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TrackWarn: An AI-driven warning system for railway track workers

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Abstract **- This contribution focuses on developing an AI-driven warning device to ensure the safety of railway track workers. Recent studies clearly show that track workers safety has become a major challenge for the railway industry despite many precautionary measures that are implemented. In this regard, many technological solutions have been proposed and developed to warn track workers of the approaching trains. However, the cost and complexity are the drawbacks of these systems. Therefore, we introduce TrackWarn, a low-cost portable smart gadget that detects the sounds of the approaching trains and provides a warning signal to track workers via a phone call. TrackWarn uses a state-of-art Convolutional Neural Network (CNN) that utilizes environmental sounds and spectrograms to classify if the train is approaching or not. This model achieves an average classification accuracy of 92.46%. With the help of Arduino Nano 33 BLE Sense microcontroller, the whole system becomes very handy and potable. This paper addresses the design of the TrackWarn and the results obtained with respect to the various test cases. Further, the performance and communication challenges are also described in detail.**

Keywords - Arduino Nano33 BlE sense, CNN, smart, track workers, spectrograms

I. INTRODUCTION

Railway track workers play a crucial role in helping to ensure safe train transport. They usually carry out mechanical work associated with railroad systems without any automated safety systems in place. Due to improper safety measures, train accidents among railway track workers are frequent. These unforeseen accidents ultimately result in loss of life and severe injuries. Although the modern rail industries implement various efforts to mitigate track workers accidents, the accident rate escalates every year unevenly. The rail accident investigations reports reveal that the unawareness of approaching train is one of the primary causes for these unforeseen accidents [1]–[3].

At present, there are two techniques that are widely used to warn people of the approaching trains: automatic track warning systems (ATWS) and lookout-operated warning system (LOWS). Based on deployment ATWS can be classified as train/wayside mounted device and portable zone device. While the train/wayside mounted devices are permanently installable devices, the portable zone devic**es** are temporarily affixed on the railroad corridor. These devices notify the arrival of trains by communicating the specific device carried by the track workers. Although many commercialized automatic track warning systems (ATWS) [4][5] are available in the market, most developing countries still rely heavily on a lookout-operated warning system (LOWS) for ensuring the safety of track workers. In LOWS, a member of the team is assigned to monitor and alert the arrival of trains. Moreover, the protection of track workers solely depends on the lookout operator. As part of this contribution, we figure out the problems of the existing ATWSs and propose a novel technique to ensure the safety of track workers with the help of AI.

The train detection task is generally considered the most challenging part of any ATWS devices. At present, there are two different techniques that are generally carried out to detect the trains: track circuit and axle-counter [6]. In the track circuits, occupancy of a section of the track has been determined by continuous sensing the short circuit. This continuous sensing technique, can also be used in condition monitoring, for example to detect broken rails. However, power failure, leaves on the track, rusting, contaminants on railheads can cause the faulty result. In addition to this, the track circuit requires continuous maintenance for prolonged use.

On the other hand, the axle-counters count the axles of the trains by measuring the inductance changes [7]. The latest axle-counters have the capability of finding the directions and speeds of the trains as well. However, power supply failures and wheel rocks are the two causes that make this system fail in counting axles. In addition to this, they are more expensive and require long installation times.

In addition, various low-cost technological solutions have been proposed and developed to address the problem of accurately detecting the locations of trains on the railways. These include systems based on global positioning system (GPS) technology [8]–[10], RFID technology [11], wireless sensor networks (WSNs) [12], [13] , GSM technology [14], Image processing with vibration sensors [15], [16] , and weighing detectors [17] , accelerometers sensors [18], [19], coding and transmitting signal measured in track circuits [20]. In particular, the adoption of GPS technology may fail when the trains travel under bridges or within long tunnels [21], [22]. However, all of these methods yield a high error rate for critical decisions. Therefore, we decided to apply the sound classification technique to detect the approaching trains.

With the advent of high-performance computing, deep learning algorithms such as neural networks, recurrent neural networks, convolutional neural networks yield negligible error rates. Especially in automatic voice recognition and computer vision, deep learning has been reached human levels of detection.

The convolutional neural networks are the popular multi-layer architecture that specially applied in computer vision associated projects. However, recent studies prove CNNs are also applicable for automatic voice recognition using spectrogram images. Therefore, we employ a state-of-art CNN architecture that utilizes sound and spectrograms to classify if the train is approaching or not.

The machine learning techniques enable the Internet of Things (IoT) to achieve its extreme level in a wide variety of applications ranging from tiny insect tracking to planets monitoring. Therefore, we analyzed several AI-enabled microcontrollers to successfully execute our deep learning algorithm. As the result of this study, we chose the Arduino nano 33 BLE sense microcontroller board to deploy our deep learning algorithm. Arduino Nano 33 BLE Sense microcontroller has a variety of built-in sensors such as accelerometer, compass, temperature, microphone, etc. In addition to this, it also supports wireless connections such as radio, Bluetooth [23].

Seamless communication is one of the crucial parts of the ATWS. We use a SIM800L GSM module that supports quad-band GSM/GPRS networks. Low cost and small footprint make this module suitable for any embedded projects that require long-range connectivity. It well operates at 3.7V with an external antenna.

The rest of the paper is organized as follows: In Section 2, we describe the existing automated solution that use acoustic features to detect the trains. In Section 3, we detail the methodology that we used to build TrackWarn. In Section 4, we showcase our results and discuss possible explanation. Finally, we draw our conclusion and future work in Section 5.

II. Literature Review

The trains produce various types of sounds such as the horn, whistle, traction, rolling and aerodynamic effects. Based on this, various acoustic feature-based automated systems have been proposed to detect the trains. Sato et al. proposed a system to detect passing trains using the mobile devices of commuters [14]. This system analyses the environment sounds and predicts the probability of train passing by the use of a logistic regression model and hysteresis thresholding. Before the analysis, a low-pass filter is applied to reduce the environmental noise. Furthermore, the location calculated by the GPS sensor at the train detected point is shared with registered authorities through a central server. However, the authors fail to discuss the detection efficacy with the distance between mobile devices and railroad.

In [22], a mobile phone-based train-localization system is proposed with the help of acceleration and microphone sensors. The microphone captures the high frequency distinct sounds of the train passing the rail joint to estimate the speed of the trains.

Singhal et al. proposed a level crossing warning system to alert road drivers of approaching trains [24]. The system takes composite sound signals (train and surrounding sounds) as input and filters out sound pressure levels between 0 to 65 dB using a band stop and equiripple filters. The filtered signal is then compared with the average sound pressure level (given by -0.241* distance(vehicle) + 85.78 dB) to detect the approaching trains at level crossings. Although the authors mention the accuracy of this system is 95%, the various test cases and the ways of affixing circuits on the road vehicles were not discussed properly.

A group of researchers applied Recurrent Neural Network (RNN) based sound recognition system to detect the trains at the level crossings [25]. The system utilizes the mixing sounds and Mel Frequency Cepstral Coefficient (MFCC) to classify the presence of trains. First, the Authors capture specific sounds such as aircraft, car, train, rain, thunder from online corpus as well as live recordings. Subsequently, with the use of NCH software, the train sound is mixed with other sounds into two categories such as two sound mixture and three sound mixture. Thereafter 12 coefficients per frame from both categories are extracted. Finally, these features are used to train RNN with the backpropagation algorithm. Moreover, the scaled conjugate gradient algorithm (SCG) is designed to reduce the time consumed in line-search. Further, the authors stated that high accuracy (90%) found in both train+rain and train+aircraft+car mixtures.

As per the literature reviews, we believe using deep learning algorithms, the sound sample of trains and the environment (noise) can be analyzed further to produce a robust prediction model with high accuracy.

III. Materials and Methods

A. *Data acquisition*

First, we determined five various locations such as remote areas, busy surroundings (near the market), seaside, near the airport, and tunnels to collect the recordings. Further, we decided to use Samsung galaxy grand prime and Apple iPhone 9 to collect the trains' sound within the 10m range from the railway track. In each location, 10 different trains' sound were recorded, which is 7 min long in total. In addition, to make a more robust classification model, environmental sounds such as thunderstorms, helicopter, aeroplane, road traffic, and background sounds also downloaded from the Kaggle corpus and labelled as noise. The recordings collected for classification are shown in Table I.

TABLE I. Types of Sounds and their Duration

Train Sound	**Length**
Train (50)	7 min
Noise	**Length**
Thunderstorms	1 min
Aeroplane	1 sec
Road traffic	2 min
Helicopter	1 min
Background	5 min

B. *Sample preprocessing*

Since the sample rate of mobile recordings is 48 kHz, we used Audacity 3.0.2 to resample them to 16 kHz, which is the actual sampling rate of Arduino nano 33 BLE sense. Subsequently, the resampled recordings were exported as a .wav format with 32-bit depth encoding.

C. *Model configuration*

In the model building process, a window with the size of 1sec with a window increase of 100 milliseconds is used to extract unique features from each raw sample. These windows (Spectrograms) are fed into the CNN model during the training process. Further, the number of epochs, learning rate, and the confidence for our CNN set as 30, 0.005, and 0.7 respectively based on the experiments. The feature extraction process for a raw data is shown in Fig. 1.

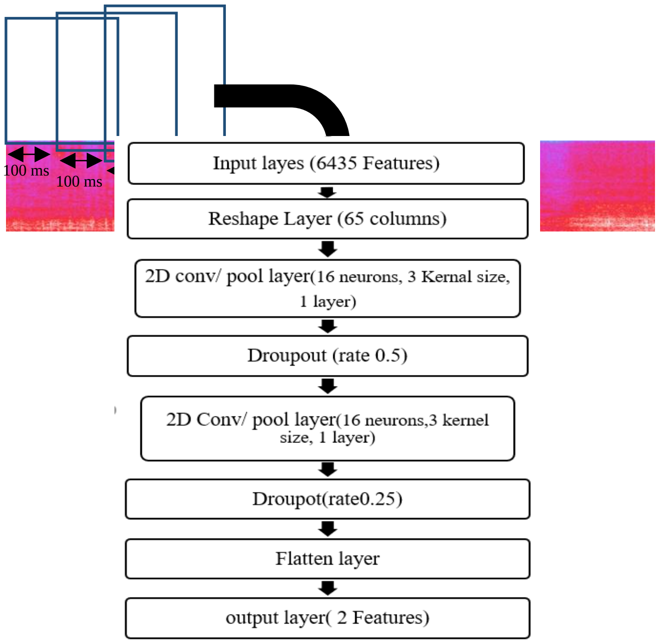

Fig. 1 Feature xtraction process

D. Device settup

The SIM800L GSM module and Arduino Nano 33 BLE Sense microcontroller board are powered up using two separate 9V batteries. Two LM2596 DC-DC step-down buck converters modules are used to provide 3.7V and 3.3V to the GSM module and microcontroller respectively. The circuit diagram of TrackWarn is depicted in Fig. 2. Since Dialog Axiata PLC has many subscribers [26], we decided to use Dialog SIM for the GSM module. Two predefined mobile numbers (Dialog) are stored in the EEPROM of the Arduino board to give alert calls when the gadget detects a train. Further, the trained CNN model is deployed to the microcontroller board to detect the trains. Finally, all the components are fixed in a compact box to use

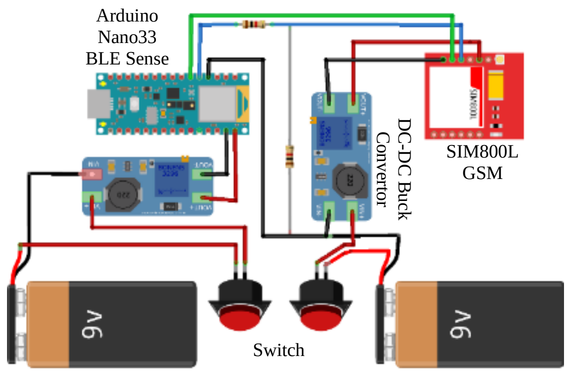

Fig. 2 Circuit diagram

E. Workflow of TrcakWarn

The system is set to send an active SMS to the stored numbers every 15 min to ensure the system is kept working without any system failure. In addition, we introduced a counter variable to ensure the approaching train. In every correct target (train sound) prediction, the counter value increases by 1. When the counter value equals 5, the system confirms the passing of a train. In consequence, the alert calls have been triggered to respective track workers successively. Finally, the system reverts to its initial state. In case the counter value is not increased by 1 within 1.5 sec, the system reset the counter to 0. The clear workflow of TrackWarn is shown in Fig. 3.

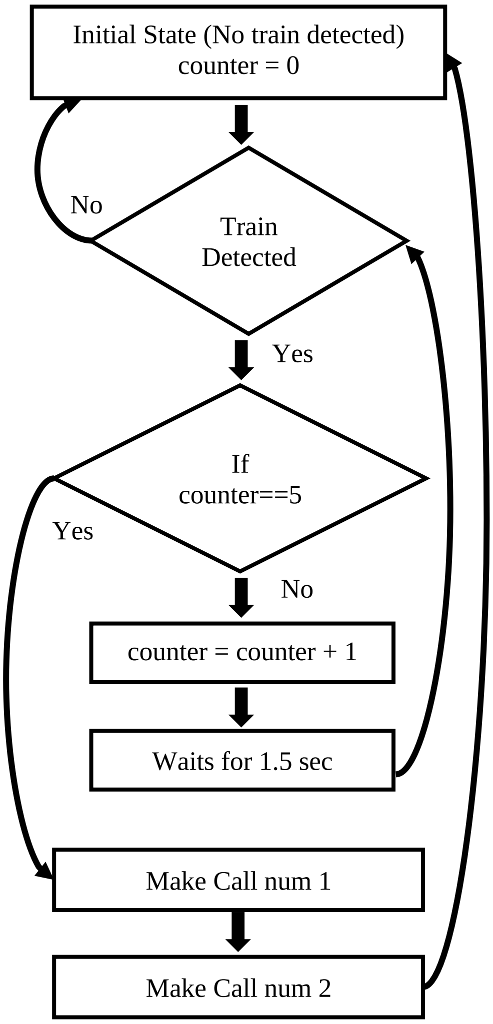

Fig. 3 Workflow of TrackWarn

IV. Results and Discussions

A. Model performance

The gadget is tested in a real environment to calculate the model efficacy. The model achieves 92.46% accuracy for unseen data with the feature extraction and inferencing times 77ms and 508ms respectively in the Arduino nano 33BLE sense. In addition, the peak RAM usage is calculated as 129.7KB. This interprets the model is optimally working for the Arduino nano 33 BLE Sense microcontroller. However, the significant accuracy loss occurred during the thunderstorms. Therefore, various thunderstorms raw data is required to improve the accuracy level.

B. *Connectivity test*

First, we selected the Western and Central provinces of Sri Lanka to conduct the communication test since, as shown in Fig. 4 the coverage (Dialog) of Western province is comparatively higher than other provinces whereas many tunnels are found in the central province according to [27].

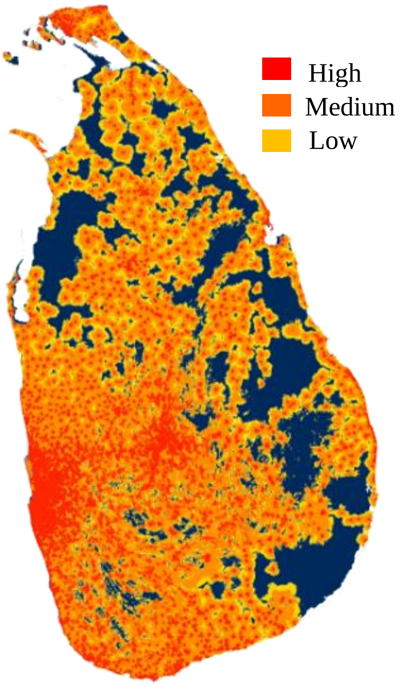

Fig. 4 Dialog coverage map in 2021

Further, we selected 20 different coordinates for various areas from both provinces. The areas and connected calls are depicted in the TABLE II.

TABLE II. CONNECTED CALLS

Area	Call Test
Remote Areas	10
Towns	18
Seaside	16
Tunnels	6

In the remote areas, 10 calls were connected successfully. In the towns and seaside, 18 and 16 calls were connected respectively. However, in the tunnels, the system was able to connect only 6 calls due to poor signal. In remote areas and tunnels the gadget experience poor connectivity. This system can be tested with various SIMs or any other specific radio frequency transmitters to avoid these connectivity issues.

V. CONCLUSION

The safety of track workers is a major concern for the railway industry nowadays. Unawareness of approaching trains causes many fatal accidents among the track workers community. Since the existing automated systems are complex and costly, track workers prefer the look-out method (manual) to alert the track workers. Our TrackWarn uses state-of-art CNN architecture to detect the trains and alert track workers via a phone call. The testing results of our CNN model shows the trains' sound and noises can be successfully classified with an accuracy of 92.46% within the 10m recording range from the railway track. Further, this outperforms the existing complex systems. Since this gadget is inexpensive and simple, anyone can handle it easily. Since this system contains a fail-safe mechanism, the failures in any components can be easily identified with the constant interval SMSs. In the future, we will use a keypad with an LCD to add dynamic numbers and to change the internal configurations. According to the Table II, some points in various areas have signal problems due to less coverage. With the use of appropriate SIM, multiple SIMs, or specific frequency transmitter, this problem can be solved in future. Further, the parallel call features will also be included for various SIMs to alert at the same time. We ensure the usage of this smart gadget will mitigate track workers' accidents and help to save the country's economy.

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