Development of a Baby Cry Monitoring Device

by

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A thesis submitted in partial fulfillment of the requirements for the
degree of Master of Engineering in
Microelectronics and Embedded systems

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Thailand
May 2019

ACKNOWLEDGEMENTS

I would first like to thank my advisor, Dr. Mongkol Ekpanyapong, for his continuous guidance, support and encouragement for this thesis study, for his immense knowledge, which helped me a lot in progressing in my thesis. I would also like to thank my committee member's Dr. A.M.Harsha S.Abeykoon and Assoc.Prof. Erik Bohez for their valuable comments and suggestions, which helped me, improve my work.

Finally, I express my gratitude to my parents and friends for their continuous encouragement and unfailing support throughout the course and through the process of writing thesis. This attainment of my work would not have been possible without them.

ABSTRACT

The aim of thesis is to design a device to detect baby cry. This device can play a vital role in providing better infant care. Mostly the working parents and deaf parents benefited from this system. The designed system detects baby cry when baby starts crying and using GSM network send information in the form SMS alerts to be registered mobile number, so that the parents able to assist the baby. To detect baby cry Mel frequency cepstral coefficients (MFCC) of baby cry sound was extracted and trained those prominent features with Convolutional Neural Network (CNN) algorithm. The CNN model training accuracy is 98 percent and testing accuracy is 96.3 percent. Similarly trained this sound features using different machine learning models like SVM, ANN, and KNN. Comparatively the CNN model got highest test accuracy 96.3%. The system architecture consists of microprocessor Raspberry pi 3B, a microphone to take input sound and GSM module to send SMS.

Keywords: Baby monitor, GSM module, artificial neural networks (ANN), Mel frequency cepstral coefficients (MFCC), Convolutional Neural Network (CNN), Support Vector Machines (SVM), K Nearest Neighbor (KNN).

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LIST OF ABBREVIATIONS

CNN	Convolutional Neural Network
SVM	Support Vector Machines
KNN	K nearest Neighbor
ANN	Artificial Neural Network
GSM	Global System for Mobile Communications
MFCCs	Mel frequency cepstral coefficients

CHAPTER 1
INTRODUCTION

1.1 Background

Nowadays, technological innovations are growing very fast in the present world. One of these advances in machine learning, Deep learning and Artificial intelligence. Most of these studies help in improving day-to-day life works make us easy. Many baby monitors are developed today there many advantages of using baby monitors they are extra pair of eyes when it comes to looking out for baby. They allow parents and caregivers to keep focus on a sleeping baby while working around the house or even outdoors. Most of the working couples have benefited greatly from using a baby cry device, which can detect a baby cry and send SMS alerts. The device is designed in such a way that only a cry is should detect excluding baby noise, baby silence, baby laugh. Infant cry is the first verbal communication used to interact with the world and the cry sections contain the baby's breathing and grumbling signals. The fundamental frequency of cry signal between 250HZ and 600HZ [1]. Most of the research papers discussed about different types of baby cries and pathological cries but not on building baby cry detection device. The goal of this thesis is to build a novel device, which can detect baby cry and send SMS alerts to the parents by using machine learning and deep learning algorithms.

1.2 Problem statement

A baby's cry is an important signal that they need care. Baby cry detection device alerts parents automatically when their baby is crying. It alerts the parents in monitoring their baby when they leave their baby at home or in any emergency case. Mostly the working parents and deaf parents benefited from the system. Most of the baby monitors for cry detection is designed with sonic sensors and drawback of the current system user experienced a lot of false alerts. To overcome the drawback of current system the proposed system is designed using CNN algorithm. Here we trained the algorithm with some specified data sets of audio sounds for accurate detection. The developed system detects baby cry when baby starts crying and send SMS alerts to registered mobile number, so that the parents able to assist the baby.

1.3 Objectives

- Build the machine learning (SVM, KNN) and Deep learning (ANN, CNN) models to detect baby cry.
- Save all the models in Raspberry pi for real-time testing.
- An alert-based system is used to send the SMS alerts to registered mobile.

1.4 Limitations and scope

The system works well in domestic environment. This system can integrate in many ways to monitor the baby (as if when baby starts cries a song is played to calm the baby).

1.5 Thesis Outline

I organize the rest of this dissertation as follows.

- In Chapter 1, I describe introduction.
- In Chapter 2, I describe the literature review.
- In Chapter 3, I propose my methodology.
- In Chapter 4, I present the experimental results.
- Finally, in Chapter 5, I conclude my thesis.

CHAPTER 2
LITERATURE REVIEW

2.1 Previous Survey

The acoustic signal made by infant cry is a greater importance. Since it contains valuable information. Infant can make different levels of cry according to hunger, pain, danger etc.

In 1964 [1] research group of Wasz-Hockert showed that the four basic types of cry can be pain, hungry, pleasure. The goal of this paper to recognize baby cry and this work done on two stages, one is feature selection and the other is pattern classification, the first is clean the cry signal like eliminating unwanted noise and analyses to extract most important information from the cry signal. In this paper, they used techniques like linear detective coefficients, cepstral coefficients, pitch intensity, spectral analysis and Mel filter bank. This obtained character represented by a feature vector for the purpose to represent unique pattern. The set of all extracted vectors used to train the classifier. In this paper, they used pattern recognition technique as Genetic Selection of a Fuzzy (GSFM) for infant cry classification. The goal of this system is to minimize average error rate. The advantage of this model to classify different levels of cry and it used for diagnosis support tool for babies at early stages of life. The disadvantage is more computation part.

The image-processing module of the system takes the image data, the image of the infant's crying face and processes it to infer the reason for its crying. "The processing involves detecting the changes that occur in certain key features, like the mouth, the eyes and the eyebrows [2]." Different arrangements of the state of the "mouth (open/closed)," " the eyes (open/closed) and the position of the eyebrows (raised up/ lowered-down) describes the basis for the infant's cry." The cry interpreter introduced in this study is based on the processing of the baby cry image and sound from a baby. "The results show that from the paper each of the two modules as well as the fused decision for each type of cry performs satisfactorily in the detection process."

Proposed system for cry detection, which aimed at warning parents in conditions of probable danger [3]. The proposed system based on two stages, first stage involves audio signal feature extraction in which "pitch related parameters," "Mel frequency coefficients and short-time energy parameters are extracted from sound." Proposed system has mainly three levels starting from signal cleaning followed by classification of sound by using an algorithm and third is post-processing. "Before extracting features from the recorded infant cry, the first step is pre-processing which can eliminate interferences and disturbances." There are seven steps in the pre-processing including: normalization; framing; Voice activity detection; cry unit detection. In the dataset, there are many silences, background noise signal. Therefore, it should remove before training. We used VAD (Voice Activity Detection) [3] processing to remove non-voice signals. We detect and remove non-voice signals by energy-based threshold. "In this paper, the recorded Crying signals are converted to WAV (Waveform Audio Format), with the bit resolution and Sampling rate at 16-bit and 8 kHz, respectively." All audio signal should be processes as normal signal, 16 kHz, mono 16bit. The next stage is the signal classified using "K-NN and later verified." "The advantage of this algorithm it shows good performance even at low SNR with a detection almost good in high SNR, segmentation improves 3-8 percent of proposed algorithm."

Two types of algorithms proposed in this paper used such as "Probabilistic Neural Network (PNN) and General Regression neural network (GRNN)" and they used for analysis of cries [4]. This method provides accuracy of 89%. The feature extraction done by wavelet packet transform.

Generally, the first year of infant born the cries of infant are simple when the age increases the frequency of cries vary from 400 to 600HZ with average value of 450HZ [5] Cry signal feature extraction is done with efficient techniques to filter unwanted noise.

Although adult face and infant face are in similar in great degree, they are different. The difference between infant face and adult face are that the proportion of infant eye is bigger and infant face is round and more lubricant eyebrows short and flat [6]. Therefore, an infant face image database is important and essential for analyzing face features of infants and recognizing facial expressions. Pre-treat these images before feature extraction including normalization and transform to gray scale image. Now we analyses on feature of infants from perspective of image processing. Describe analysis on mouth and eye features this paper proposes a method for infants FER by judging open and closed degree of infant's eyes and mouth. Here they applied mathematical statically methods to get the area of eyes and mouth. After binarization, we calculate sum of black pixels of eyes and mouth. Area representing eye and mouth marked. In this paper, they choose 70 as the binary threshold the paper employs partial completion processing. During this processing, we scan the mouth and eye area and judge it. If there are more than one black pixel in the same row, we make pixels between blacks.

The author proposed two methods to detect baby cry signals. The first method is logical regression algorithm and second method is convolutional Neural Networks (CNN) model but before going to classification task between audio signals. Some pre-processing should be done on input audio to remove unwanted noise and extract the most important part of audio signal for classification task. The following feature proposed by author are Mel frequency, formats, and pitch coefficients. CNN uses log Mel frequency as feature extraction coefficients. In this method for detection of cry signal, input data divided into "4096 samples for each segment 950-dimensional feature vector is computed [7]." In the second method, they used convolution neural network (CNN) as model to classify two audio signals. Here the input signal is extracted with log Mel filter bank. "To work with a CNN classifier, the audio signal is divided into consecutive segments of 4096 samples. Each segment is further divided into frames of 512 samples, with a step size of 128 samples." "As the contribution of high frequency bands to the detection of cry signals is limited, a low-pass filter at 11025 Hz is applied. A log Mel-filter bank (LMFB) representation is then produced for each frame, using 40 filters distributed according to the Mel scale in the frequency range Hz." "Given segments of 4096 samples and a step size of 128 samples, this leads to a 40×29 image representation of each segment." From the both classifiers we came to conclusion by comparing results, the CNN classifier algorithm has less false rate compare to logistic regression algorithm.

The SVM is a supervised learning algorithm, feature vectors of the separate categories are mapped in a higher dimensional feature space, to find an optimal hyper plane to separate the two classes and which are divided by a clear gap that is as wide as possible. SVM widely and successfully used in classification tasks. "Experimental results have revealed the good performance of the proposed system and the classification accuracy is up to 92.17 % [8]."

Infant cry is a non-stationary signal. Time frequency analysis has been proposed by researches as it is a good tool for analyzing the infant cry signals both time and frequency scale at the same time.' In this study, STFT selected as feature extraction of the input signal. Statistical features derived from time-frequency plots, time maximum amplitude plots. "The DWT coefficients usually sampled from the Continuous Wavelet Transform (CWT) on a dyadic grid [9]."
The approach used in this paper done in three steps: the first is signal decomposition, Second step is features extraction, and third step is classification. In the first stage, "short-time Fourier transform, Empirical Mode Decomposition (EMD) [10]," and wavelet packet transform have been proposed followed by In the second stage, various set of features have been extracted from

the audio signal and finally in the third stage, two supervised learning methods have been proposed like “Gaussian mixture models and hidden Markov models,” with four and five states, have been discussed. The main goal of this work is to investigate the EMD performance and to compare it with the other standard decomposition techniques. “In conclusion, by using Gaussian mixture model as classifier GMM results obtained with low error rate of 8.9%.” The future work is to reduce error rate.

2.2 Short Time Energy (STE)

This is used to analyses signal in time domain. It is used for voice and unvoiced energy detection. The STE is a function of time, the frame length of STE ranges from 10-30 msec; hence, the total STE extracted from the sounds. The total STE can be calculated. That is the sum of square of each signal. The energy associated with a sound varies across the signal, the noise will have the highest energy at a particular time, follow by the baby cry, while the silence will have the least sound, therefore the STE features can be used to classify the four types of sounds, which are the baby cry, noise, laugh and silence. The sound file used to read the sound into the code and the output to this is the array of sound signals and the rate of the sound.

2.3 Artificial Neural Network

A neural network is combination of many hundred thousand of artificial neurons arranged in form of layers in building neural network model. It as input layer, hidden layer and output layer. A number called a weight, which can be either positive or negative, represents the connections between one layer and another layer. The higher the weight, the more influence one layer has impact on another layer. The models work when the input is passed to input layer of neural network, the weighted sum of each input neuron is compared with an activation function and pass the information to next layer. For this thesis target, output is 0 or 1 and we should use sigmoid activation function, sigmoid activation function triggers output when it got 0 or 1 output. A general neural network consist of three layer input layer, hidden layer and output layer coming to input layer the input information is passed through the nodes, the hidden layer is not connected to outside world, the information get to hidden layer from the input layer with an activation function specified between input layer and hidden layer, finally the output layer the computation part take place and shows the output to outside world.

2.4 Dropout Layer

Dropout is a technique where randomly selected neurons ignored during training. “Dropout easily implemented by randomly selecting nodes dropped-out with a given probability each weight update cycle.” It is simple way to prevent model over fitting. Dropout typically in limit (0 to 0.5).

2.5 Loss Function

Loss function measures how far an estimated value of a quantity is from the true value. Loss function is attempting to minimize by continuously update weights in the model during training.

2.6 Adam Optimizer

Adam is a replacement optimization algorithm for stochastic gradient descent for training deep learning models. Computationally efficient. Little memory requirements. Well suited for problems that are large in terms of data and/or parameter.

2.7 Batch and Epoch

The batch size defines the gradient and how often to update weights. An epoch is the entire training data exposed to the network, batch-by-batch. The number of training examples in one forward/backward pass. The higher the batch size, the more memory space you will need. Epochs used the data to update weights. Data set is divided into epochs and each epoch consist of samples and each epoch used to build model (call it iteration cycle in which set of training samples are trained).

2.8 Literature Survey Matrix

The proposed system compared with all the existing work from literature survey as shown in Table 2.1. The journal 1 [2]shows infant cry detection using both combination of image processing and sound processing. The journal 2 [3] shows infant cry is detected using audio signals using KNN model and in journal 3 [7] baby cry is detection model is build using logistic regression and CNN.

Proposed system	Journal 1 [2]	Journal 2 [3]	Journal [7]
The proposed system work using audio signal processing to detect baby cry in real-time.	The system work on combine of audio and image processing to detect emotion of baby.	The system work on signal processing to classify the sounds.	The system work on signal processing to classify the sounds.
The proposed method uses the MFCC feature extraction technique to select prominent features of the sounds.	Signal feature extraction is done on the fundamental frequency(F0) of infant vocalization Image processing module It takes baby crying images and do analysis on the face like mouth eyes positions (open/closed)	Signal extraction features like Harmonicity factor, Pitch frequency, HAPR (Harmonic-to-average-power ratio)	Signal extraction features like short-time energy (STE), Pitch median value, Harmonicity factor, HAPR, spectral roll off point, band energy ratio, ZCR Log filter bank energies
The designed system sends output in the form of SMS alerts when baby cries.	No prototype to show output	No prototype to show output	No prototype to show output
Compared model performance of ANN, CNN, SVM rbf kernel and KNN.	KNN model is used for this task	KNN model is used for this task	Compared model performance of logistic regression and CNN
Hardware: Raspberry pi 3b, GSM module 900 microphone	Hardware like microphone and camera.	No hardware	No hardware
System tested in real-time by taking baby cry audio as input.	real-time testing	No real-time testing	No real-time testing
Compared all model test accuracies, CNN got best train accuracy 98% and	The accuracy with signal processing is 64% and video processing 74% by	The classification rate is almost good, but accuracy not mentioned.	The accuracy is 82.5% for CNN classifier, 65% for logistic regression classifier

test accuracy 96.3%.	combining overall accuracy is 74.5%		

Table 2.1: Literature Survey

CHAPTER 3
METHODOLOGY

3.1 System Overview

Key components of the system consist of Raspberry pi model 3B, USB (Universal serial Bus) microphone, and output as GSM.

3.2 System Design

The methodology of the system development achieved in three stages.

- Audio data collection of baby cry sounds and other domestic sounds.
- Trained the data using SVM, KNN, ANN and CNN.
- Deploy all trained algorithms in Raspberry pi for testing.

Training on PC

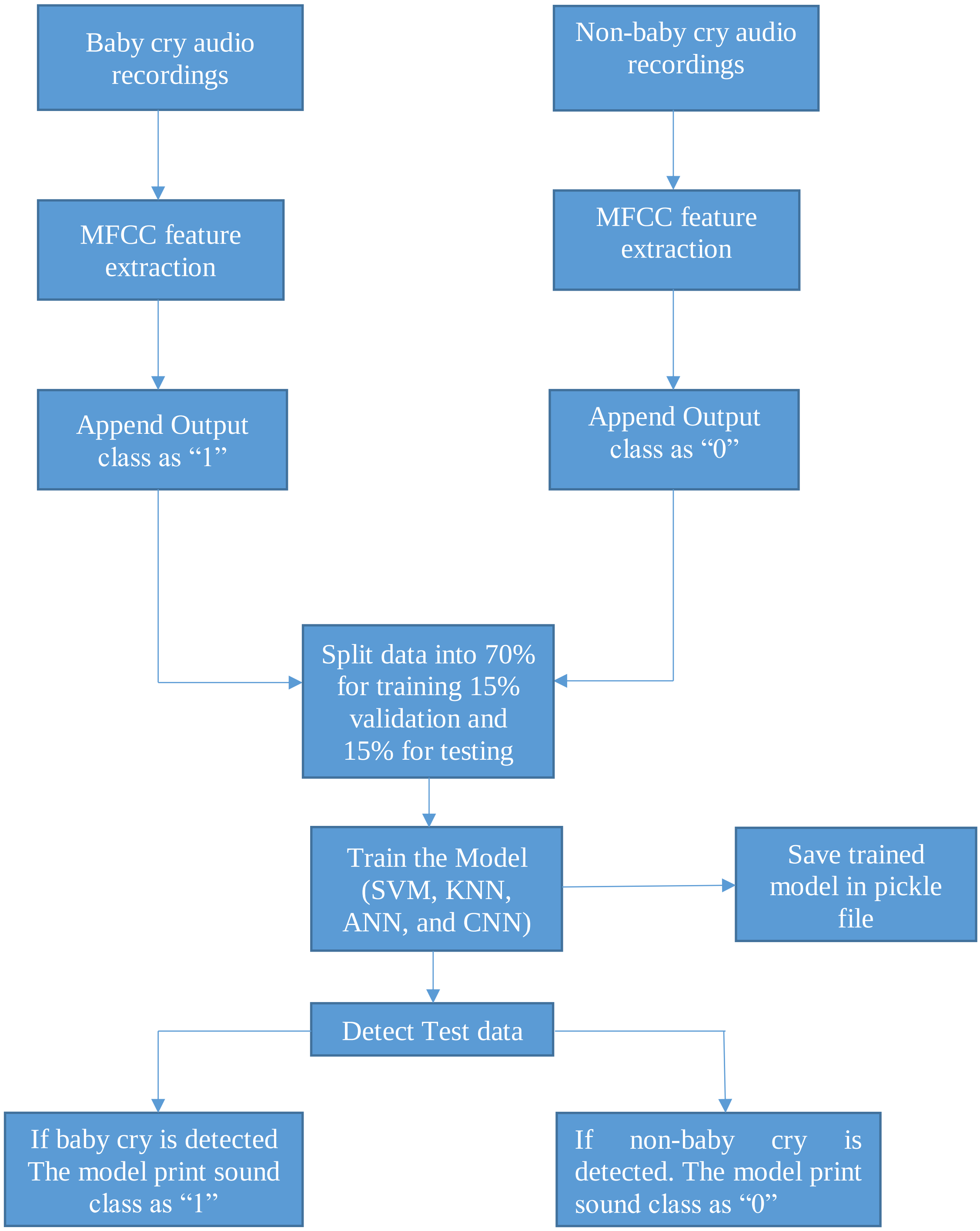


Figure 3.1: Block diagram of the model training and testing

Above Figure 3.1 illustrates the model building, Training and Testing and Training should do on Personal computer.

3.3 Flow Chart

In below Figure 3.2 the flow chart of proposed system working is shown in below. It states when sound data is collected from microphone, then the MFCC features was extracted from the sound signal and detect the sound using the pre-trained model. The model that was imported was used to detect the sound, the result is to be either 1 or 0, 1 signifies that the model was able to classify the signal as baby cry signal while 0 signifies that the signal was classified as a non-baby cry signal. If model detects “1” as output, then it sends SMS alert to registered mobile number.

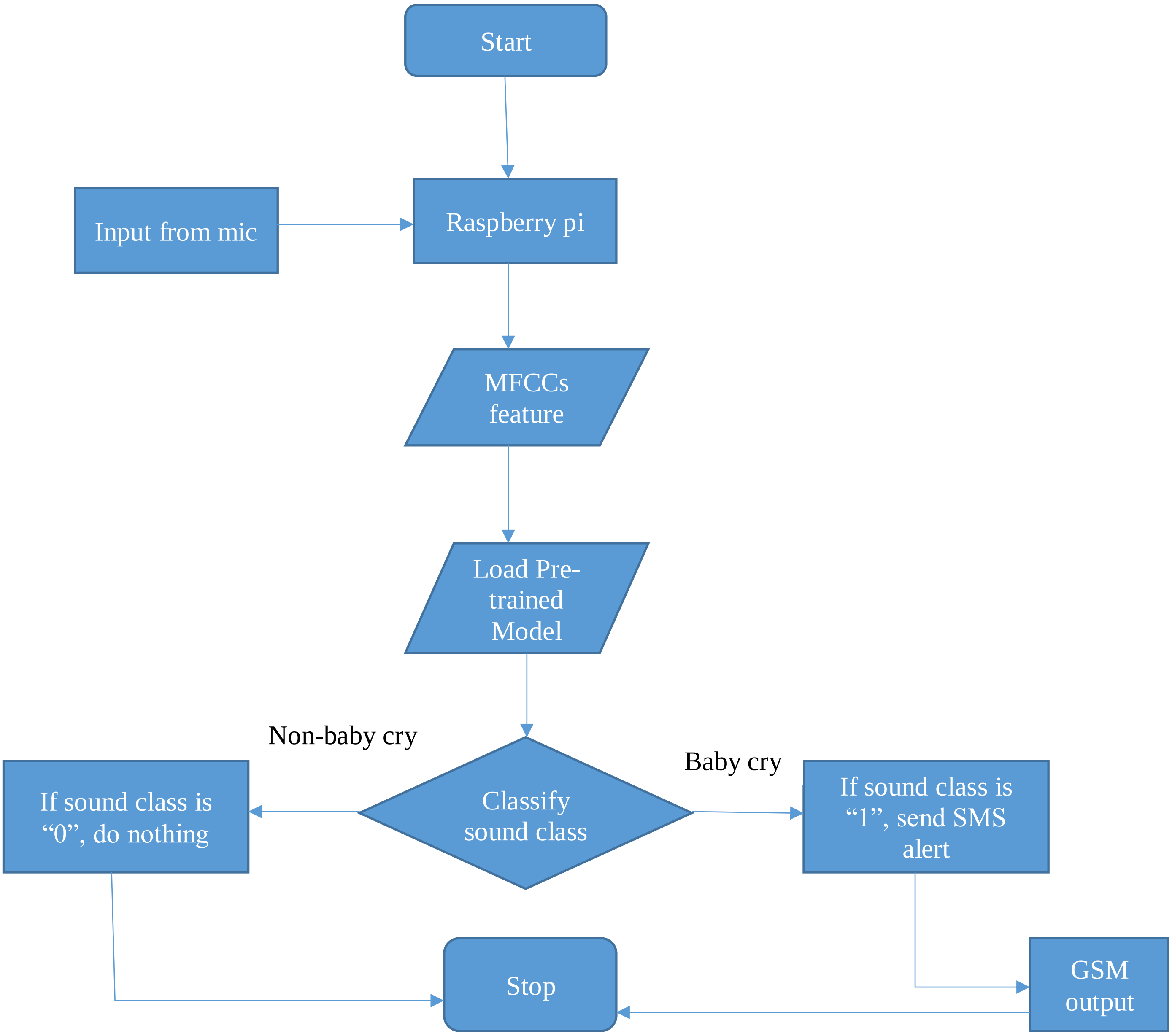


Figure 3.2: Flow chart of system working

3.4 Hardware Specification

The hardware setup consists of Raspberry pi3b, Microphone and GSM SIM 900. Below Figure 3.3 shows the hardware connections for the proposed system and Whole hardware setup consist of two connections and power supply of 5V to Raspberry pi, 3.4V -4.5V to GSM. Microphone input to Raspberry pi USB port and Raspberry pi to GSM module to send output. Raspberry pi 14GPIO pin uart TXD is connected to RXD of GSM and 15GPIO pin uart RXD is connected to GSM TXD.

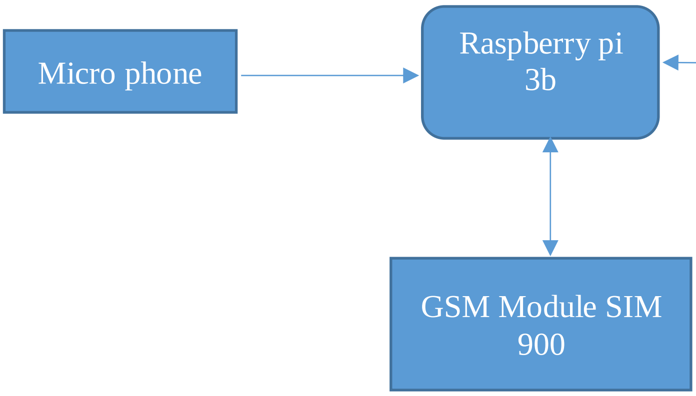


Figure 3.3: Hardware Block Diagram

3.5 Raspberry pi

The Raspberry pi model 3b is small credit card sized consists od 1.2GHz 64-bit quad-core ARMv8 CPU, 802.11n Wireless LAN, bluetooth 4.1, 1GB RAM and 40GPIO pins. Raspberry Pi is a tiny computer containing developed in the United Kingdom by the Raspberry Pi Foundation. It is used specifically to teach and learn programming. Raspberry Pi is regarded as a Linux computer and provide the expected abilities a Linux computer. Unlike modern laptop or desktop, Raspberry pi is slow. The image of Raspberry pi module is shown in below Figure 3.4.

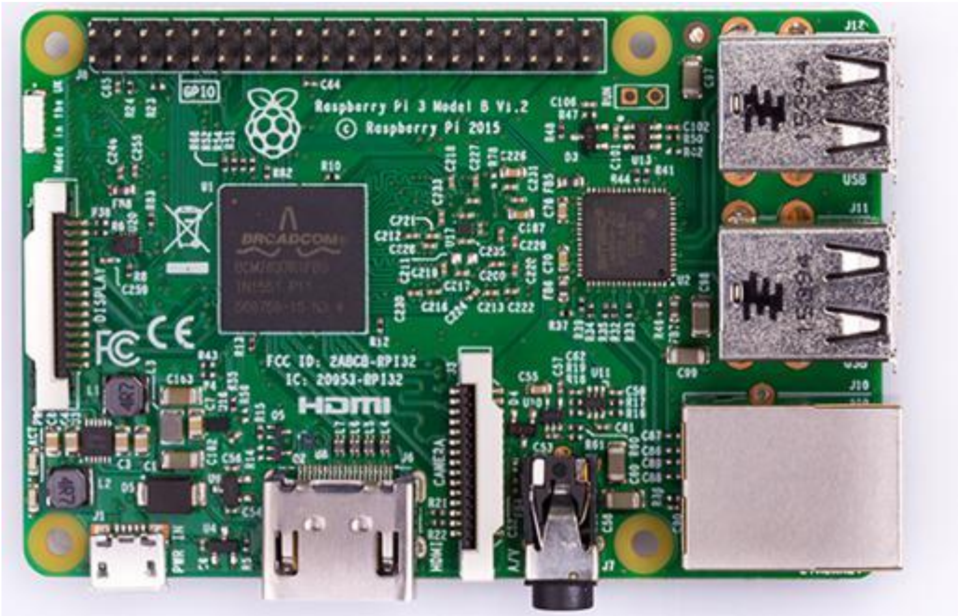


Figure 3.4: **Raspberry pi 3b module Reprinted from the website [11]**

3.5.1 Component of a Raspberry pi

The Raspberry pi module is used in this proposed system and their specifications are listed below.

- “ARM CPU/GPU
- GPIO
- RCA
- Audio out
- Audio in
- LEDs
- USB
- HDMI
- Power
- SD card slot
- Ethernet.”

3.5.2 Setup up the Raspberry Pi

a) Hardware Setup

- Power supply: A 5v power supply was provided
- USB keyboard
- USB Mouse
- Micro SD USB card reader
- Monitor
- An Ethernet cable
- Component of the set up
- The setup of is made microphone, GSM module, power supply, and monitor.

b) Software Setup

- Downloading operating system
- The operating system was downloaded from Raspberrypi.com, NOOBs was downloaded to computer
- Formatting micro SD card
- Copying the operating system file into the SD card
- Slotting the SD card into Raspberry pi
- Power on Raspberry pi
- Waiting for installation process.

3.5.3 GSM SIM 900

The GSM module used in this proposed system is the SIM 900 seen in below Figure 3.5 and their specifications are listed below

- “Quad-Band 850/ 900/ 1800/ 1900 MHz
- GPRS multi-slot class 10/8
- GPRS mobile station class B
- Compliant to GSM phase 2/2+
- Size: 15.8 x 17.8 x 2.4 mm
- Weight: 1.35g
- Control via AT commands
- SIM Application Toolkit
- Supply voltage range: 3.4 ~ 4.3V
- Low power consumption.”

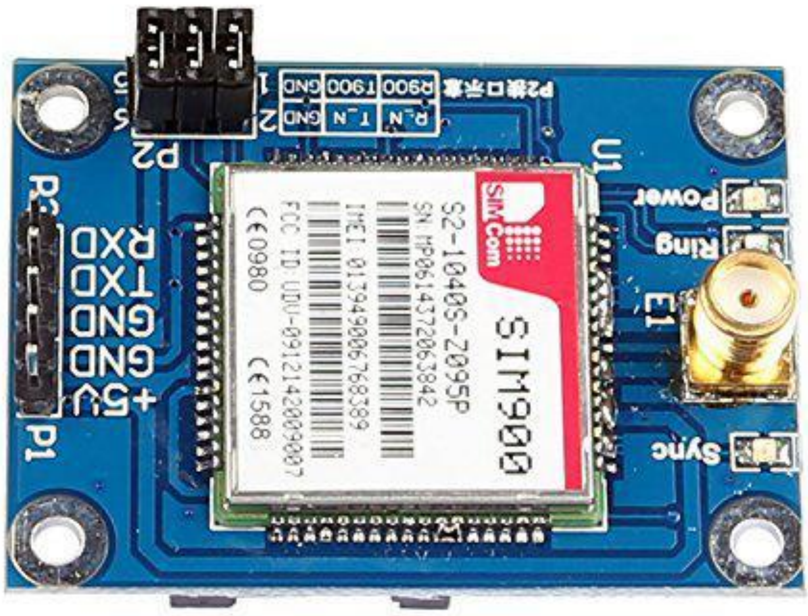


Figure 3.5: GSM SIM 900 Reprinted from website [29]

3.6 Training the model on Personal computer

The entire work is done in python [12] programming language. Below Table 3.1 shows the list of required python Libraries and their commands should install on personal computer and in Raspberry pi. To run deep learning model, we need to install Tensor flow [13]and Keras API [14].

Steps involved in model building

- Installing python packages in personal computer.
- Loading dataset
- Extracting MFCCs coefficients.
- Train the extracted features using CNN, KNN, SVM, ANN.
- Save all models to pickle file.

Libraries	**Command Line**	**functions**
Pip	sudo apt-get install python-pip	
NumPy [15]	sudo pip install NumPy	NumPy is used to perform operations on N dimensional array
Sound file [16]	sudo apt-get install libsndfile1 sudo pip install cffi sudo pip install pysoundfile	Sound file is used to covert sound file into signal array
Pyaudio [17]	sudo apt-get install python-Pyaudio	Pyaudio is used to relate with the port Audio, it is used to record sound
Librosa [18]	sudo pip install llvmlite sudo pip install librosa	Librosa has the MFCCs features, which is used to extract sound features
Tensor flow [13]	sudo apt-install libatlas-base-dev sudo pip install tensor flow	Tensor flow serve as a backend to deep learning algorithm
Keras [14]	sudo pip install keras	
Threading [19]	sudo pip install threading	Threading is used for timing loop, to repeat lines of code at a particular time continuously
SMS [20]	sudo pip install sms	SMS is used to send sms message using the GSM modem

Table 3.1: Python Libraries

3.6.1 Model Building

The entire work is done on Jupiter notebook and with keras backend API [14]. Python functions was written to produce the for mentioned features from the sounds, the file paths in the baby cry array was used to extract the sound features by calling each of the functions. The first thing that was done is importing the necessary modules.

3.6.2 Loading Dataset

Dataset of baby cry recordings and other sounds download from source [21] the data set consist of baby cry, baby laugh, silences, noises and some traffic sounds of total length 1275 files [22]. The audio is in .ogg format which can be used for pre-processing. Extraction of sounds paths into an array, the downloaded data was kept in different folders. The file paths were specified in the python program. The sounds were classified into two arrays in the code which was the baby cry array and the non-baby cry array. The baby cry array entails sound from the baby cry folder while the non-baby cry array consists of sounds from the baby laugh, baby silence and noise. And other domestic sounds. Module os was used to access the directory of the sounds file using the attribute listdir. The directory of each folder (baby cry, baby laugh, silence and noise) was defined as variables.

3.6.3 Mel-Frequency Cepstrum Coefficients (MFCCs)

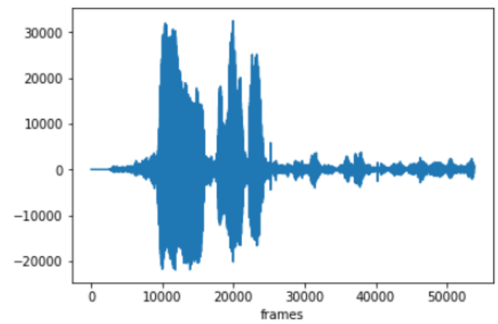
- Frame the signal into short frames.
- For each frame calculate the periodogram estimate of the power spectrum.
- Apply the Mel filter bank to the power spectra, sum the energy in each filter.
- Take the logarithm of all filter bank energies.
- Take the DCT of the log filter bank energies.
- Keep DCT coefficients 2-13, discard the rest.

The entire process explained step by step to make MFCCs features.

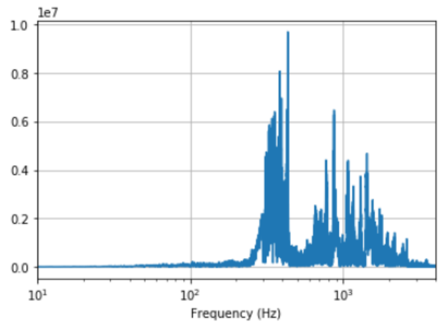
An audio signal is constantly changing, so to simplify things we assume that on short time scales the audio signal doesn't change. This is why we frame the signal into 20-40ms frames. If the frame is much shorter, we don't have enough samples to get a reliable spectral estimate, if it is longer the signal changes too much throughout the frame [23].

The next step is to calculate the power spectrum of each frame. This is motivated by the human cochlea (an organ in the ear) which vibrates at different spots depending on the frequency of the incoming sounds. periodogram helps to identify which frequencies are present in the frame. The periodogram spectral estimate still contains a lot of information not required for Automatic Speech Recognition (ASR), should take clumps of periodogram bins and sum them up to get an idea of how much energy exists in various frequency regions. This is performed by Mel filter bank; the first filter is very narrow and gives an indication of how much energy exists near 0 Hertz. Figure 3.6 shows power spectrum of audio signals taken in dataset (a) represents baby cry, (b) represents baby Laugh, (c) represents baby silence, (d) represents alarm sound.

Power spectrum of some audio signals

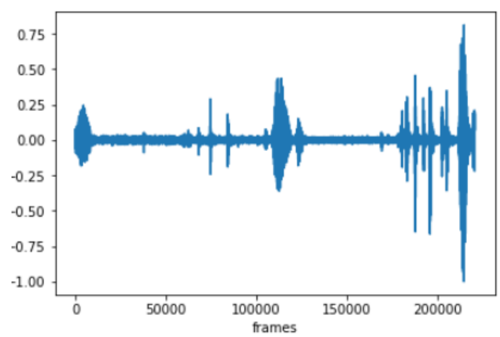


FFT

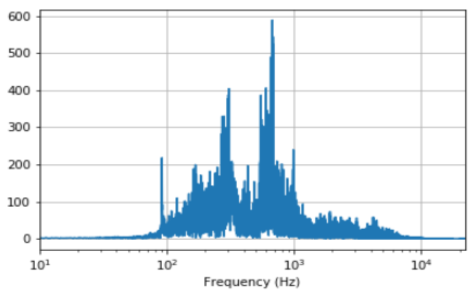


(a) Baby cry signal in Time domain

(a) Baby cry signal in Frequency domain

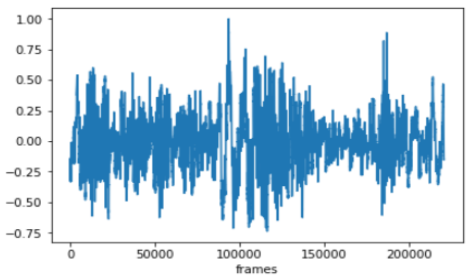


FFT

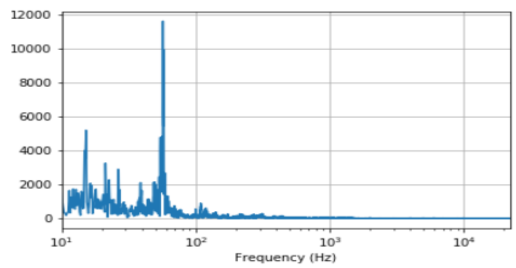


(b) Baby laugh signal in Time domain

(b) Baby laugh signal in Frequency domain

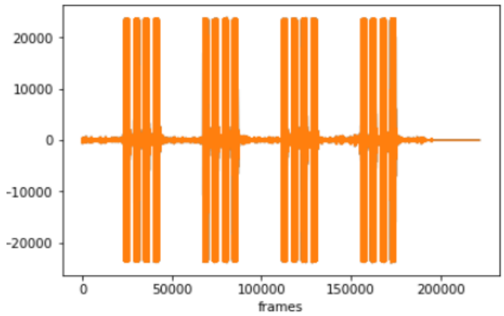


FFT



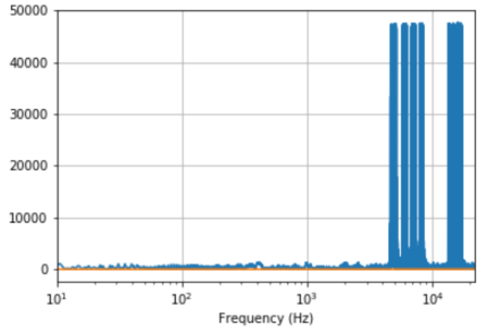
(c) Baby silience signal in Time domain

(c) Baby silience signal in Frequency domain



(d) Alram signal in Time domain

FFT



(d) Alram signal in Frequency domain

Figure 3.6: FFT of audio signals

Once the filter bank energies is extracted , we take the log of them. This means that large variations in energy may not sound all that different if the sound is loud to begin with. This compression operation makes our features match more closely what humans actually hear. The final step is to compute the DCT of the log filter bank energies. There are 2 main reasons this is performed. Because our filter banks are all overlapping, the filter bank energies are quite correlated with each other. “The DCT decor relates the energies which means diagonal covariance matrices can be used to model the features.” But notice that only 12 of the 26 DCT coefficients are kept.

Making MFCC to extract features of audio signal

Generally, the audio is read with python library and pass over step by step to get MFCC feature. Below Figure 3.7 illustrates the source code of MFCCs to extract MFCCs features of sounds, here a function is created to extract the MFCCs coefficients of all the sound files.

```
def Mfcc(audiofile):
    s,r=sf.read(audiofile)
    #print(len(s.shape))
    if len(s.shape)==2:
        s=s[0,:]
    #print(len(s.shape))
    x=np.mean(mfcc(s,r, numcep=12,nfft=2048),axis=0)
    return x
```

Figure 3.7: Source code of MFCCs

Output of MFCCs

Below figure 3.8 shows output of baby cry signal MFCCs in time domain, similarly can plot output of all the audio signals in the dataset. X axis has Time and Y axis indicates 12 MFCCs.

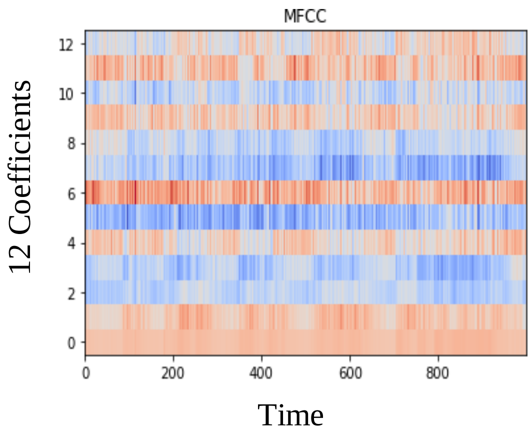


Figure 3.8: output of MFCCs

Data Split

The data is split into 70% for training 15% validation and 15% for testing using sklearn [24] python package and source code of data split is shown in below Figure 3.9. Here 70% data is given for training the model 15% data is used to validate the trained model and after hyper parameter tuning then test the best selected trained model with 15% test set.

```
from sklearn.model_selection import train_test_split
X_train, X_temp, y_train, y_temp = train_test_split(input, output, test_size=0.30, random_state=None)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, stratify = y_temp, test_size=0.5, random_state=None)
```

Figure 3.9: split data

3.6.4 ANN model building

Models in Keras [17] are defined as a sequence of layers The first hidden layer was set to be 64 with input shape (12,) The second layer was set to be 36 The output layer was set to be 1 The number of the hidden layer was gotten by several trials in the attempt to get the one with the best accuracy. The rectifier (relu) activation function was used for two layers and the sigmoid function was used for the third layer, which is the output layer. Sigmoid was used to achieve a binary output, it ensures that the output is between 0 and 1 The model was compiled, and the binary cross entropy was defined by the problem the model was fitted with input and output with an iteration of 100 after training the model and save the trained model in job lib to export to Raspberry pi. Up to here the ANN part is finished and next we have to run this pre-trained model on Raspberry pi.

3.6.5 Proposed Convolutional Neural Networks

After extracting MFCC coefficients of size (1275, 12). The size is reshaped to (1275, 64, 12) to have spatial dimensional to feed input to CNN. Below Figure 3.10 explains the proposed CNN architecture model step by step in blocks. The CNN architecture consists of input layer, 2 convolutional layers + max pooling layer followed by two fully connected layers and output layer. To specify the input shape first we passed sequential layer. Convolution is applied to input data using a convolutional filter to produce a feature map. For conv1D layer the filter size is set 64 filters, kernel size set 2, input shape given (64, 12) with relu activation function. We perform the convolution operation by sliding this filter over the input. At every location, we do element-wise matrix multiplication and sum the result. This sum goes into the feature map. We again pass the result of the convolution operation through relu activation function. So, the values in the final feature maps are not actually the sums, but the relu function applied to them. The output of this layer is given another convolutional layer with 40 filters and kernel size set to 2 with padding, strides set to 1 and relu activation function is used. Padding is commonly used in CNN to preserve the size of the feature maps. "The next hidden layer is Global max pooling layer which helps effectively down sample the output of prior layer reducing the number of operations required for all the following layer, but still passing on the valid information from the previous layer. In between layers we added dropout layer to avoid over fitting of the model it as a regularization technique the dropout hyper parameter is set 0.2 after the convolution + pooling layers we add a couple of fully connected layers to wrap up the CNN architecture. The next hidden layer is dense layer 40 neurons for linear operation of previous layer. Batch normalization layer is added in between two convolutional layers substitute of dropout layer. "The use of Batch Normalization between the linear and non-linear layers in the network, because it normalizes the input to your activation function". One more dense layer is used as hidden layer and finally we used sigmoid activation function in the output layer because the model detects the output in form of 0 or 1.

CNN Architecture

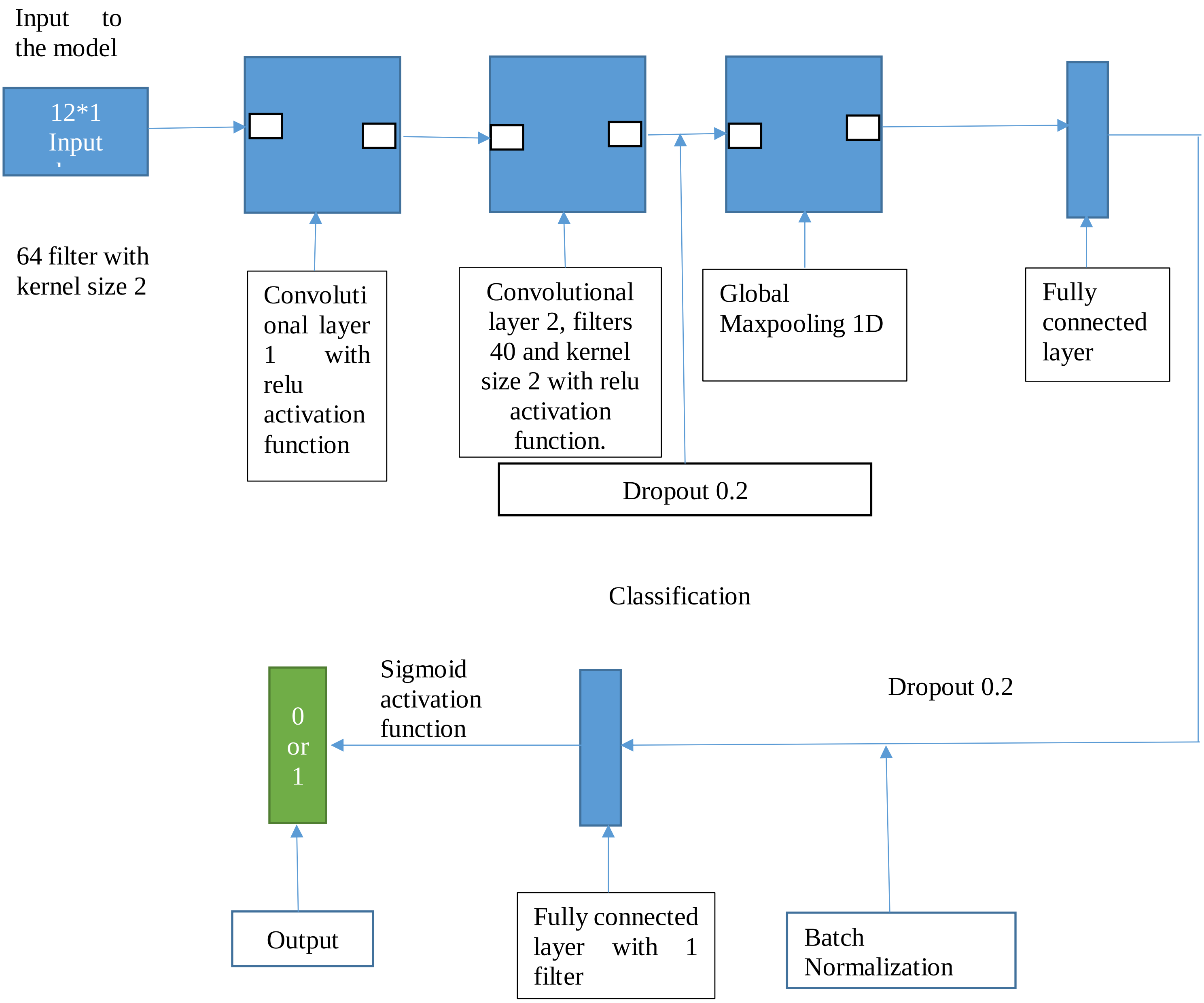


Figure 3.10: CNN Block diagram

Implemented source code of CNN

Below Figure 3.11 explains implemented source code of proposed CNN model, here the Line 1 explains forming sequential layers, line 2 explains convolutional layer with 64 filters with kernel size 2 of input shape (64, 12) and relu activation function, line 3 is another convolutional layer it takes output of previous layer. This layer has filters 40 with kernel size 2, valid padding with strides 1 and relu activation function. Line 5 explains about max pooling layer. Line 7 explains about dropout layer and it fixed value to 0.2, it helps to avoid over fitting while training. line 9 explains about batch normalization layer, the use of Batch Normalization between the linear and non-linear layers in the network, because it normalizes the input to your activation function and line 10 are fully connected layer with one neuron because our model detects one class of output either 0 or 1 with use of sigmoid activation function.

```
from keras.layers import Reshape, Flatten, Dropout, Concatenate, BatchNormalization

Line 1 model2 = Sequential()
Line 2 model2.add(Conv1D(64, 2, activation='relu', input_shape=(64, 12))) # first convolutional layer
Line 3 model2.add(Conv1D(40,2,padding='valid', activation='relu',strides=1)) # second convolutional layer
Line 4 model2.add(Dropout(0.2))
Line 5 model2.add(GlobalMaxPooling1D())
Line 6 model2.add(Dense(40))
Line 7 model2.add(Dropout(0.2))
Line 8 model2.add(Activation('relu'))
Line 9 model2.add(BatchNormalization(epsilon=0.001, mode=0, momentum=0.9, weights=None))
Line 10 model2.add(Dense(1))# fully connected layer model predicts 1 or 0
Line 11 model2.add(Activation('sigmoid'))
```

Figure 3.11: Source code of CNN

Compile the model

The summary of the model is shown in below Figure 3.12, shows the information about each layer and we identified total 8601 parameters which include trained parameters 8521 and non- trainable parameters 80.

```
from keras.optimizers import Adam
model2.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
```

```
model2.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv1d_1 (Conv1D)            (None, 63, 64)            1600      
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 62, 40)            5160      
_________________________________________________________________
dropout_1 (Dropout)          (None, 62, 40)            0         
_________________________________________________________________
global_max_pooling1d_1 (Glob (None, 40)                0         
_________________________________________________________________
dense_1 (Dense)              (None, 40)                1640      
_________________________________________________________________
dropout_2 (Dropout)          (None, 40)                0         
_________________________________________________________________
activation_1 (Activation)    (None, 40)                0         
_________________________________________________________________
batch_normalization_1 (Batch (None, 40)                160       
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 41        
_________________________________________________________________
activation_2 (Activation)    (None, 1)                 0         
=================================================================
Total params: 8,601
Trainable params: 8,521
Non-trainable params: 80
```

Figure 3.12: Model summary

3.6.6 Support Vector Machines

SVM [25] is a discriminative classifier formally defined by a separating hyper plane. In two Dimensional space this hyper plane is a line dividing a plane in two parts where in each class lay in either side. Coming to our thesis we had two classes of data one is baby cry and non-baby cry the hyper plane separates two classes of this data. SVM algorithms use different kernels. Figure 3.13 explains the implemented source code of proposed SVM rbf kernel, here SVM rbf kernel is used to train the data with regularization called c parameter is fixed to 25 and gamma parameter set to gamma=0.001 is seen in below Figure 3.13 line 1. Line 1 describes the choosing of the kernel and adjusting regularization c parameter and gamma parameter, here in the model we choose ‘rbf kernel’. Line 2 fits the input (X_train) and output (y_train) data for training the model. Line 3 is for detecting output for new data given as test data.

```
from sklearn import svm
#Create SVM clasifier
Line 1 lin = svm.SVC(kernel = 'rbf',C= 25,gamma = 0.001)
#Fit input data and target data to svm
Line 2 lin.fit(X_train, y_train)
#Predict test data
Line 3 y= lin.predict(X_test)
```

Figure 3.13: Source code of SVM RBF

3.6.7 K Nearest Neighbor

KNN is a supervised machine learning model. KNN models work by taking a data point and looking at the ‘K’ closest labelled data points [26]. The data point is then assigned the label Of the majority of the ‘k’ closest points. The “K” is KNN algorithm is the nearest neighbor we wish to take vote from. Below Figure 3.14 shows the implemented source code of KNN, Let’s say K = 2 (n_neighbors = 2). We can tune K value up to 32. Research [27] has shown that no optimal number of neighbors suits all kind of data sets. Each data set has own requirements. Research has also shown that a small number of neighbors are most flexible fit which will have low bias, but high variance and a large number of neighbors will have a smoother decision boundary which means lower variance but higher bias [27]. Final line explains to fit the input (X_train) and output (y_train) data to the model.

```
#create KNN Clasifier
neig = KNeighborsClassifier(n_neighbors=2)
#fit input and target data to  KNN Clasifier
neig.fit(X_train, y_train)
```

Figure 3.14: Source code of KNN

3.7 Hardware installation and loading pre-trained model (objective 2)

The code is divided into scripts
1. main.py
2. Sendsmsgsm.py

main.py

The main.py script contains the whole code which is necessary for run the program

- Importing Libraries
- Specifying functions
- Importing the pre trained model

The pre-trained model was used in the code.

Sendsmsgsm.py

The script Sendsmsgsm.py consist of code for GSM Module to send SMS to registered mobile number.

3.8 Configuring Auto run

It is very important to auto-start all the programs upon booting-up of the Raspberry pi. It is done using rc.local.

This was done with the steps below

- Change boot from desktop to CLI
- Editing profile configuration to setup program to run automatically when power up the Raspberry pi.

Final setup after installation of the system

The final setup of Raspberry pi connected with USB microphone and GSM module. It is placed near baby cradle with required power supply and when baby starts crying then the model takes 5 seconds sound from the input microphone and detect sound with the help of pre-trained model, if the model detects baby cry then system can send SMS alerts to registered mobile number.

CHAPTER 4
EXPERIMENTAL RESULTS

4.1 Models

Data taken total 1275 sounds (718 baby cry, 557 non-baby cry) here 892 sounds are given for training. 191 sounds are used to validate the trained model and finally after hyper parameter tuning test best model with test set of 192 sounds.

- Artificial Neural Network (ANN)
- Convolutional Neural Network (CNN)
- Support Vector Machine RBF kernel (SVM)
- K Nearest Neighbor (KNN)

4.2 GSM Output

Below Figure 4.1 shows received SMS to registered mobile number when baby cry is detected.

Figure 4.1: Output as SMS alert

4.3 Accuracy and loss plot of ANN

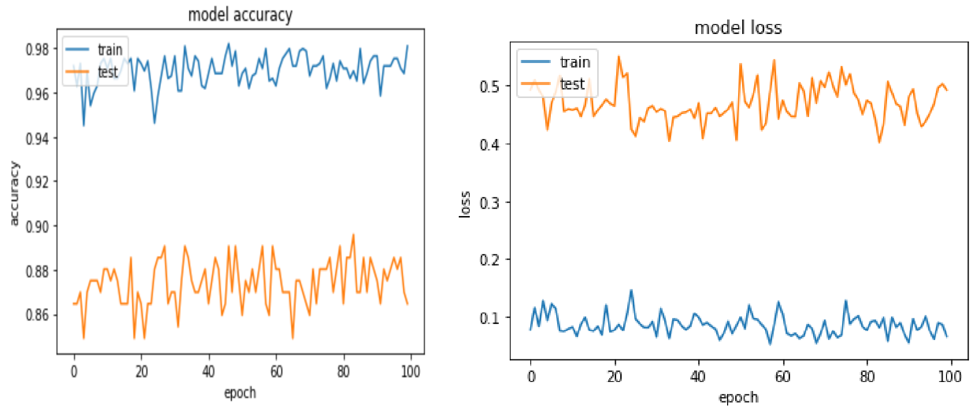


Figure 4.2: Accuracy and loss plot of ANN

Above Figure 4.2 shows model Accuracy on left side and model loss plot on right side of ANN model, here blue label indicates training accuracy is 98 percent and orange label indicates testing accuracy is 86 percent after 100 epochs. Training accuracy and testing accuracy far away for every epoch. The testing loss is increasing and decreasing for every epoch and finally test loss is decreasing at final epoch. The model suppers with over fitting.

4.4 Accuracy and loss plot of CNN

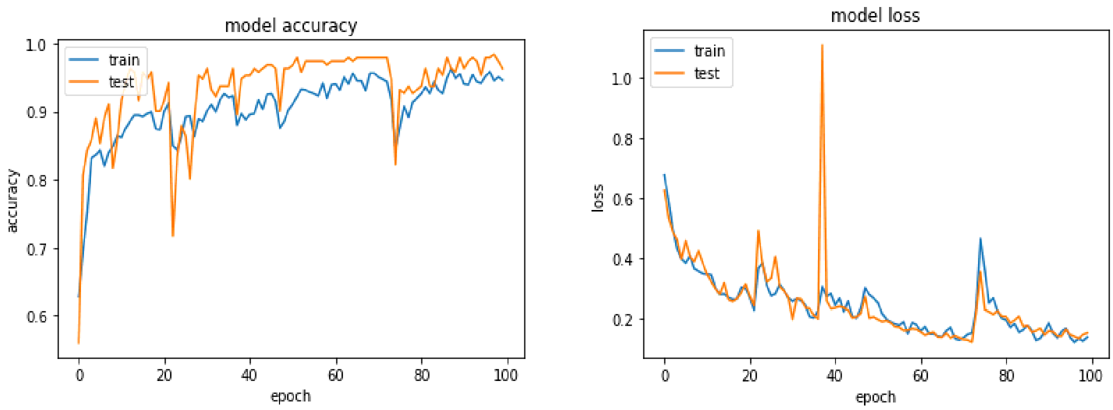


Figure 4.3: Accuracy and loss plot of CNN

Above Figure 4.3 shows Accuracy and loss plot of CNN model, here blue label indicates training accuracy is 98 percent and orange label indicates test accuracy is 96.3 percent after 100 epochs. Model train accuracy and test accuracy gradually increasing at every epoch. Slight difference between training loss and testing loss decreasing at final epoch.

4.5 Confusion Matrix

In our case positive case is baby cry (our model aims to detect baby cry). Using confusion Matrix, we can calculate Accuracy, Precision, recall [28]. The accuracy is calculated using Equation 4.1, recall can be calculated using Equation 4.2 and precision can be calculated using Equation 4.3.

$$\textbf{Accuracy} = \frac{\mathbf{TP+TN}}{\mathbf{TP+TN+FP+FN}} \quad \textbf{(4.1)}$$

$$\textbf{recall} = \frac{\mathbf{TP}}{\mathbf{TP+FN}} \quad \textbf{(4.2)}$$

$$\textbf{Precision} = \frac{\mathbf{TP}}{\mathbf{TP+FP}} \quad \textbf{(4.3)}$$

Below Table 4.1 explains the following cases

- **True Positives (TP):** These are cases in which we detected 1 (they have detected baby cry), and yes, it is baby cry.
- **True Negatives (TN):** We detected 0, and not a baby cry.
- **False Positives (FP):** We detected 1, actually not a baby cry. (Also known as a "Type I error.")
- **False Negatives (FN):** We detected 0, but actually it is baby cry. (Also known as a "Type II error.")

	Detected: 0	Detected: 1	
Actual: 0 Non-baby cry	TN	FP	Total samples detected 0
Actual: 1 Baby cry	FN	TP	Total samples detected 1
	TN + FN	FP + TP	

Table 4.1: sample confusion matrix

4.6 Confusion matrix of ANN

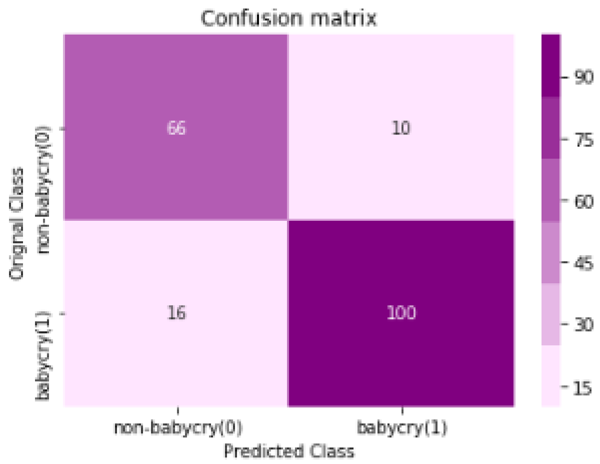


Figure 4.4: Confusion matrix of ANN

Above Figure 4.4 shows the Confusion matrix of ANN, here 0 represents non-baby cry and 1 represents baby cry. The model detects True positive 100 as baby cry and True Negative 66 as non-baby cry among 192 samples.

To calculate accuracy of the ANN model from Figure 4.4

$$\textbf{Accuracy} = \frac{\textbf{TP+TN}}{\textbf{TP+TN+FP+FN}} \quad \textbf{(4.1)}$$

$$\text{Accuracy} = \frac{100+66}{100+66+10+16}*100$$

$$\text{Accuracy} = 86\%$$

TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

To calculate recall from Figure 4.4

$$\textbf{recall} = \frac{\textbf{TP}}{\textbf{TP+FN}} \quad \textbf{(4.2)}$$

$$\text{recall} = \frac{100}{100+16}*100$$

$$\text{recall} = 86\%$$

High Recall indicates the class is correctly recognized (small number of FN).

To calculate precision from Figure 4.4

$$\textbf{Precision} = \frac{\textbf{TP}}{\textbf{TP+FP}} \quad \textbf{(4.3)}$$

$$\text{Precision} = \frac{100}{100+10}*100$$

Precision = 90%

4.7 Confusion matrix of CNN

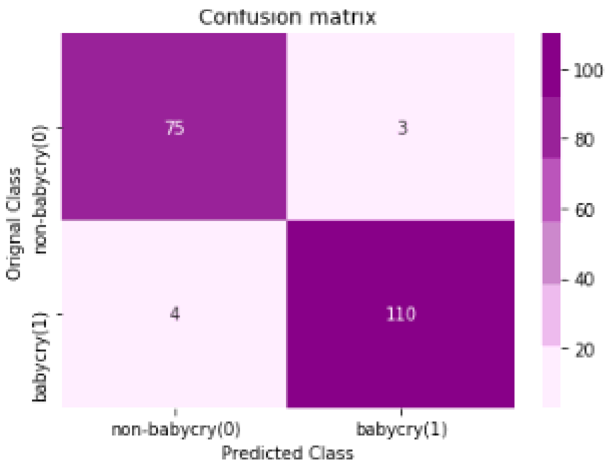


Figure 4.5: Confusion matrix of CNN

Above Figure 4.5 shows the Confusion matrix of CNN, here 0 represents non-baby cry and 1 represents baby cry. The model detects True positive 110 as baby cry and True Negative 75 as non-baby cry among 192 samples.

To calculate accuracy of the CNN model from Figure 4.5

$$\textbf{Accuracy} = \frac{\textbf{TP+TN}}{\textbf{TP+TN+FP+FN}} \quad \textbf{(4.1)}$$

$$\text{Accuracy} = \frac{110+75}{110+75+3+4}*100$$

Accuracy = 96.3%

TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

To calculate recall from Figure 4.5

$$\mathbf{recall} = \frac{\mathbf{TP}}{\mathbf{TP+FN}} \quad \textbf{(4.2)}$$

$$\text{recall} = \frac{110}{110+4} * 100$$

recall = 96.4%

High Recall indicates the class is correctly recognized (small number of FN).

To calculate precision from Figure 4.5

$$\mathbf{Precision} = \frac{\mathbf{TP}}{\mathbf{TP+FP}} \quad \textbf{(4.3)}$$

$$\text{Precision} = \frac{110}{110+3} * 100$$

Precision = 97.3%

4.8 Confusion matrix of SVM

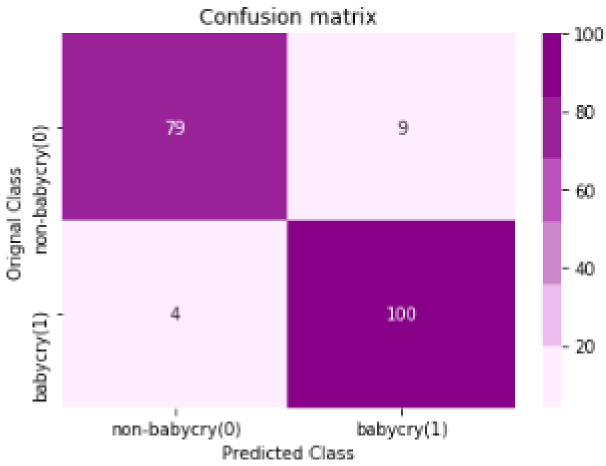


Figure 4.6: Confusion matrix of SVM

Above Figure 4.6 shows the Confusion matrix of SVM. Here 0 represents non-baby cry and 1 represents baby cry. Model detects True Negative 79 as non-baby cry and True Positive 100 as baby cry among 192 samples.

To calculate accuracy of the SVM rbf from Figure 4.6

$$\mathbf{Accuracy} = \frac{\mathbf{TP+TN}}{\mathbf{TP+TN+FP+FN}} \quad \textbf{(4.1)}$$

$$\text{Accuracy} = \frac{100+79}{100+79+4+9}*100$$

Accuracy = 93.2%

TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

To calculate recall from Figure 4.6

$$\mathbf{recall} = \frac{\mathbf{TP}}{\mathbf{TP+FN}} \quad \textbf{(4.2)}$$

$$\text{recall} = \frac{100}{100+4} *100$$

recall = 96%

To calculate precision from Figure 4.6

$$\textbf{Precision} = \frac{\textbf{TP}}{\textbf{TP+FP}} \quad \textbf{(4.3)}$$

$$\text{Precision} = \frac{100}{100+9} * 100$$

Precision = 92%

4.9 Confusion matrix of KNN

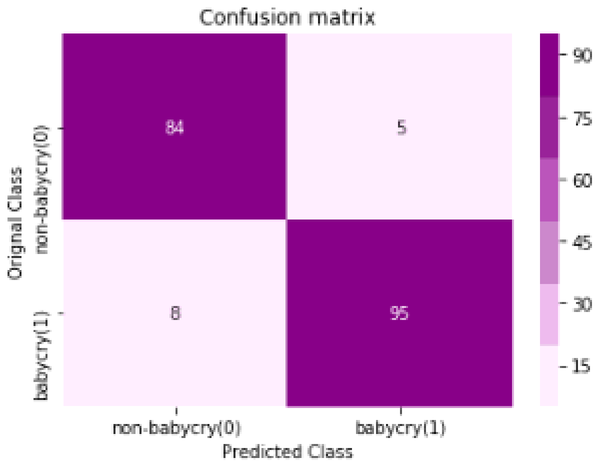


Figure 4.7: Confusion matrix of KNN

Above Figure 4.7 shows the Confusion matrix of KNN, here 0 represents non-baby cry and 1 represents baby cry. Model detects True Negative 84 as non-baby cry and True positive 95 as baby cry among 192 samples.

To calculate accuracy of the KNN model from Figure 4.7

$$\textbf{Accuracy} = \frac{\textbf{TP+TN}}{\textbf{TP+TN+FP+FN}} \quad \textbf{(4.1)}$$

$$\text{Accuracy} = \frac{95+84}{95+84+8+5} * 100$$

Accuracy = 93.2%

TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

To calculate recall from Figure 4.7

$$\textbf{recall} = \frac{\textbf{TP}}{\textbf{TP+FN}} \quad \textbf{(4.2)}$$

$$\text{recall} = \frac{95}{95+8} *100$$

recall = 92.2%

High Recall indicates the class is correctly recognized (small number of FN).

To calculate precision from Figure 4.7

$$\textbf{precision} = \frac{\textbf{TP}}{\textbf{TP+FP}} \quad \textbf{(4.3)}$$

$$\text{Precision} = \frac{95}{95+5} *100$$

Precision = 95%

4.10 Comparing model performance

Algorithms	Train Accuracy	Test Accuracy	Precision	Recall
SVM rbf	97.3%	93.2%	92%	96%
ANN	98%	86%	90%	86%
CNN	98%	96.3%	97.3%	96.4%
KNN	97.4%	93.2%	95%	92.2%

Table 4.2: Comparing model Accuracy

Here the above Table 4.2 shows comparison of Train Accuracy, Test Accuracy, Precision, Recall of ANN, KNN, SVM rbf and CNN models. Chooses evaluation metrics as confusion matrix and Accuracy is calculated for all the models, CNN got highest Train Accuracy **98%** and highest Test Accuracy **96.3%** among all the models.

CHAPTER 5
CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This thesis goal is to develop a system to detect baby cry. The goal is reached in proposed three objectives. The goal of objective one is to train the data using SVM, KNN, ANN, and CNN. The second goal is to load the pre-trained model in Raspberry pi for real-time testing and final objective is to send SMS alert when cry is detected. The developed system detects baby cry when baby starts crying and send SMS alerts to registered mobile number. Finally, CNN model is loaded in Raspberry pi and the device is tested in real-time and it performed well.

5.2 Recommendations

This system can be integrated in many ways to show output.

- If the baby cries, we can set output to play a song. In this way the baby may stops crying.
- Can integrate too many applications related to baby care.

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