with algorithms. Data preprocessing is an integral step in machine learning as the quality of data and the useful information that can be derived from it directly affects the ability of classification model to learn. In preprocessing, noise reduction and removal of silences and unvoiced regions are included. The next stage involves feature extraction. The extraction of the relevant and important information from the speech signals of the human voice is an important task to produce the good classification performance. In this system, MFCC speech features are used for prediction. In the last stage, extracted features are evaluated using machine learning classifiers to predict children’s gender. The performance of five classifiers is compared in this study. Figure 4.1 shows the design of proposed children gender classification system using speech.

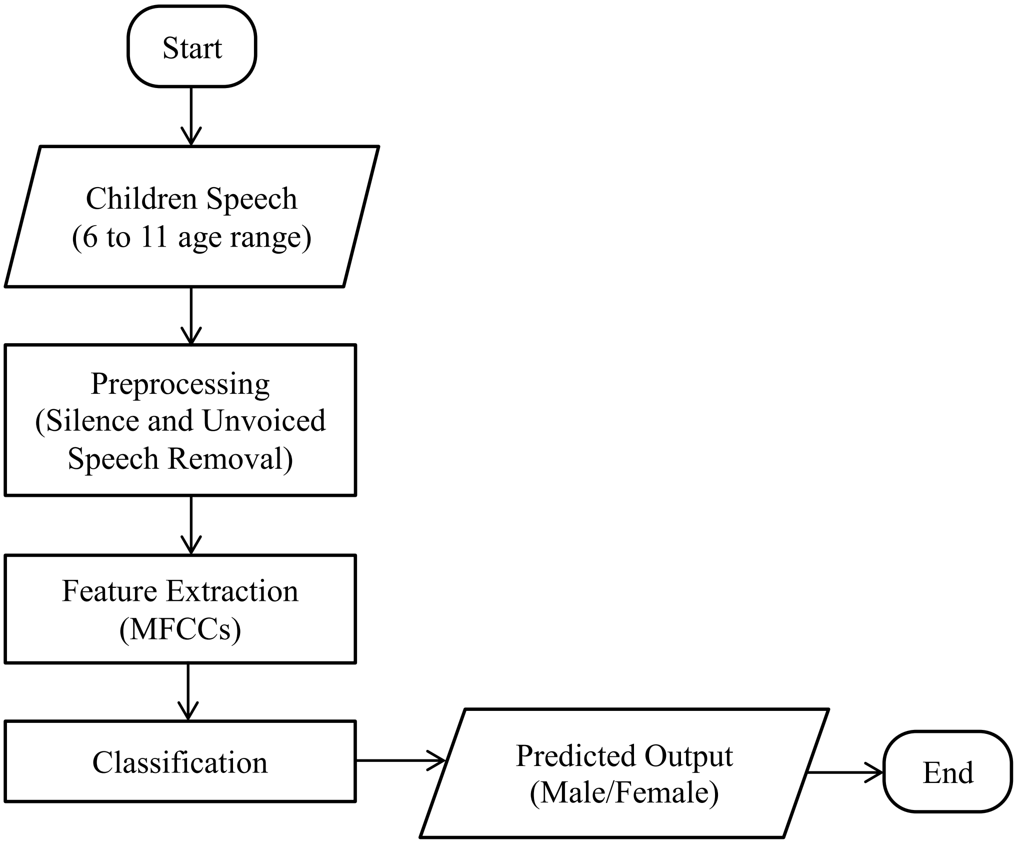


Figure 4.1. System Flow Diagram

4.1.1. Dataset Preparation

The database used in this system consists of sentences read aloud by children both male and female in Myanmar language. It was designed to create a training set of speech from children of KG to Grade V (age range 6 to 11 years). The database contains audio recordings of individuals from different grades. Firstly, 10 Myanmar sentences were prepared. They are:

1. မင်္ဂလာပါ။
2. ကျေးဇူးတင်ပါတယ်။
3. နာမည်ဘယ်လိုခေါ်လဲ။
4. ဘယ်သွားမလို့လဲ။
5. နေကောင်းလား။
6. ဘယ်မှာနေပါသလဲ။
7. စာမေးပွဲဖြေနိုင်လား။

8. အမေကိုခေါ်လာခဲ့ပါ။
9. ဘာဖြစ်လို့လဲ။
10. ဘာဝါသနာပါလဲ။

Utterances from children are recorded with SONY Digital Stereo High Definition. These voice clips are preprocessed and evaluated. There are total of 1200 audio records. The female records contain 600 samples where male records have 600 samples. Recording specification used for dataset is shown in table 4.1.

Table 4.1. Recording Specifications

File Type	.wav format
Duration	2 or 3 second
Numbers of Channel	Mono (1 Channel)
Sampling Frequency	44.1 kHz
Number of Bits	16 bits ~ 32 bits

4.1.2. Preprocessing

Only voiced region of speech contains most of the gender related information. Leading/trailing silence in the audio may not contain much information and thus is not useful for the classification. There are many silence and unvoiced regions in the recording files of children. Hence, removing this silence and unvoiced regions is done in preprocessing step. These regions are removed from the speech using librosa.effects.trim function which is a build in function of Python.

4.1.3. Feature Extraction

Features efficient in discriminating female and male voice in children speech should be identified. The most commonly used acoustic features in gender classification are MFCCs. They play a significant role in applications such as speech recognition, speaker recognition, etc. MFCCs mimics human speech production and speech perception, by logarithmic perception of loudness. MFCCs, which are short term spectral based features, are extracted from children speech. The length of the analysis window used in MFCC feature extraction algorithm is 0.025s. The step between successive windows is 0.01s. Hamming window is used as the analysis window to apply to each frame. FFT size is 2048 and the value of pre emphasis filter coefficient is 0.97. The number of cepstrum to return is 13 that is number of MFCC feature points. After computing MFCC features using these parameters, a numpy array of size (number of frames by number of cepstrum) containing features. Each row holds 1 feature vector. MFCC features are frequently used by many researchers for speech recognition and in music/ speech classification problem.

4.1.4. Classification

A classification model attempts to draw some conclusion from observed values. When one or more inputs are given, a classification model will try to predict the value of one or more outcomes. The classification task involves the implementation of various classifiers for gender identification task. Classification is establishing a mathematical model that separates into male and female based on the features of children's speech. Classification model is built on the training set and the accuracy of the model is checked by using it on the testing set. In this system, machine learning classification algorithms are compared using MFCC feature dataset. Train and test set accuracies are observed for five classification algorithms. The classifiers are chosen mainly based on the non-linear nature of data. Random Forest (RF), Artificial Neural Network (ANN), Logistic Regression (LR), Support Vector Machine (SVM) and Gaussian Naive Bayes (GNB) are used to develop the gender prediction task.

4.2. Implementation of the Proposed System

Figure 4.2 illustrates the home page of the proposed children's speech based gender classification system. In the system, two main parts are categorized for the gender classification: performance analysis and classification. In classification section, voice of a children that is needed to classify can be selected from any folder and classify the speaker of this audio is boy or girl. In performance analysis, classification performance for each machine learning classifier can be analysed using training and testing dataset divided by randomly.

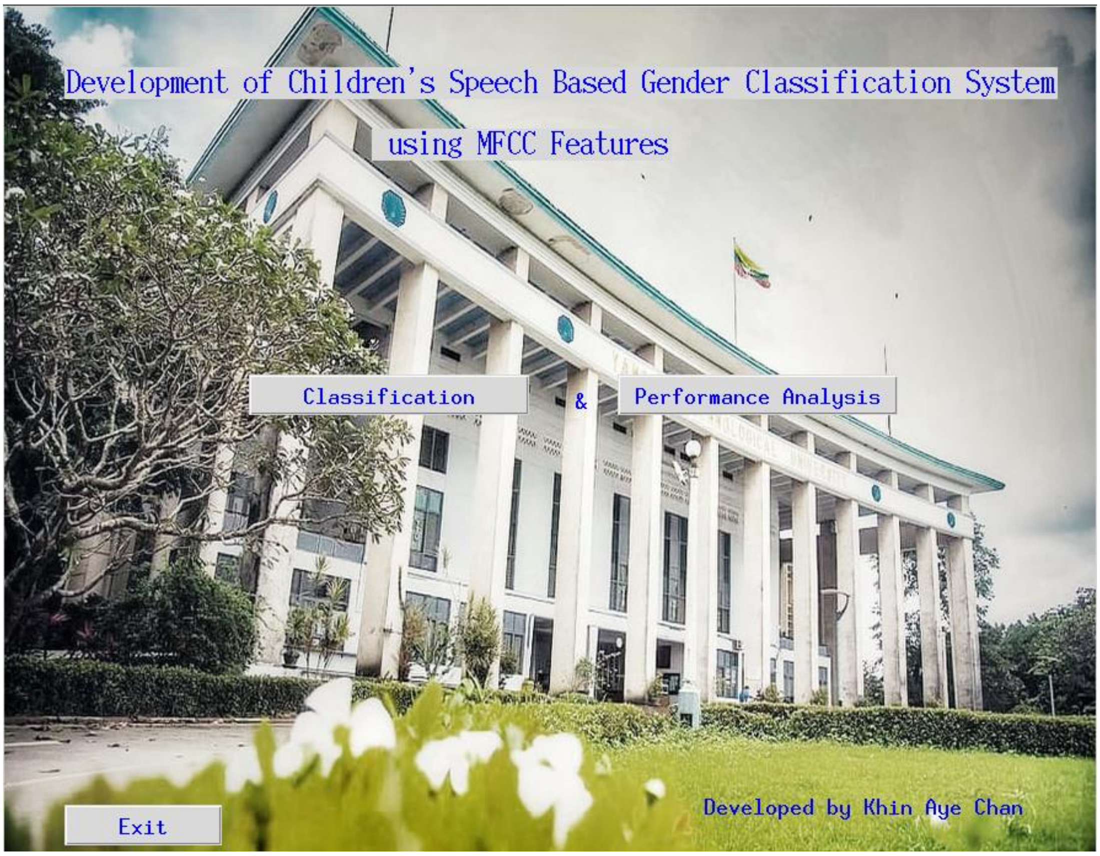
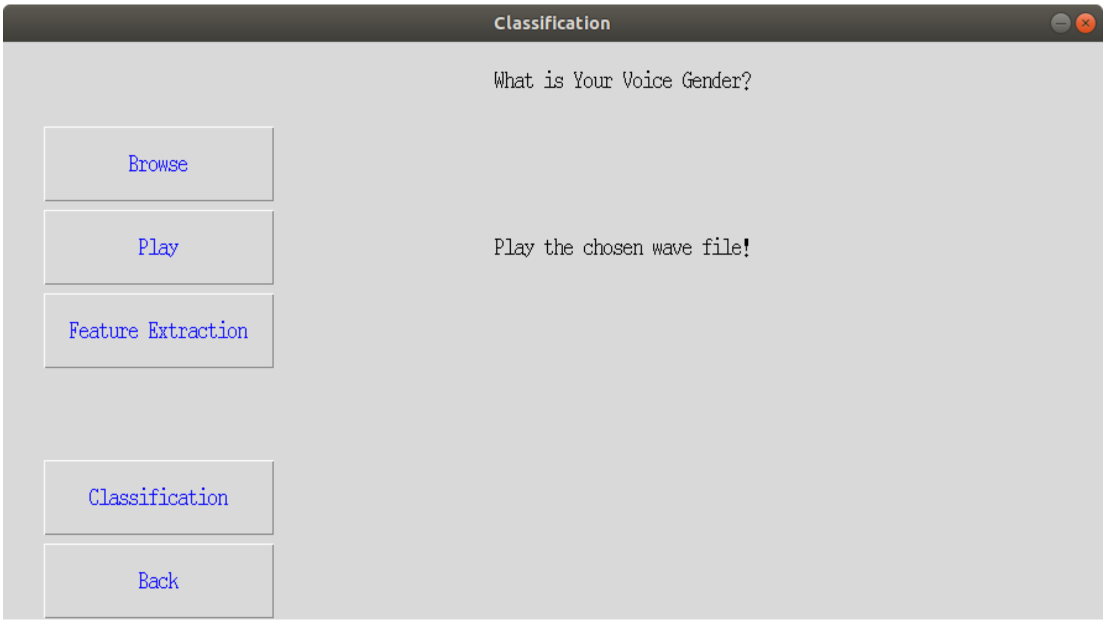

Development of Children's Speech Based Gender Classification System
using MFCC Features
Classification
&
Performance Analysis
Exit
Developed by Khin Aye Chan

Figure 4.2. Start Form for Children's Speech Based Gender Classification System

4.2.1. Real Time Classification

Real time classification of each audio file can be done in classification page as shown in Figure 4.3.

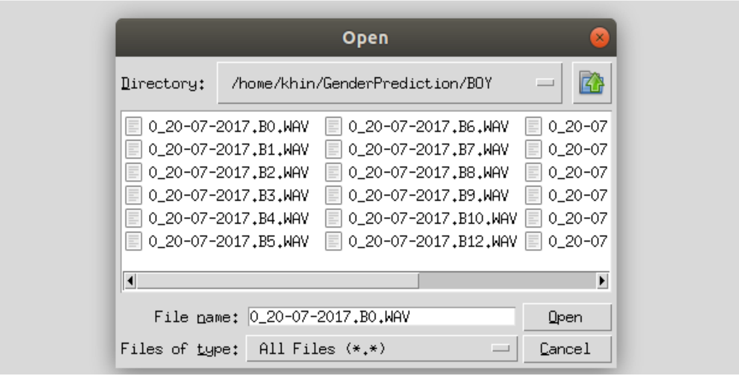


What is Your Voice Gender?

Play the chosen wave file!

Figure 4.3. Classification Form

User can browse a child's voice from any folder and upload to the system. After uploading audio, selected audio file can also be listened. MFCC features of this audio are extracted by using feature extraction algorithm and machine learning algorithms classify the gender of the speaker of this uploaded file. Firstly, browse button displays open file dialog box as shown in Figure 4.4. The open file dialog component allows users to browse the folders of their computer. The dialog box returns the path and name of the file the user selected in the dialog box.



Directory: /home/khin/GenderPrediction/BOY

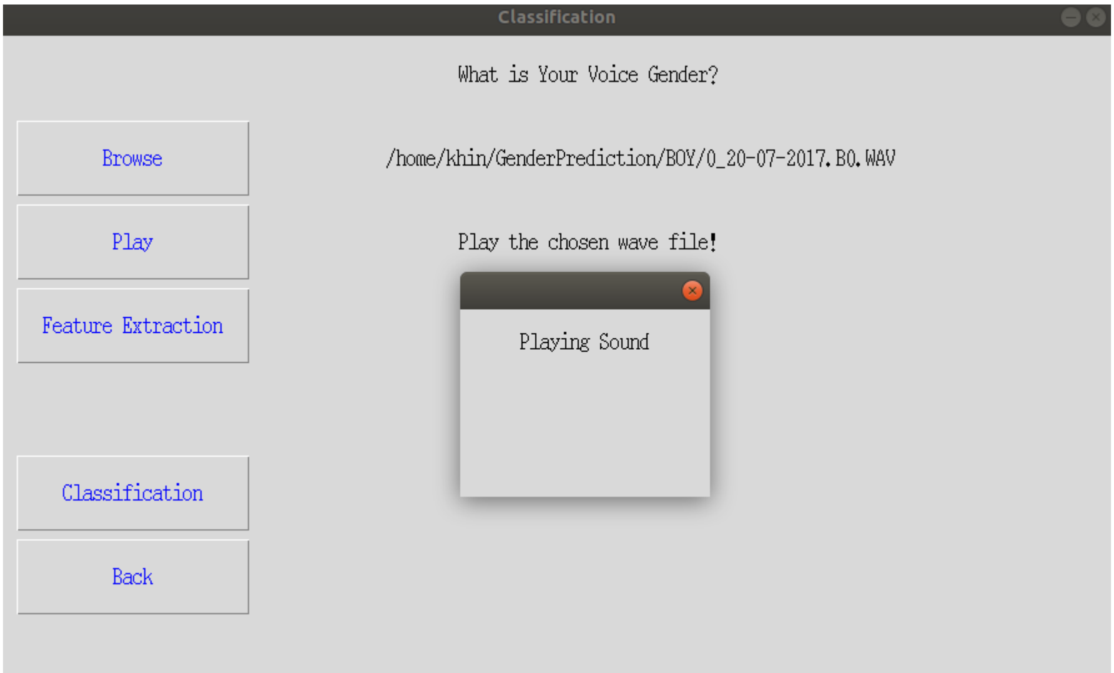
```
0_20-07-2017.B0.WAV   0_20-07-2017.B6.WAV    0_20-07
0_20-07-2017.B1.WAV   0_20-07-2017.B7.WAV    0_20-07
0_20-07-2017.B2.WAV   0_20-07-2017.B8.WAV    0_20-07
0_20-07-2017.B3.WAV   0_20-07-2017.B9.WAV    0_20-07
0_20-07-2017.B4.WAV   0_20-07-2017.B10.WAV   0_20-07
0_20-07-2017.B5.WAV   0_20-07-2017.B12.WAV   0_20-07
```

File name: 0_20-07-2017.B0.WAV

Files of type: All Files (*.*)

Figure 4.4. Browsing an Audio File from a Folder

The sound of chosen audio file can be listened. Figure 4.5 shows the screen of playing the wave file selected in a folder of the computer. After that, MFCC feature extraction method extracts speech features from the selected audio file.



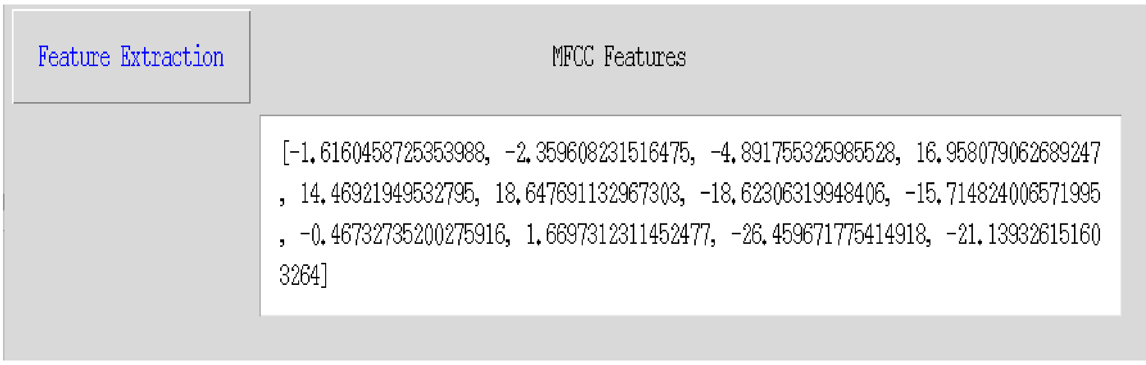
What is Your Voice Gender?

/home/khin/GenderPrediction/BOY/0_20-07-2017.B0.WAV

Play the chosen wave file!

Playing Sound

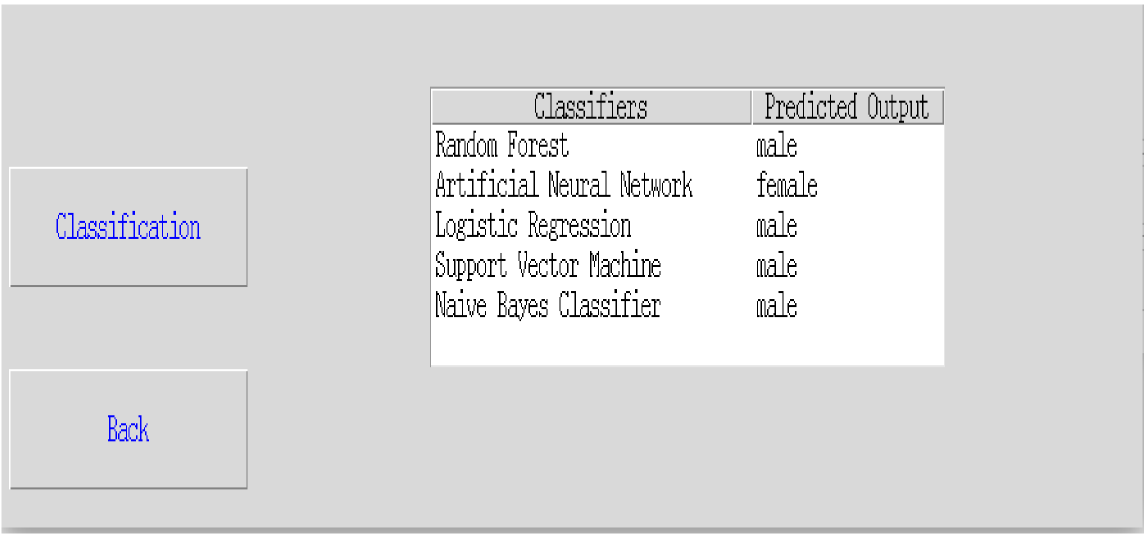
Figure 4.5. Playing Selected Audio File



```
[-1.6160458725353988, -2.359608231516475, -4.891755325985528, 16.958079062689247
, 14.46921949532795, 18.647691132967303, -18.62306319948406, -15.71482400657l995
, -0.46732735200275916, 1.6697312311452477, -26.459671775414918, -21.13932615160
3264]
```

Figure 4.6. MFCC Features

Figure 4.6 is MFCC features of selected wave file resulted by MFCC method. And then classification can be done based on these extracted features. Figure 4.7 shows classification results of five machine learning algorithms applied in the proposed system after testing speech of a boy.



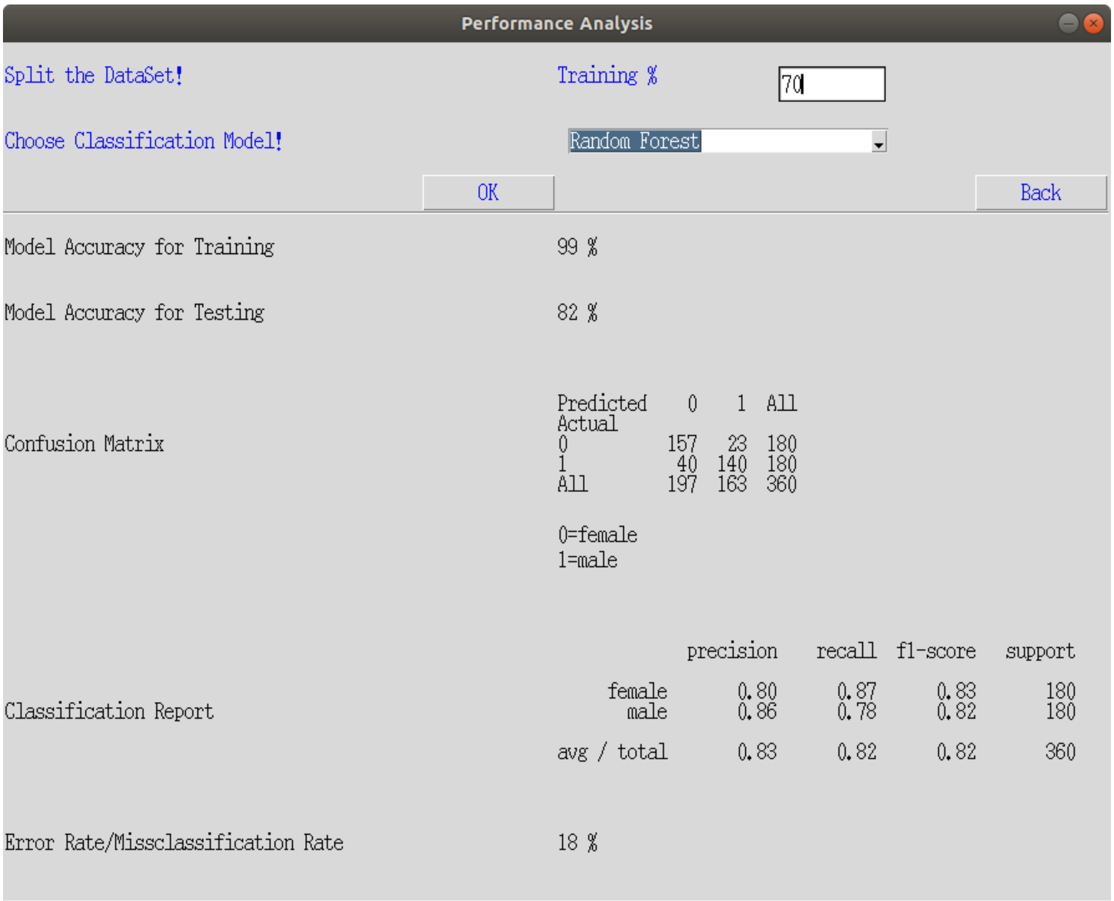
Classifiers	Predicted Output
Random Forest	male
Artificial Neural Network	female
Logistic Regression	male
Support Vector Machine	male
Naive Bayes Classifier	male

Figure 4.7. Results of Classifying a Boy’s Speech

4.2.2. Performance Analysis

Figure 4.8 shows performance analysis page for machine learning algorithms used for gender classification. In this experimental study of classification algorithms, performance of machine learning algorithms can be analyzed for gender classification using MFCC voice feature dataset. User can split feature dataset into random train and test subsets and choose a classification model among classifiers used in the system. Any classifier displayed in combo box can be chosen for classification. And performance measures: training accuracy, testing accuracy, precision, recall, F1-score, and support are used to evaluate performance of learning algorithms. The system displays training and testing accuracy and other performance measures of selected classifier.

Classification performance of RF can be seen in Figure 4.8. In this testing, 70% of features dataset is trained and testing is done on 30 % of dataset. Testing dataset includes the number of male which is 180 and the number of female which is 180. RF classifier can predict male 140 and female 157 correctly and others are wrongly classified. RF has 99% training accuracy and 82% of testing accuracy. Performance of other classification algorithms can study using different ratio of the train set and test set based on MFCC feature dataset. Accuracies of classification models can change, depending on the ratio of training and testing data set.



Split the DataSet! Training % 70

Choose Classification Model! Random Forest

Model Accuracy for Training 99 %

Model Accuracy for Testing 82 %

Confusion Matrix

```
Predicted    0    1  All
Actual
0          157   23  180
1           40  140  180
All        197  163  360

0=female
1=male
```

Classification Report

```
             precision    recall  f1-score   support

     female       0.80      0.87      0.83       180
       male       0.86      0.78      0.82       180

avg / total       0.83      0.82      0.82       360
```

Error Rate/Missclassification Rate 18 %

Figure 4.8. Classification Results of RF Classifier

4.3. Comparison of Performance Evaluations of Different Classifiers

In this system, voice dataset contains 1200 audio records where recordings of female child contain 600 speech samples and male child recordings have 600 speech samples. The performance of the proposed system is specified, based on classification results for testing data set. Two tests are done to estimate the performance of the machine learning models: simple train-test split and k-fold cross validation method. Moreover, different performance metrics: confusion matrix, precision, recall, F1-score, support are used to evaluate performance of classifiers.

4.3.1. Simple Train-Test Split

To do gender classification, a machine learning model is established and needed to train using voice features dataset. After training, the model accuracy is checked on some test dataset. Splitting test dataset and train dataset can make by any ratio and size of datasets can be declared as test size and train size. Splitting test dataset and train dataset can make by any ratio and size of datasets can be declared as test size and train size. In the beginning, all of the stated classifier models were trained and tested for 70% and 30% of the total dataset respectively. Then in different ratios of the experiment, it was changed to 80% with 20% and 90% and 10%. Confusion matrices resulting after using these data set ratios can be seen in the following tables. Table 4.2 and table 4.3 are confusion matrices for data ratio 70:30. Table 4.4 and table 4.5 display classification results of 80:20. Confusion matrices for 90:10 can be seen in table 4.6 and table 4.7.

Table 4.2. Confusion Matrix of RF, ANN, SVM for Data Ratio 70:30

	RF		ANN		SVM	
	Predicted: male	Predicted: female	Predicted: male	Predicted: female	Predicted: male	Predicted: female
Actual: male	149	31	147	33	142	38
Actual: female	26	154	37	143	47	133

Table 4.3. Confusion Matrix of LR and GNB for Data Ratio 70:30

	LR		GNB	
	Predicted: male	Predicted: female	Predicted: male	Predicted: female
Actual: male	146	34	137	43
Actual: female	53	127	43	137

Table 4.4. Confusion Matrix of RF, ANN, SVM for Data Ratio 80:20

	RF		ANN		SVM	
	Predicted: male	Predicted: female	Predicted: male	Predicted: female	Predicted: male	Predicted: female
Actual: male	90	30	91	29	91	29
Actual: female	15	105	18	102	35	85

Table 4.5. Confusion Matrix of LR and GNB for Data Ratio 80:20

	LR		GNB	
	Predicted: male	Predicted: female	Predicted: male	Predicted: female
Actual: male	86	34	90	30
Actual: female	42	78	29	91

Table 4.6. Confusion Matrix of RF, ANN, SVM for Data Ratio 90:10

	RF		ANN		SVM	
	Predicted: male	Predicted: female	Predicted: male	Predicted: female	Predicted: male	Predicted: female
Actual: male	46	14	39	21	46	14
Actual: female	5	55	8	52	11	49

Table 4.7. Confusion Matrix of LR and GNB for Data Ratio 90:10

	LR		GNB	
	Predicted: male	Predicted: female	Predicted: male	Predicted: female
Actual: male	42	18	45	15
Actual: female	50	10	13	47

Each classifier is trained for feature dataset and observed the train and test set accuracies for five classification algorithms. The accuracy is percentage of total number of instances correctly identified. Classification accuracy of a machine learning classifier can be calculated by using values of confusion matrix. Table 4.8 shows training and testing accuracy results of five classifier tested on different ratios.

Table 4.8. Accuracy Results

Data Ratio	**70:30**		**80:20**		**90:10**	
Classifiers	Train Accuracy	Test Accuracy	Train Accuracy	Test Accuracy	Train Accuracy	Test Accuracy
RF	99%	84%	99%	81%	99%	84%
ANN	83%	81%	80%	80%	82%	76%
SVM	76%	76%	76%	73%	76%	79%
LR	75%	76%	77%	68%	77%	76%
GNB	77%	76%	77%	75%	76%	76%

According to resulting accuracies, it can be seen that train-test ratio 70: 30 achieves highest accuracy for testing. RF classifier has better performance than other classifiers in this system. RF is efficient in building an accurate classifier which can efficiently run on the small and large sized datasets of non-linear nature. Hence RF is observed achieving good accuracy compared to the other four classifiers. ANN is low accuracy compared to the RF. Though ANN is efficient in modeling the non-linear data, small size of may affect the performance of ANN as they need large data for training. RF is efficient in discriminating features non-linear in nature. It also works well with the small sized data. RF outperforms ANN with overall highest accuracy of 84% for feature dataset used in this system. Moreover, RF classifier achieves 83 % for male prediction and 86 % for female prediction. LR has only 75% training accuracy and 76% testing accuracy, SVM achieves 76% and 76% and GNB obtains 77% and 76% respectively.

4.3.2. K-Fold Cross-Validation

K-fold cross-validation is a resampling procedure used to evaluate machine learning models on a limited data sample. This procedure is implemented by randomly dividing the set of observations into k groups, or folds, of approximately equal size. It is a popular method because it is simple to understand and because it generally results in a less biased or less optimistic estimate of the model skill than other methods, such as a simple train/test split. The general procedure is as follows:

1. Shuffle the dataset randomly,
2. Split the dataset into k groups,

3. For each unique group:
    1. Take the group as a hold out or test data set,
    2. Take the remaining groups as a training data set,
    3. Fit a model on the training set and evaluate it on the test set,
    4. Retain the evaluation score and discard the model.
4. Summarize the skill of the model using the sample of model evaluation score.

Table 4.9. Cross Validation Score

Classifiers	RF	ANN	SVM	LR	GNB
10-fold Cross Validation Score	80%	77%	75%	73%	75%
	80%	76%	70%	69%	71%
	88%	75%	77%	76%	78%
	85%	80%	74%	75%	77%
	79%	77%	78%	79%	75%
	85%	76%	76%	77%	78%
	75%	75%	71%	74%	68%
	81%	74%	79%	80%	81%
	85%	78%	77%	78%	77%
	89%	72%	68%	68%	82%
Average	83%	76%	75%	75%	76%

Classifiers models are trained and tested for 70% and 30% of the total dataset respectively. Table 4.9 describes average testing accuracy of classifiers by K-fold cross validation. The table shows that RF classifier has highest average accuracy among five classification algorithms.

Table 4.10. Performance Matrices

Classifiers	**Gender**	**Precision**	**Recall**	**F1-score**	**Support**
RF	Female	83%	86%	84%	180
	Male	85%	83%	84%	180

Table 4.10. Continued;

ANN	Female	81%	79%	80%	180
	Male	80%	82%	81%	180
LR	Female	77%	77%	77%	180
	Male	77%	77%	77%	180
SVM	Female	78%	74%	76%	180
	Male	75%	79%	77%	180
GNB	Female	76%	78%	77%	180
	Male	78%	75%	76%	180

Table 4.10 gives performance measures of each classifiers calculated on feature dataset divided into 70% training and 30% testing.

4.4. Summary

This chapter presents the proposed system design and detailed work flows of children gender classification system. Feature extraction algorithms and machine learning algorithms are used. To get good efficient features, MFCC feature extraction algorithm is applied. Experimental results are analyzed using five different machine learning algorithms: RF, ANN, LR, SVM and GNB. Implementation of gender classification is explained step by step in this chapter. Usage of performance measures of machine learning classifiers is also considered. The conclusion, further extensions, and limitations are discussed in next chapter.