Road Safety Analysis Framework Based on Vehicle Vibrations and Sounds using Deep Learning Techniques

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Research Article

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Abstract

Road accidents in India occur due to potholes. These potholes are not repaired because the authorities will not be aware of it unless the public raises an issue. Lack of adequate techniques to identify potholes has caused huge trouble to the public. The primary goal of this study is to build a deep learning model that would analyze the patterns in the sound recording of the vehicles and label the Road Anomaly Events (RAEs). Deep learning techniques like Convolutional Neural Network (CNN) and BLSTM are used to classify the sound signature and then are labelled accordingly. The idea can be implemented in areas where there is regular movement of vehicles to identify the exact locations of the pothole and inform the concerned authorities so that the public can experience smoother roads. From the analysis, it is found that the model has an accuracy of 83% with ADAM Optimizer while RMSProp produces 54–60% accuracy.

1. Introduction

The surfaces/smoother roads are constantly under high traffic and the weather conditions also affect the road quality due to factors like rain, heat. This causes traffic delays and reduces road safety [1]. The deformations due to this leads to formation of potholes and cracks which are a threat to vehicles [2]. The task of avoiding road irregularities can be tackled using trained drivers, but in recent times due to the invention of self-driving cars, it has become more necessary to have timely detection of road surfaces and provide a detailed report for optimal performance of the vehicles and safety of the passengers [3].

Road Transportation is one of the most prominent means of transportation. Almost 90% of the country's passenger traffic is routes using road transportation. The roads in India are mostly narrow with poor surface quality and maintenance. The roads are not satisfactory. In any part of India driving is a difficult affair due to the poor road conditions.

Unexpected appearance of dangerous potholes and speed breakers on the road, makes it difficult for automobile drivers to travel at a consistent speed [4]. The automobile is also severely damaged as a result of this. Current road surface monitoring relies on manual effort to check the state of the road, which is time consuming and inefficient. A system capable of automatically identifying road irregularities without the need for human intervention could drastically improve the efficiency of today's road transportation system [5].

In today's society, deep learning techniques are widely used. These strategies have been extremely beneficial to the organizations. Machine learning is the process of developing applications that can access data and learn from previously learned experience. The main goal is to enable computers to learn on their own, without assistance from or interaction with humans, and to adapt their behavior accordingly.

Deep Learning Techniques are broadly used in today's world. These methods have benefited the organizations in a tremendous way. Machine Learning deals with development of computer programs which access the data and use it in prediction. The main aim of it is to allow systems to learn autonomously without human interruption [6].

In Deep Learning, two major methodologies are used: Convolutional Neural Network (CNN) and Bi-Directional Long Short Term Memory (BLSTM). CNNs are used for Image classification and once the images are classified, the sequence of events are analyzed using BLSTM as sequence of events may result in a different inference [7].

The popularity of smartphones and ease of access to large numbers of sensors on general purpose smartphones makes it possible to perform analysis and data collection [8]. Building a client for a mobile client provides the best use case. Using the sound generated by the vehicle engine due to interaction with the ground, an analysis can be made to classify the events [9].

The application will provide the user with the map interface that will show the user the current road condition which will help the user decide on whether they want to travel on that particular road. The map will also show the areas of the road where a particular event (i.e., pothole, bumps etc.) will be shown. The purpose of this paper is to build a model to identify and annotate the road conditions using sound data from the vehicle engine/gearbox system recorded with a smartphone mic using deep learning technique.

Section 2 discusses the existing technologies and papers in the field of pothole detection. In Section 3 the data collection process and what kind of data is used along with how it is collected is discussed. Section 4 discusses the methodology and the architecture of the proposed solution and how it is implemented in this paper. In Section 5 results and analysis of the model is discussed and Section 6 concludes our observations and future scopes.

2. Related Works

This section provides a brief overview of the previous research works related to the detection of road anomalies:

A traffic congestion detection model was designed using machine learning algorithm based on audio [10]. The experiment was done by studying the data from the sensors in vehicles such as image and audio. Here the classification is done mainly as two types of traffic i.e., free flowing traffic and Congested traffic using Mel Frequency Cepstrum Coefficient (MFCC). The advantages of using these sensors is that it is affordable and available for the experiment. The data retrieved from these sensors is easily to deploy for processing.

An embedded system was built for measuring road irregularities within the suspensions of the vehicle [11]. Two major sensors like Vehicle Level Sensor (VLS) and an Acceleration Sensor (AS) are used to get input data. Both of the sensors are the most common components in present vehicles which simplifies the process. The variation of damper movement based on road types. According to the assumptions, vehicles will travel only on concrete or tar roads. But the assumption was not accurate as in India there are scenarios where vehicles travel on gravel roads.

The sensors of a smartphone are used for the detection of different irregularities in several areas such as environment, healthcare and road conditions [12]. According to the January 2022 survey, it is found that 83.96% of people own smartphones. The study compares the performance and accuracy of embedded systems with smartphone sensors. Inputs like GPS, microphones, cameras, magnetometers, accelerators, are collected and compared. This gives insights about increased chances for the development of sensor systems in a smartphone [13].

Conventional road situation surveillance is methodically held through vehicles that have specialized instruments, which demands high investments in money and time but covers only a bounded area of the road network [14]. Here smartphones' built-in vibration sensors and global positioning system receivers are used. The data gathered from the sensors was subjected to a variety of processing methods, and features from multiple frequency domains were analyzed, alongside different machine learning classifiers. With a precision of 88.5 percent and a recall of 75 percent, the Random Forest technique had the best classification performance for potholes.

The challenge of detecting road anomalies was addressed by recasting it as a classification problem and employing deep learning techniques to solve it. Aside from the usual road anomalies, additional anomalies are introduced depending on the vehicle's perspective [15]. The pattern representation is given special attention in order to aid the learning process. The Standard Set, Performance Set, and All-signal Set are three sets of numeric features proposed to increase the performance of a deep learning model with an adequate pattern representation of road conditions. To solve the categorization challenge, three deep learning approaches are being examined. Through data gathering from a vehicle, Convolutional Neural Network (CNN), Deep Feed forward Network (DFN) and Recurrent Neural Network (RNN) approaches are employed to train and assess the detectors.

The quality of the road surface is crucial to make driving more enjoyable and fewer road accidents. Traditional road condition monitoring systems have limitations when it comes to responding swiftly and geographically to preserve overall road quality. The vehicle vibrations might be used for automated road inspection [16]. The multiple machine learning approaches such as *support vector machines (SVM)*, decision trees, and neural networks were used for multiclass categorization. In particular, a benchmarking study is being conducted to determine the potentials and limitations of various machine learning algorithms for detecting road deterioration.

Traffic accidents can be automatically detected by surveillance systems based on image recognition, allowing emergency crews to respond rapidly. However, in some circumstances, visual representation of information is insufficiently dependable, but adding a sound detector to the surveillance system can significantly boost the overall reliability. A technique is used for extracting deep audio representations based on a multi-stage deep auto-encoder network which fuses data from multiple input features and is thus more robust than those input features [17]. Because of the significant contextual relationship between sounds and the usefulness of neural networks in obtaining sound-sequence information, a Bidirectional Long Short-Term Memory network classifier was implemented instead of classifiers like SVMs.

With the development of self-driving automobiles it is critical to identify road irregularities such as potholes and make appropriate avoiding manoeuvres to ensure a smooth ride for passengers or equipment on board. A fully automatic real-time road crack and pothole detection methodology was presented that can be run on any GPU-based processing board with a camera [18]. Based on a deep neural-net architecture that uses texture and spatial characteristics to detect cracks and potholes. It consists of a CNN that learns spatial information through images and an encoding layer that distinguishes between the images based on texture.

Smart vehicles have progressed to the point where they can now use inbuilt sensor data to recognize environmental road elements such as potholes and road inclination angle [19]. It is difficult to extract information from vehicle data. Extraction of information from vehicle data is difficult due to under sampling sensors, sensor mobility, asynchronous sensor operation, sensor noise, vehicle and road variation, and GPS position error [20]. Developed a crowd-sourced technique to locate potholes in multi-lane scenarios using accelerometer sensor data from embedded sensors in the car. To evaluate the system, examine trade-offs in the number of cars and bandwidth required for efficient detection using simulated and real-world data.

Road transportation in India outnumbers all other modes of transportation. Passengers enjoy smooth and comfortable travel thanks to well-maintained roads. Detecting potholes and roughness levels is critical for monitoring road conditions, which has an impact on transportation safety, driving comfort. A method was proposed to monitor, detect, and anticipate the degree of anomalies by monitoring the vibration signals produced by the vehicle when it moves [21]. To minimize normal conditions, max-abs filters are applied to the data acquired from the sensors according to the event. To find the abnormality, use the Gaussian and x-z filters. However, recognizing many irregularities in a split second is impossible.

Roads that are well-maintained contribute significantly to the country's overall economy. Identification of road distress, such as potholes and speed breakers, not only aids drivers in avoiding accidents and car damage, but also aids authorities in road maintenance [22]. Potholes and humps are detected using ultrasonic sensors, which can also be used to assess their depth and height. A GPS receiver is used to gather the geographic location coordinates of potholes and humps [23]. On the basis of the data, the Support Vector Machine Algorithm (SVM) algorithm is utilized to distinguish the various abnormalities.

The feasibility of employing sound characteristics for vehicle identification and categorization was investigated [24]. For a two-lane undivided road carrying modest traffic, the sound emitted by vehicles is recorded. After examining numerous features, smoothed log energy was shown to be effective for autonomous vehicle detection by locating peaks. A multilayer feed-forward neural network had been used to differentiate the categories of vehicles Heavy, Medium, Light, and Horn utilizing traffic sound recordings. The performance of formant-based features on a manually labelled set of traffic noises is compared to that of MFCC applying a KNN classifier on a manually labelled set.

3. Data

In this modern and technologically developing world, data plays the most important role. Nowadays people have access to smartphones with ease which have multiple sensors embedded in them. So the application uses the audio and location sensors of the smartphone to record the audio and track the location through the journey. The audio and location is captured in real time and stored in the firebase.

The user also gets a basic screen with an option for uploading the audio for processing. The audio is uploaded by the user from their local machine to the firebase storage on cloud and processing is done. This data is used for training the model to improve the accuracy of the model. The audio data stored in the firebase is retrieved for noise reduction and spectrograph generation. The spectrograph generated is fed into the Road Safety Analysis Model for classification.

4. Proposed Methodology

The proposed "Road Safety Analysis Based on Vehicle Vibration and Sound" is built to study the road conditions appropriately. Once the road condition is studied through sound, with the help of the sound, the classification is done and location is added in-order to provide the accurate location of the events, the application provides a map output which helps the user get a clear idea about the road conditions. The architecture diagram for the proposed model is shown in Fig. 1:

- Collection of Initial Dataset: The initial training dataset is collected and the system is trained before the deployment of the model which was collected using a specialized tool built to manually label road events through the use of smartphones.
- Pre-processing the Data: The data once collected, the first thing that has to be done is removal of noise so that it is easier to analyze the sound signatures.
- Classification of Captured Sound: The next stage of the sound processing is classification. The methods used for the classification are Bi-directional Long Short Term Memory (BLSTM) and CNN.

The data flow in the Road Safety Analysis begins when the user records and uploads the audio into the system. The data is then pre-processed wherein the audio is split into windows or desired size for better event detection, noise reduction is done and spectrograms are generated for the events.

The data is then given to a Convolutional Neural Network for classification in the end the user is expected to get an audio file which has annotated audio. The Data Flow Design of the Road Safety Analysis Model is shown in Fig. 2. The user uploads the audio file either by recording or uploading an already existing audio file. The data that is sent goes through data pre-processing which involves noise reduction and audio splitting, later feature extraction is done where events like potholes, bumps, honks are marked and spectrograms for each of the event is generated. These spectrograms are given to the CNN to be analyzed and learnt for performing the classification on the test data. Once the data is annotated, the output is given to the user through the map interface.

The algorithm for splitting audio and spectrogram generation is given below:

Algorithm 1

Splitting Audio

Input: Read the road audio file AUDIO, d: Split Duration

Output

Directory with segmented audio files

Create Audio and Spectrogram segment directory

Calculate length of audio file

For i, every d duration within length Do

Store AUDIO [i: i + d*1000]

End For

Algorithm 2

Spectrograph Generation

Input

Read audios of split durations AUDIOS

Output

Spectrograph images of the audio

For each audio in AUDIOS Do

Read audio file

Generate spectrogram for the audio with the scale, hop length, frame sizes as per the type of data.

Store the generated spectrogram to feed to the neural network.

End For

The audio file given in .m4a, .wav formats are read and split duration is mentioned. To view the split audio files and the visualization of these files we would need 2 directories for storage. The total length of the audio file is calculated and looping is implemented in order to obtain the audio files of desired length.

The Fig. 2 (a) represents the segment of spectrogram of regular throttle, a constant mid-low frequency is persistent. In Fig. 2 (b) is the gear-change scenario where an acceleration curve is shown, in Fig. 2 (c) shows the bumpy road sound signature. Figure 2 (d) shows the horn sound signature generated by the vehicle or other nearby vehicles.

In order to generate the spectrograms the audio files that were created earlier are read by the convolutional neural network. Using the librosa package in python, visualization of the audio signals are done and images of specified length are created and stored in the respective directory. Later the images are fed to the neural network for further processing and classification.

In the spectrogram, the sound is concentrated mainly around the frequencies that are brighter in the figure; as the color gets darker, the sound becomes increasingly empty or dead. These can be utilized to help the neural network have a clear sense of the form and organization of the audio.

Split the audio into overlapping windows in order to calculate the spectrograms. On each window, perform the Short Time Fourier Transformation. A vertical line showing the magnitude vs. frequency can be seen in each window that results. Convert the resultant window to decibels. The output should then be displayed after converting these windows back to the original song's duration.

In Fig. 3, the structure of the neural network is shown which explains the data flow between each layer from spectrogram to the prediction. The first layer is the image input which is 310px x 154px having 3 values for indicating the color (R, G, B). In the intermediate layers the pixel values of the image analyzed and the model is trained. The final output of the model is the probability of the image being in one of the 4 indicated events.

5. Results And Discussion

The basic UI involves providing the user with a screen to upload the audio shown in Fig. 4. The user can upload recorded audio if the user did not have internet access during the period of recording the audio. Once the audio is uploaded onto the cloud (firebase).

The URL of the audio is passed to the model, the audio is downloaded and the preprocessing steps are done accordingly, the audio files are split and spectrograms are generated. An Audio signal can be represented as a simple wave form which is shown in Fig. 5. We can achieve more value by using the Spectrogram of a signal as shown in Fig. 6. When noise reduction is done on the data, all the unnecessary noise is removed and we get a clear audio signal visualization so that the pixel values can be read efficiently and only informative parts of the spectrograms are captured which is shown in Fig. 7.

CNN does the classification and feature extraction. The classified events obtained from the CNN are then integrated with a map interface for a user-friendly experience.

The user is presented with a home screen as shown in Fig. 8, in this case the home screen has a button to start recording the audio as well as the location. The user may record the audio of the complete journey or a part of it. Once the user hits the record button there are several buttons available which indicate different events (potholes, roadwork, speed bump, horn, hard-stop, gear-change) respectively. As shown in Fig. 9, when the user marks the events it is annotated as a particular event which will help the CNN to classify the audio more efficiently. The processing is done by the model and finally the output is shown in Fig. 10 as a map with annotated events identified on the path, events are indicated based on colors, for instance red stands for potholes, yellow for regions with minor bumps etc.

The Adam optimization algorithm is an extension to stochastic gradient descent for deep learning applications in computer vision. The RMSprop optimizer is similar to the gradient descent algorithm with momentum. The vertical oscillations are restricted by the RMSprop optimizer. The ADAM Optimizer is significantly more accurate when compared to the RMSProp Optimizer for the smaller data-set than currently is in use.

Figure 11 and Fig. 12 gives the comparison between the RMSProp Optimizer and ADAM Optimizer loss percentage. The ADAM Optimizer is significantly more accurate when compared to the RMSProp Optimizer for the smaller data-set than currently is in use. ADAM Optimizer produces 83% accuracy within the validation set while RMSProp Optimizer produces 54% accuracy with validation set.

In Fig. 13 and Fig. 14 the comparison between the losses of both the optimizers are shown, the losses in RMSProp are spiking at regular intervals which indicate a higher loss of data when compared to the ADAM Optimizer which has a much smoother and a consistent curve. The ADAM Optimizer is better than the RMSProp Optimizer in both the fields, hence the ADAM Optimizer is used here.

6. Conclusions And Future Work

It is noticed that day by day the conditions of the roads are worsening and there are a lot of mishaps happening in the society. Monitoring the conditions of the road on a regular basis is a challenging task for humans as well as cost effective, and to gain full control over the road conditions on a regular basis is a difficult task. With the help of sensors in a smartphone the audio and location of the path can be recorded and this audio can be used to analyze the condition of the road. This reduces human efforts in analyzing the road condition manually and is cost efficient. The main drawback of the current system would be reporting the road conditions to the authorities responsible for road maintenance, the reporting is only done once the official has travelled on that route and found it bumpy. This system aims to automate the procedure by reporting it to the responsible authorities automatically just by recording sound. This system with the help of microphones and GPS sensor data would be able to predict the conditions of the road and get a map output on if the road is safe to travel or not. The map output will indicate the road condition by providing appropriate indicators based on the events. All in all, with the help of deep learning models the system can be made to make decisions like a human mind provided the model is trained appropriately with the help of datasets.

Future work of the model includes having larger datasets for training the model in various scenarios and getting a more robust and accurate prediction. A separate hardware module that would be connected to the bodies of the heavy vehicles so that the exact sound patterns can be captured and better classification can be done. Improvements in the already existing algorithm used to make the model more efficient.

Declarations

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Competing Interests

The authors declare that they do not have any competing interests.

Authors' Contributions

All authors contributed to the study conception, data collection, design and analysis. The first draft of the manuscript was written by Rithesh Pakkala P. and all other authors reviewed the draft manuscript. All authors read and approved the final manuscript.

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Availability of Data and Materials

The data generated and analyzed during the current study are available from the corresponding author on reasonable request.

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Figures

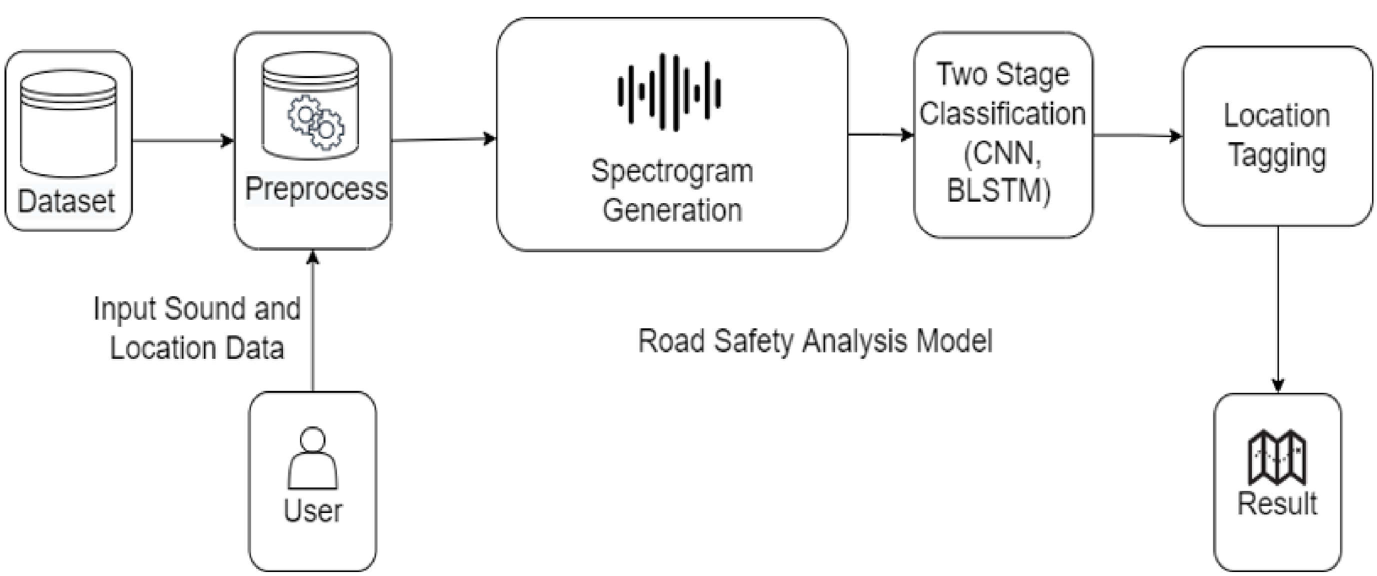

Figure 1

Architecture Diagram of Road Safety Analysis Model

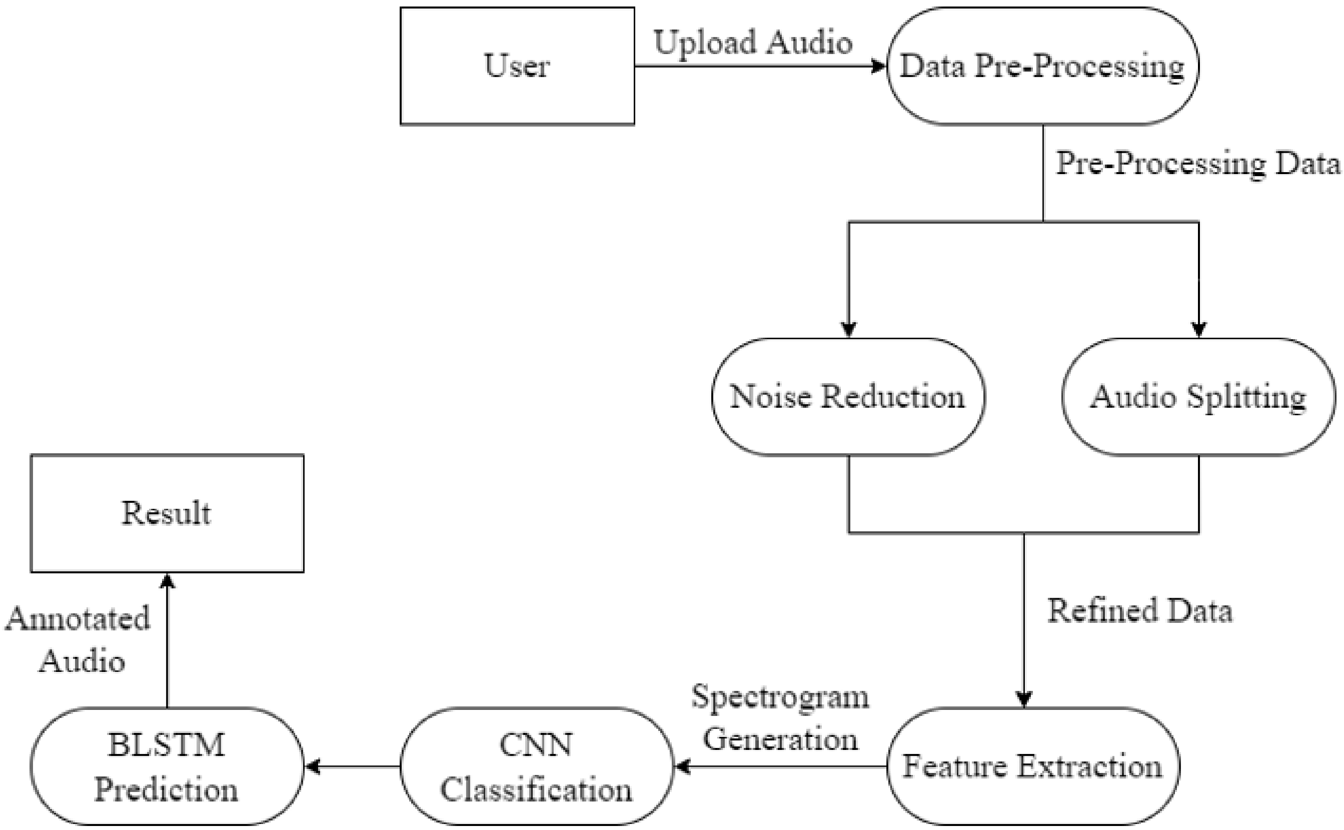

Figure 2

Data Flow Design of Road Safety Analysis Model

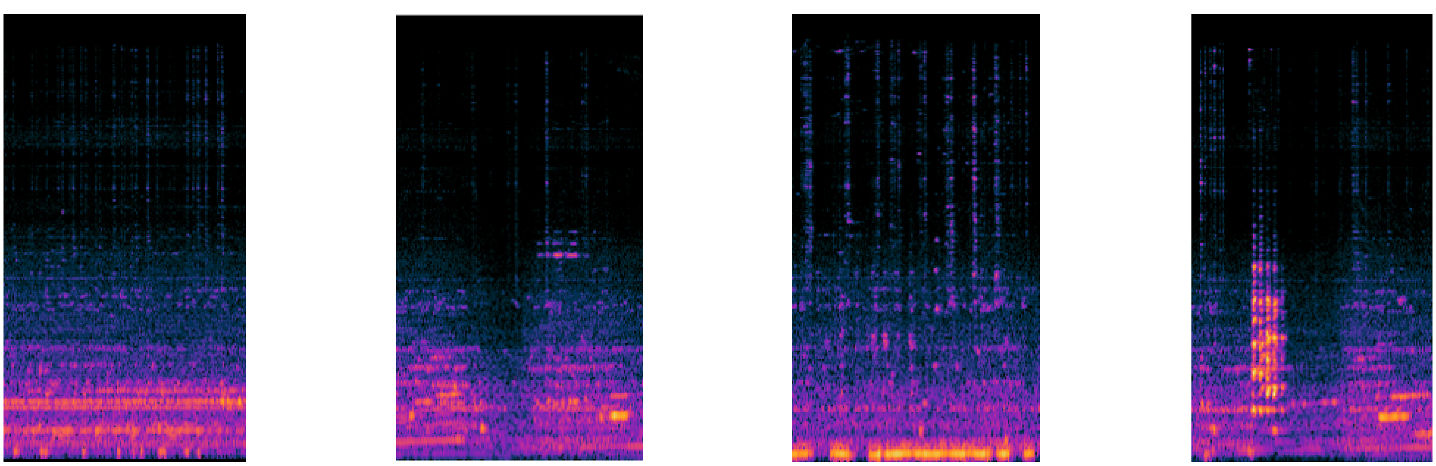

Fig 2 (a). **Fig 2 (b).** **Fig 2 (c).** **Fig 2 (d).**

Figure 3

Fig 2 (a). Spectrogram of Regular Throttle

(b). Spectrogram of Gear Change

(c). Spectrogram of Bumpy Road

(d). Spectrogram of Horn

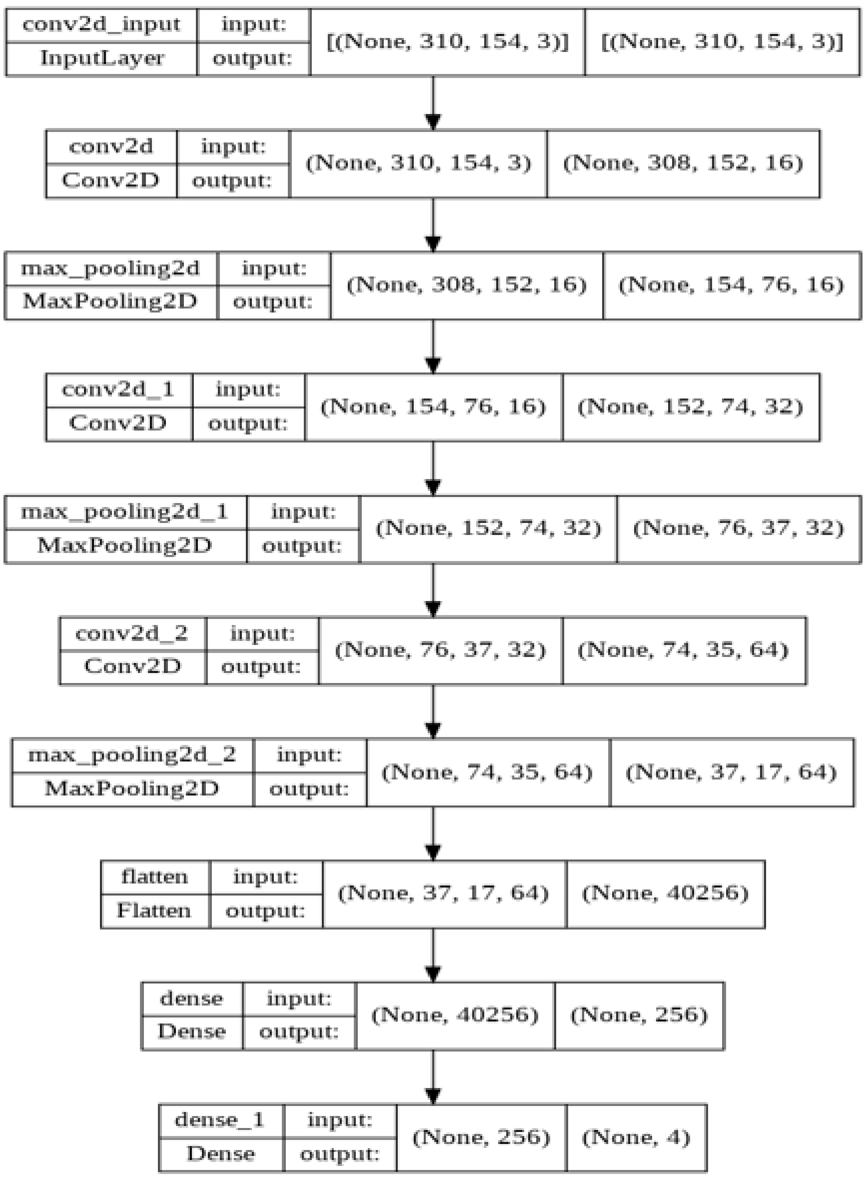

Figure 4

Fig 3. Neural Network Structure

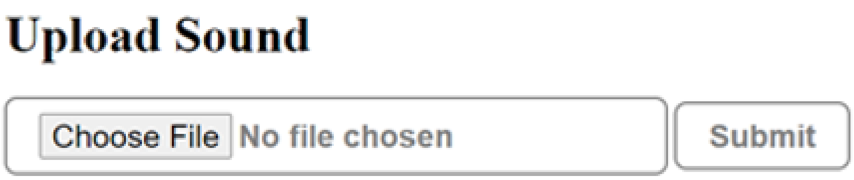

Figure 5

Fig 4. Basic Audio Upload Screen on Web

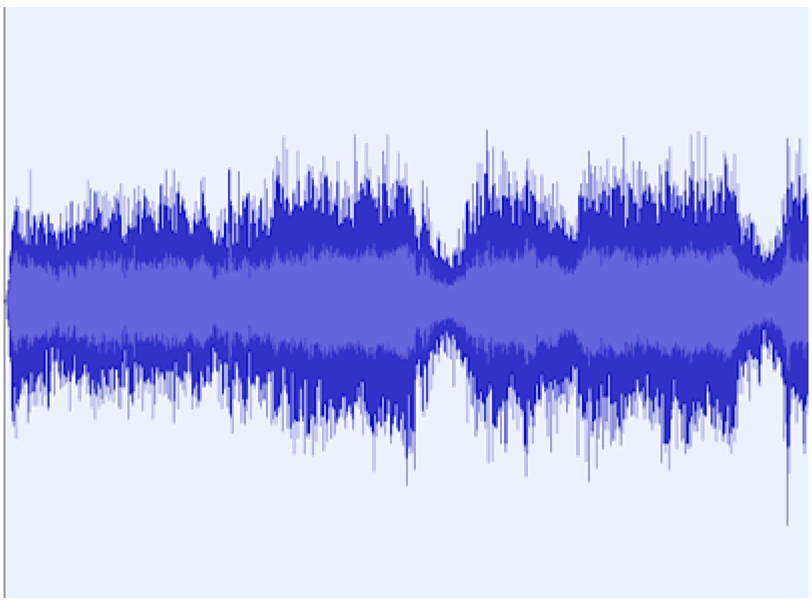

Figure 6

Fig 5. Waveform of Audio Signal

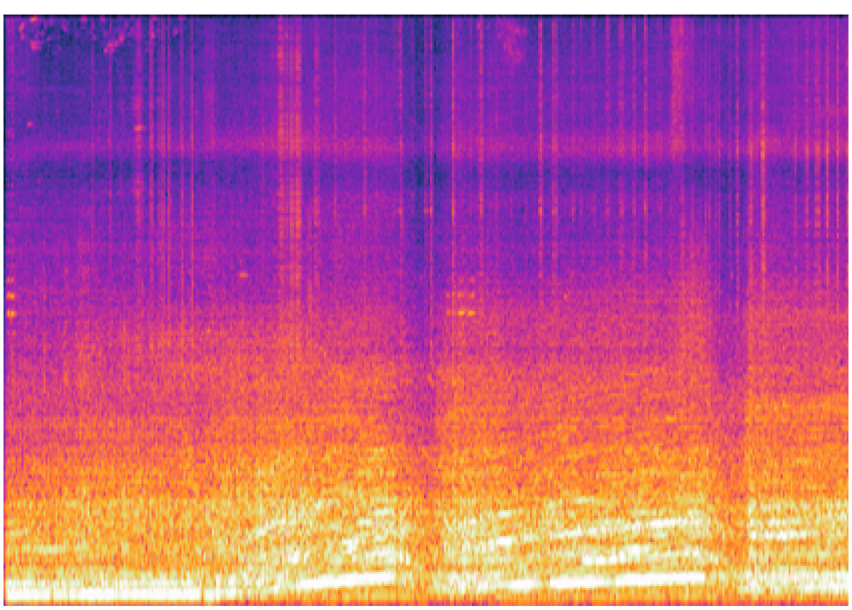

Figure 7

Fig 6. Spectrogram of the Audio Signal

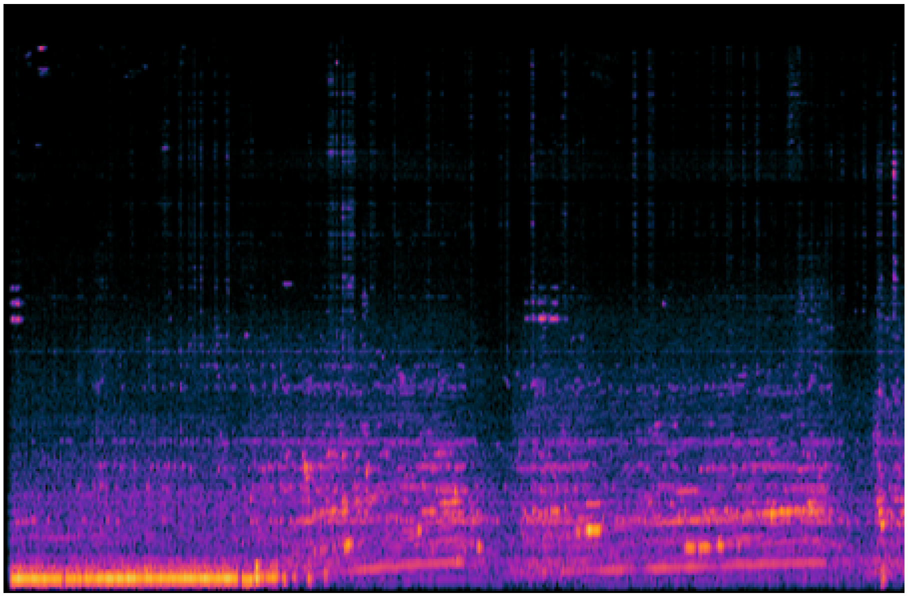

Figure 8

Fig 7. Spectrogram after Noise Reduction

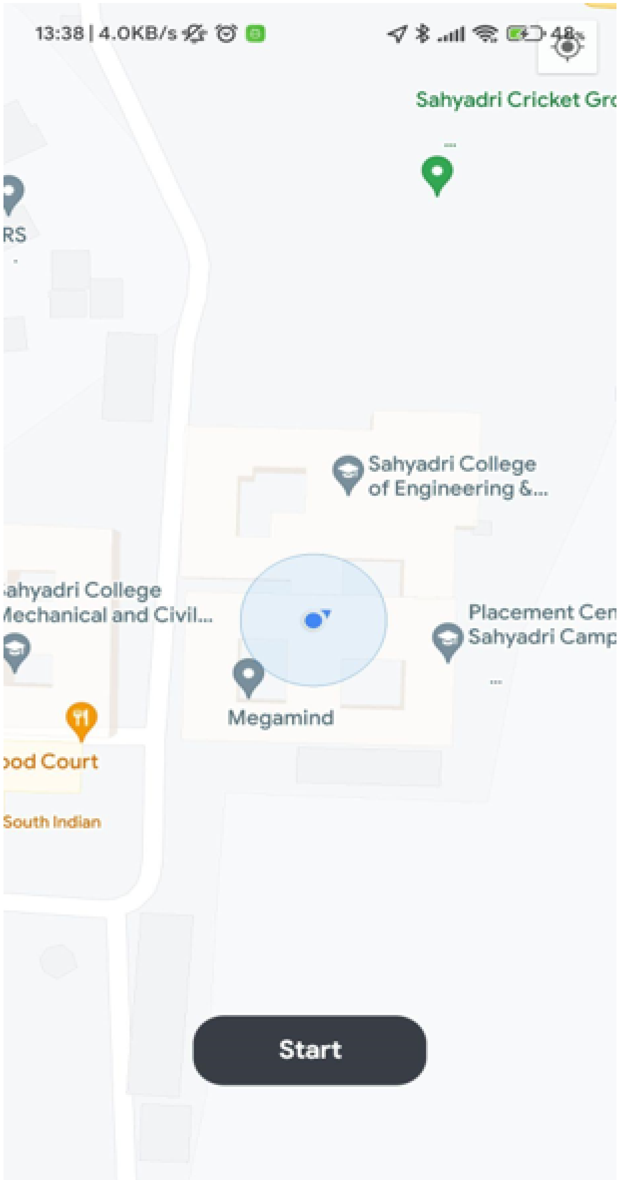

Figure 9

Fig 8. Home Screen

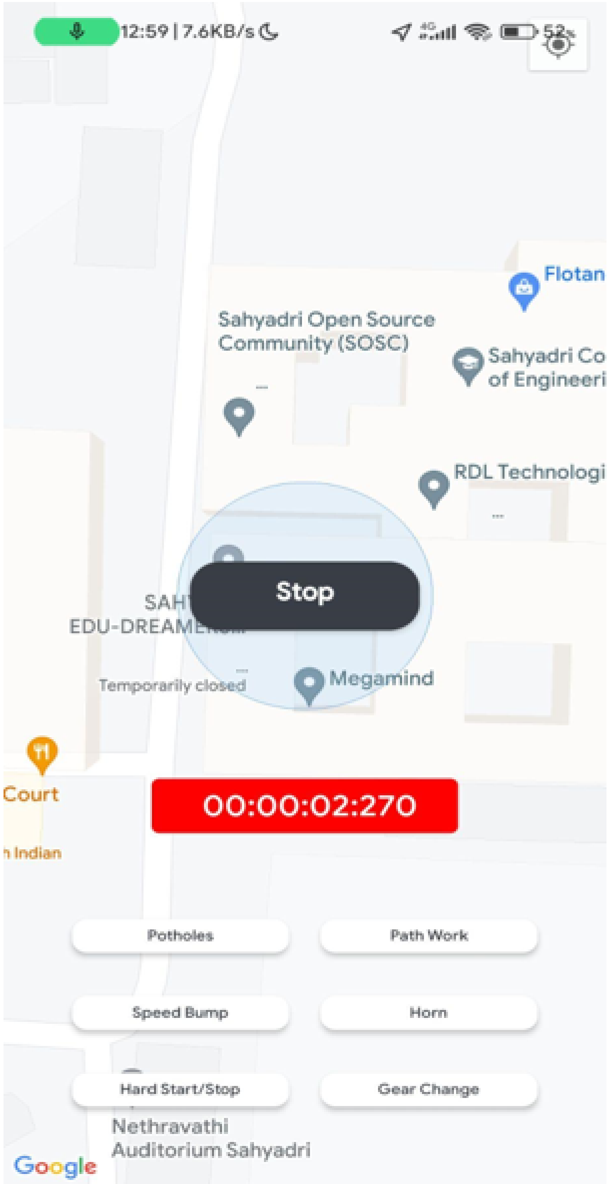

Figure 10

Fig 9. Recording Screen

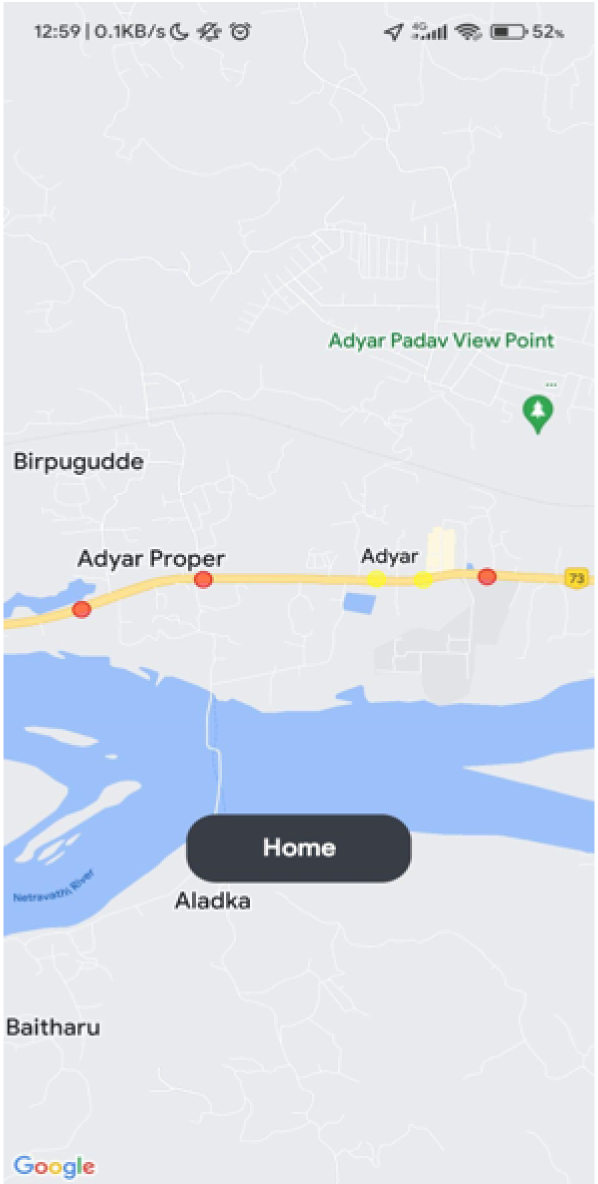

Figure 11

Fig 10. Map Output Interface

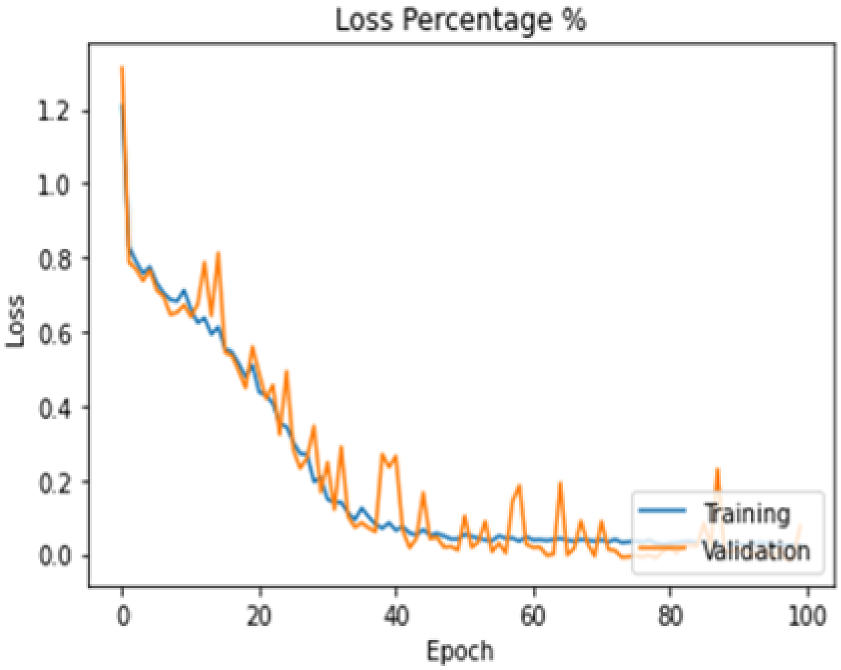

Figure 12

Fig 11. Adam Loss Percentage

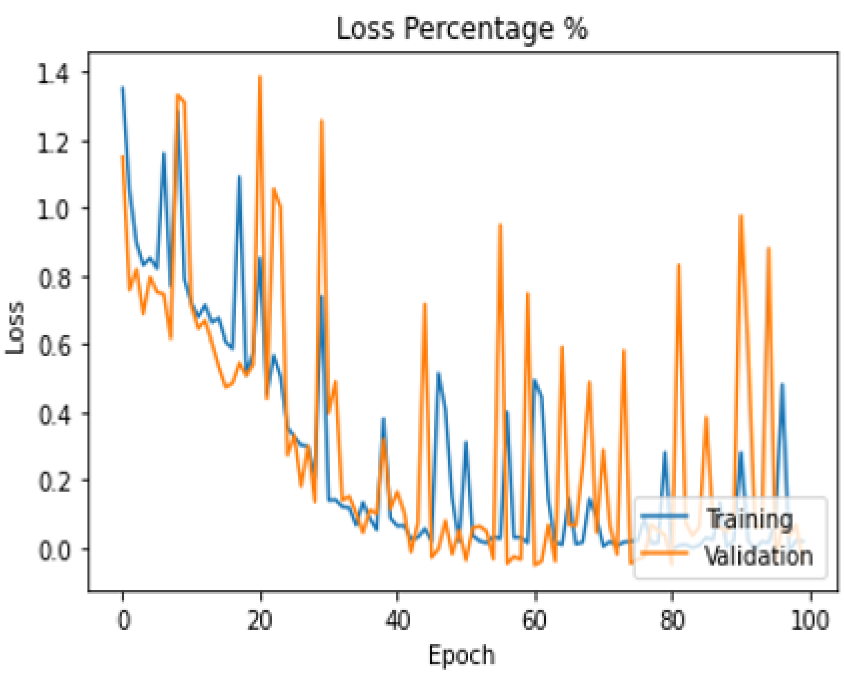

Figure 13

Fig 12. RMSProp Loss Percentage

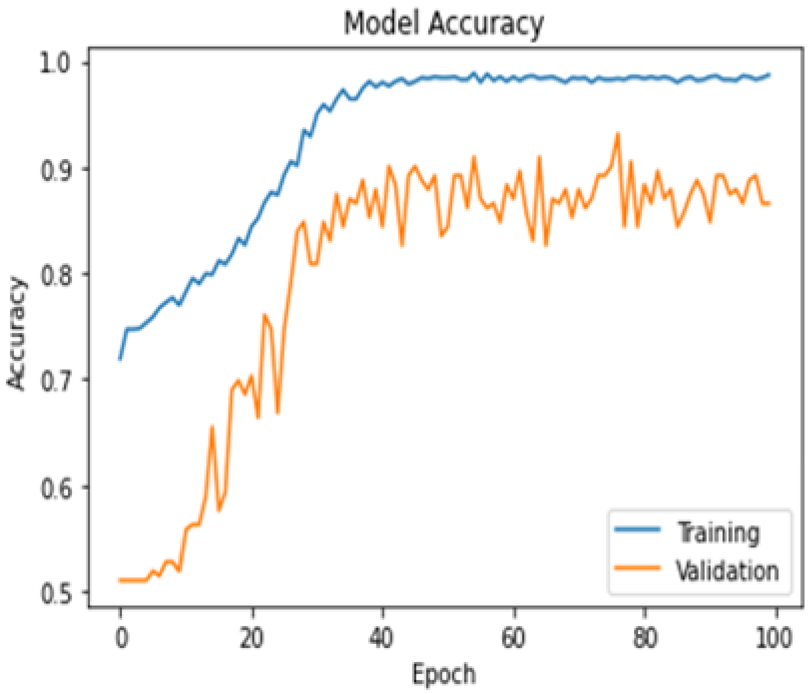

Figure 14

Fig 13. Accuracy of ADAM Optimizer

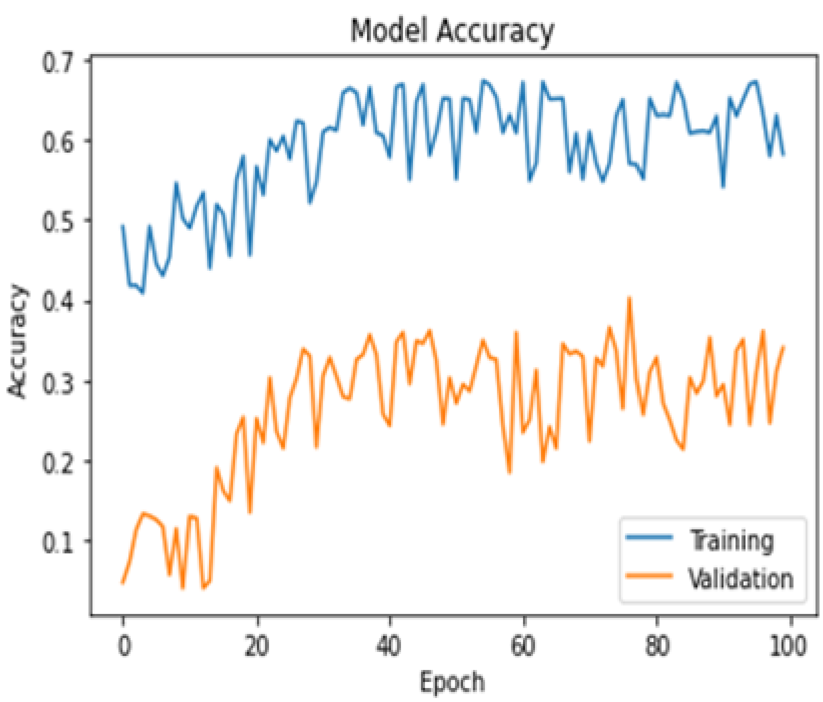

Figure 15

Fig 14. Accuracy of RMSProp Optimizer