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Acoustic-based Emergency Vehicle Detection Using Convolutional Neural Networks

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ABSTRACT This work investigates how to detect emergency vehicles such as ambulances, fire engines, and police cars based on their siren sounds. Recognizing that car drivers may sometimes be unaware of the siren warnings of the emergency vehicles, especially when in-vehicle audio systems are used, such that they may block or even collide with the emergency vehicles. Therefore, we aim to develop an automatic detection system that determines whether there are siren sounds from emergency vehicles nearby to alert other vehicles' drivers to pay attention. We propose a convolutional neural network (CNN)-based ensemble model (SirenNet) with two network streams to classify sounds of traffic soundscape to siren sounds, vehicle horns, and noise, in which the first stream (WaveNet) directly processes raw waveform, and the second one (MLNet) works with a combined feature formed by MFCC (Mel-frequency cepstral coefficients) and log-mel spectrogram. Our experiments on a diverse dataset with the SirenNet showed a promising accuracy of 98.24%, also indicating that the raw feature can complement the MFCC and log-mel features in siren sound detection. Besides, the proposed system can work appropriately with the changeable input length; even with short samples of 0.25 seconds, it still yielded a high accuracy of 96.89%. The results of this work not only be able to help drivers reduce car accidents, but also provide a necessary safety function for autopilot systems.

INDEX TERMS Audio recognition, convolutional neural networks, emergency vehicle detection, siren sounds.

I. INTRODUCTION

Siren is a special signal sounded by alarm systems or emergency service vehicles such as fire trucks, police cars, and ambulances. When an emergency vehicle performs its task, the siren sound is issued to alert other drivers of an officer's need for the right of way on the road. Sometimes, private cars' drivers may not listen to nearby siren sounds due to the interference of the in-car audio signal, the modern car's soundproofing ability, or even the distraction of drivers themselves. This problem could lead to a delay in providing emergency services or even traffic accidents because of inappropriate communication and cooperation. Thus, this study proposes an acoustic-based method to detect the presence of emergency vehicles on the road. At this stage, we focus on the detection of siren sounds from standard emergency vehicles including ambulance and fire engine, and police car. In view of the fact that each country may have itself regulation on the types and frequency band of siren sounds, we aim to develop an emergency vehicle detection system (EVD) that has an excellent ability of generality, which can work stably under diverse siren types/specifications and traffic conditions. For practical applications, we roughly separate the traffic soundscape into three sub-source of sounds, including siren sounds, vehicle horns generated by ordinary vehicles, and noises. This consideration is particularly significant for the assessment of the system's reliability. More specifically, since vehicle horns and background noises are primary sources of the acoustic signal in the downtown street environment, the reliability of our proposed system can be partially assessed by not misidentifying vehicle horns and noises to siren sounds, and vice versa. Therefore, we deal with the EVD problem as classifying traffic sounds to siren sound, vehicle horn, and noise.

Generally, the siren sound is a sub-type of auditory danger signals standardized by the International Organization of Standard (ISO), and ISO 7731 [1] provides rough guidelines for alarm sounds. However, in reality, the

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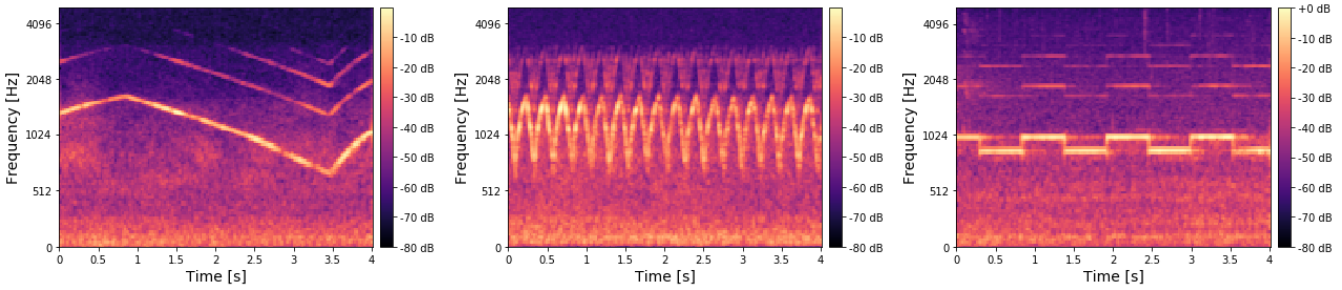

(a) (b) (c)

Fig. 1. Spectrograms of three examples of siren sounds: Wail (a), Yelp (b), and Two-tone siren (c).

regulation and standard for siren sounds are different from country to country; for instance, New Zealand and the USA generally adopt the similar types of wail, yelp, or phaser sirens while England commonly uses the two-tone pneumatic horn. In Taiwan, the frequency of fire trucks' siren sounds continuously changes from low-frequency 650-750Hz to high-frequency 1450-1550Hz, while the siren sounds of ambulances consist of two alternating tones, the first tone is 650-750Hz and the second tone is 900-1000Hz [2]. Similarly, Japanese law [3, 6] defines a different specification for the ambulance's siren sound, in which the sirens repeat two tones of 960 Hz and 770 Hz, and the repetition period is 1.3s. In Europe [7], the ambulances and fire vehicles use two tones of 392 Hz and 660 Hz, while 466 Hz and 622 Hz are two tones used for police cars. Fig. 1. shows the spectrograms of the three common types of siren sounds, including a Wail siren whose frequency changes continuously (Fig. 1(a)), a Yelp siren which changes the frequency more quickly (Fig. 1(b)), and a two-tone siren of two alternating tones (Fig. 1(c)). During our data collection, we found that Wail, Yelp, and two-tone sirens are the most common types of siren sounds used world-wide. In this work, we build the EVD system on the diverse datasets formed by different types of siren sounds and collected from various countries around the world, rather than training the system on the data recorded in a single country like in [4, 5, 11], so that the system can meet the requirement of generality.

The primary method applied to this work is audio recognition based on convolutional neural networks (CNN). In terms of data processing, we can roughly divide the techniques used in audio recognition into two broad categories; the first one generally applies audio feature engineering techniques to extract useful features in time-domain and/or frequency-domain before performing the recognition task, the second one is to take full advantage of deep neural networks to build an end-to-end recognition system which learns features directly from raw waveforms rather than extracting hand-crafted features. Each approach has its advantages and success when being applied to different works; however, for acoustics-based EVD problem, almost all works only rely on the first approach with the use of neural networks or shallow learning algorithms such as SVM, GMM, and k-NN. In this work, our idea is to apply both approaches and examine if it is possible to boost the system accuracy by aggregating models of these two approaches; in other words, we also examine if the features extracted by the deep neural network itself can complement the hand-crafted features in dealing recognition task or not.

The success in developing an acoustic-based EVD system can pave the way for many applications. The first example of its application is providing aid to hearing-impaired people in driving scenarios and even in daily activities. Specifically, in the real-world environment where the background noise is deafening, such a siren sound detection system can alert them of dangerous situations by converting the warning signals to appropriate messages such as text or flashlight. Apart from helping people who lost the hearing, the EVD system is also useful to alert drivers without hearing-problem of approaching emergency vehicles when they are unintentionally unaware of the warning signals. Besides, the automatic detection of emergency vehicles provides more function and a higher level of safety for driverless vehicles. Another application of the EVD system is that we can integrate it as a part of the intelligent transport system, for instance, integrating the siren detection into smart traffic light controlling system to give priority to direction with the presence of siren sounds by changing the light status and adjusting passing time accordingly.

The significant contribution of this work is that we provide a comprehensive study on acoustic-based EVD using CNN. We consider vital aspects of a reliable, stable detection system as follows. (1) In terms of experimental data collection, we consider the diversity of the data in order to achieve the generality of the detection system. We collect siren signals of emergency vehicles in real-world traffic from many countries in America, Europe, and Asia instead of considering a single country such as Taiwan [4], Italy [5], or the UK [8]. Partially, this is because of the difference in the specification of siren sounds among countries. Also, we collect data in various scenarios such as different traffic locations and weather conditions, different siren types, and even overlapped sirens. To our knowledge, the collection and consideration of an extensive siren sound

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dataset are first introduced in this work; especially the large dataset is collected in real-life environments where include different levels of noise, collection distances, and the Doppler Effect. (2) We propose a 2D-CNN model (MLNet) for EVD based on the combination of the MFCC log-mel spectrogram features. Our experiment results indicate that MLNet yields higher accuracy compared to the related works, which also proves that the aggregated features are beneficial for acoustic-based EVD. (3) We further develop an end-to-end 1D-CNN model (WaveNet) which automatically learns from raw waveform the useful features for classification, our experiment results also show the promising accuracy of this model. (4) We propose an ensemble architecture of MLNet and WaveNet to boost the detection accuracy and to prove the complementary relationship between the raw features and hand-crafted features in acoustic-based EVD. (5) Last but not least, the success of this work is a good fundamental for the applications listed above.

We organize the rest of this paper as follows. In Section II, we introduce the works related to acoustic-based emergency vehicle detection. Section III analyzes the methods we use for classifying the siren sounds, vehicle horns, and noises. Then, we present the experimental results in Section IV and provide a conclusion in Section V.

II. RELATED WORKS

Till now, there are only a few studies on the recognition of siren sounds, such as [4-15]. J. Liaw et al. proposed to recognize the ambulance siren sound in Taiwan by the Longest Common Subsequence (LCS) [4], such an LCS-based system yielded an accuracy of 85% on a small dataset. Another system based on typical speech recognition techniques was introduced in [5], in which MFCC was used together with multi-layer neural networks to detect the siren sounds through the voting method. The system in [5] relatively met the need of low-computational complexity, but it was lack of the analysis on various sources of noises and a diverse dataset, and it created the training and testing data by reproduction method. In [6], the detection of alarm sounds was investigated using two approaches including a multi-layer neural network system and a sinusoidal model system, in which the former relied on techniques borrowed from speech recognition, and the latter exploited the structure of alarm sounds and attempted to separate signal from the background to diminish the influence of noise interference. The two systems were tested on a small dataset, and both of them yielded similarly imperfect error rates.

In [7], the authors proposed to employ part-based models (PBMs), a method initially proposed in computer vision, in the spectro-temporal domain for detecting siren sounds in traffic noise. Evaluation with self-recorded police sirens and traffic noise collected on-line indicated the potential of applying PBMs to siren-based EVD. The PBMs approach demonstrated better results than hidden Markov models (HMMs) trained on MFCC or log-mel features, but its accuracy was lower than 90%. L. Marchegiani et al. [8] proposed a two-stage approach for acoustic-based EVD in smart vehicles, in which the first stage was to detect the presence of an abnormal sound, and the later stage involved noise reduction and classification. The framework in [8] borrowed the idea from image processing as it analyzed the spectrogram of the incoming signal as an image and employed spectrogram segmentation to isolate and extract the target signal from background noise. Utilizing the k-NN classifier on Empirical Binary Masks (EBM) generated after the noise-reduction step, the system yielded the highest accuracy of 83%, which is still far from a requirement for practical applications.

The vehicle classification system in [9] added siren detection as an extra function, and the detection process also heavily relied on the analysis of acoustic signals based on digital signal processing techniques, such as finding the main frequency components in a given frequency band. Since current emergency vehicles produce siren sounds with different specifications, the configuration in [9] could not be flexible to use in general scenarios. An alarm sound detection system based on SVM in combination with feature selection of hand-crafted features was proposed in [10]. It obtained an accuracy of more than 90% on evaluating the system's performance with a small dataset of 35 alarm sound samples and 35 background noise samples. This work was also lacking in evaluating the system's stability and the time cost of the feature engineering process on a massive dataset.

There are several works based on microcontrollers [11, 12, 13] and hardware design [14, 15] for siren sound detection. In [11], the ambulance's siren sound could be detected by employing two times Fast Fourier Transform (FFT) on a dsPIC microcontroller. Although this detection method could work even under the Doppler Effect, it was computationally expensive; averagely, it needed 8 seconds to make a single prediction. F. Meucci et al. [12] developed another microcontroller-based system that employed the frequency content and the periodic repetition characteristics of siren sound to implement a pitch detection algorithm suited for EVD. The system was designed and optimized only for two-tone siren of 392 Hz and 660 Hz, and the authors did not evaluate its performance on other siren types or two-tone siren with other parameters yet. A simple algorithm to detect siren sound using the linear prediction model for hearing-impaired drivers was presented in [13], in which the Durbin's recursive algorithm made predictions if the coefficients maintained within a preselected tolerance for a preselected time. Although we can quickly implement this algorithm on Texas Instrument TMS DSPs, it was concluded to be not foolproof and may result in false detection. R. Dobre et al. [14, 15] proposed low-computational methods for siren detection based on analog electronics circuits. The authors used SPICE to simulate the initial design [14] and its improved version [15] of the circuit block used for siren

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detection. The circuits were tested with a siren signal using the SPICE simulator and showed success in detection. However, it lacked the tests on a larger dataset and the evaluation on the real printed circuit board (PCB).

In general, the prior works on acoustic-based EVD and alarm sound recognition have both advantages and disadvantages. Their limitations include: (1) the limitation of experimental data, in which the authors only recorded small amount of recordings, used simulated data, or collected data in a single country only, this could lead to a low level of generality for acoustic-based EVD problem; (2) the use of shallow learning algorithms or microcontroller-based approaches results in imperfect performances and the stability of the systems was not thoroughly evaluated yet; (3) the effects of background noise on system performance was lacking or was not well evaluated; (4) in the prior works, the authors modeled audio data only using handcrafted time-domain and/or frequency-domain features, and no work directly employed raw data for recognition; (5) they did not consider or report the efficiency of systems according to different audio durations and the processing time. Recognizing this, we summed up and improved the above limitations by conducting comprehensive experiments on a larger dataset formed by the integration of our self-collected data and available standard datasets (UrbanSound8K [16] and ESC50 [17]). Moreover, inspiring by the recent success of neural networks in audio recognition, we propose using convolutional neural networks to handle this task. Primarily, we propose to directly use raw data of audio clips to train the networks.

III. ACOUSTIC-BASED EVD USING CNN

A. CNN for Audio Recognition

CNN has recently been employed for audio recognition problems successfully, such as in music tagging, environmental/urban sound classification [ESC] [18-21], and automatic speech recognition (ASR) [22, 23]. V. Boddapati et al. [18] explored the use of two well-known image recognition networks, Alexnet and GoogLeNet, for classifying environmental sounds. Those networks trained on audio's image-based representations, including spectrogram and MFCC, yielded classification accuracies up to 90%, indicating the potential of the [18] proposed approach. Works of J. Salamon et al. [19] and K. Piczak [20] also showed the possibility of CNN-based ESC. Training with log-mel spectrogram input, models in [19], and [20] attained similar accuracies smaller than 80%. In this work, we focus on using CNN for acoustic-based EVD problems, which employs the approach applied in image classification together with the idea of training CNN with raw audio waveforms.

CNN is partially similar to conventional deep neural networks, but it uses additional layers, namely convolutional layers and pooling layers, instead of only using a series of fully-connected layers. A CNN in classification task contains two major components, feature learning and classification. In the first component, a series of convolutional layers learn appropriate representation or useful features from the input; thus, we can consider this part as the feature extraction stage. In the later part, fully-connected layers play the role of a classifier, which processes the extracted features and assigns the probability to each class for making the prediction.

Generally, during the training phase, a CNN of L layers approximates the relationship between all input-output pairs $(\mathbf{x}, \mathbf{y})$ of the training dataset. The approximation can be described by Eq. (1), in which the operation of the l^{th} $(l = 1, 2, ..., L)$ convolutional layer is expressed by Eq. (2), where $\mathbf{W}^{(l)}$ is a set of kernels used for extracting useful features from the input, and $\otimes$ indicates the convolutional operation. For the stacked fully connected layers customarily added at the end of a CNN model, they can be described by Eq. (3), where $\mathbf{W}^{(l)}$ is the weight matrix. In both convolutional layer and fully connected layer, $\mathbf{b}^{(l)}$ and $f^{(l)}$ are respectively the bias vector and the activation function of in the l^{th} layer. At the input layer $(l = 0): \mathbf{a}^{(0)} = \mathbf{x}$. Lastly, placing at the end of the model is an output layer that has the number of neurons equal to the number of classes. The optimization problem of the CNN is to minimize the value of loss function computed from the difference between predicted output $\hat{\mathbf{y}}$ and ground-truth $\mathbf{y}$. Accurately, during the training process, the parameters of CNN are updated and optimized according to the back-propagated prediction error to reach the appropriate minima of the loss function.

$$\mathbf{y} \approx \hat{\mathbf{y}} = g^{(L)}(g^{(L-1)}(...(g^{(2)}(g^{(1)}(\mathbf{x}))))) \quad (1)$$

$$\mathbf{a}^{(l)} \triangleq g^{(l)}(\mathbf{a}^{(l-1)}) = f^{(l)}(\mathbf{W}^{(l)} \otimes \mathbf{a}^{(l-1)} + \mathbf{b}^{(l)}) \quad (2)$$

$$\mathbf{a}^{(l)} \triangleq g^{(l)}(\mathbf{a}^{(l-1)}) = f^{(l)}(\mathbf{W}^{(l)}\mathbf{a}^{(l-1)} + \mathbf{b}^{(l)}) \quad (3)$$

Intuitively, there are two approaches to organizing audio input for CNN models. Firstly, since the CNN conventionally works with image data, we can organize the audio data by 2D arrays to feed into the 2D-CNN model. With this consideration, we represent audio data by its spectrogram, a representation of the audio frequency spectrum over time, or by MFCC features extracted from sub-frames of an audio file. The second approach is in the case we employ 1-dimensional CNN, in which we should organize the input as 1D arrays. Thus, we can directly feed raw data of the audio signal to the 1D-CNN model, or we can extract hand-crafted features from the audio signal and represent them as a 1D arrays before feeding them to the model. In this work, we propose to use raw data of audio waveform as the input of the 1D-CNN model rather than organizing handcrafted features in the 1D format.

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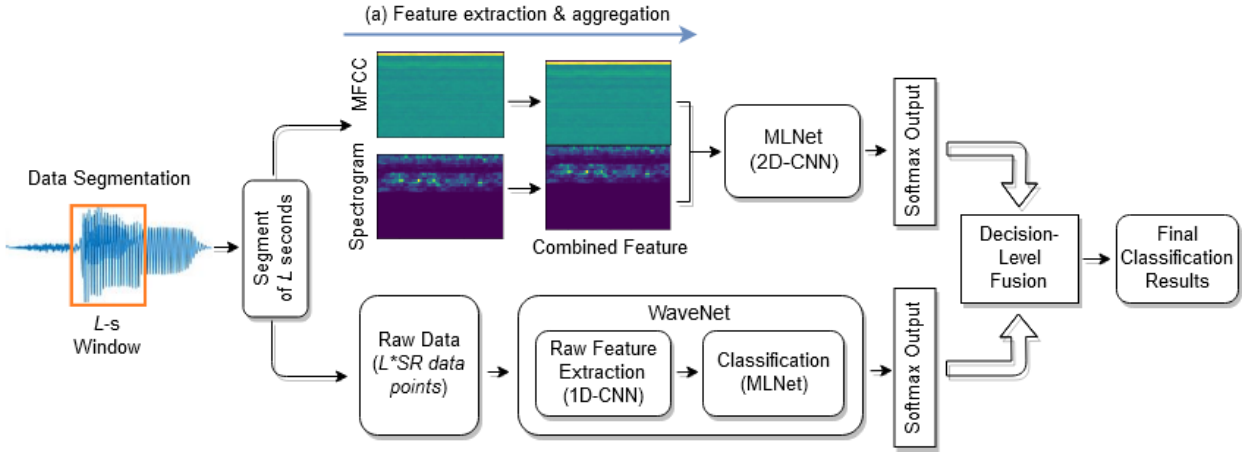

Fig 2. The framework of the CNN-based ensemble model (SirenNet) for acoustic-based EVD.*SR* is the sampling rate.

B. SirenNet: The proposed CNN-based Ensemble Model for Acoustic-based EVD

With an assumption that the features directly learned from raw waveforms and handcrafted features like MFCCs and log-mel spectrogram may contain different patterns and information of a given sound, we explore the complementary relationship between these kinds of features by building an CNN-based ensemble model based on these two feature inputs and assessing the proposed model's performance in classifying siren sounds, vehicle horns, and noises. Such an ensemble model is called SirenNet, as presented in Fig. 2. The proposed architecture consists of two parts: a 2D-CNN stream and a 1D-CNN stream, which are referred to as MLNet and WaveNet, respectively. The WaveNet works directly with raw waveform, while the MLNet is trained with aggregated features formed by image-based features (MFCC, and log-mel spectrogram). Then, the prediction results (softmax values) derived from MLNet and WaveNet are combined using the averaging method to make the final predictions.

As a necessity for building the network, the length of the input samples must be equal. However, since the collected data have various lengths, we have to split the original audio signal to fixed-length samples before feeding them to the network, as shown in Fig. 2. During the training phase, using a sliding window of size L-s (L seconds) and stride of (L-s/2), we separate the original raw waveform into segments of L seconds and use them as the fixed-length inputs. At each training epoch, we select different segments of the same recording, but the segments have the same label. This process naturally increases the number of training samples so that it also plays the role of sample-level data augmentation. We test the network using the majority voting approach, in which we also split a test sample to various fixed-length segments and then input them to the network and perform majority voting of the predictions corresponding to all input segments to obtain the final prediction result.

Finding a suitable length for the input samples is also a vital factor in training the acoustic-based EVD system because the input duration directly affects the network's computational demand and prediction performance. If the input has too small length, it may not contain sufficient information for classification, resulting in low classification accuracy. On the other hand, if the input length is overly long, it results in a high dimensionality of the input, leading to the higher computational cost for training the model. Thus, this work also investigates the suitable audio length for acoustic-based EVD problems, which partially contributes to building an efficient EVD system.

1) Image Recognition Approach with 2D-CNN (MLNet) and Aggregated Features

We apply the advantages of CNN in image recognition for acoustic-based EVD by employing 2D-CNN to classify audio signals based on their 2D representations consisting of the log-mel spectrogram (log-mel feature) and the MFCC. Many auditory features have been introduced for audio recognition applications [24]. However, we only consider those two well-known features instead of diving into many handcrafted features. MFCC feature takes into account the nonlinear frequency resolution, which can simulate the hearing characteristics of human ears, while the spectrogram shows the change in frequency components of an audio signal over time. Thus, these two auditory features may provide useful representation for siren recognition. Also, it has been proven by several studies that feature aggregation can help to improve the accuracy in audio recognition, such as in ESC [25], ASR [26-28], and breath-based person identification [29]. Inspiring by the success of those works, we explore the efficiency of feature combinations in this work. We combine log-mel features and MFCCs of an audio signal into a single feature map before feeding into the 2D-CNN network, as shown in Fig. 2(a). The combination of the two features is conducted linearly.

We use librosa [30], a python library for audio signal processing, to extract MFCCs and log-mel features. For each data sample, we select fixed-length segments of L seconds. Then, the corresponding MFCCs and log-mel features of those segments are computed. Each data segment is divided into 50% overlapping frames of 23 ms,

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resulting in 65 frames for a segment of 1.5 seconds and a sampling rate of 22.05 kHz. Next, 40 MFCCs and 64 log-mel features are extracted from each frame. Accordingly, we can represent MFCCs and log-mel features as matrixes of sizes 40×65×1 and 64×65×1 corresponding to frequency×time×channel, so that the combined feature is a 104×65×1 matrix. The proposed MLNet is presented in Table VI and Table VIII, and we discuss detail about the design of this model in Section IV.

2) The end-to-end System with 1D-CNN (WaveNet)

We propose to build an end-to-end model (WaveNet) for acoustic-based EVD. The advantage of this model is that it can automatically learn from the raw audio signal discriminative representations, bringing about a promising performance of the EVD system. EnvNet in [31] partially inspires the design of the proposed WaveNet, and Table VIII presents the architecture of WaveNet, indicating that this model has two parts consisting of raw feature extraction with a series of 1-dimensional convolutional layers (1D Conv-layers), and the remaining part is for classification. For the 1D Conv-layers in the former part, $\mathbf{W}^{(l)}$ in Eq. (2) is a set of 1D kernels employed for transforming raw waveforms into useful features, which are also the input of the network's later part. Conceptually, the first 1D Conv-layer is responsible for catching the global view of the raw waveform and extract the local features, while the remaining 1D Conv-layers play the role of getting a more in-depth view of the data to find the useful discriminative features for the classification task.

For the classification part, our idea is to use the optimized MLNet as the classification part of WaveNet because we regard and process the features extracted by 1D Conv-layers as time-frequency representation such as log-mel spectrogram. In doing so, we set the number of filters of each 1D Conv-layer to 64, which are conceptually the same as the number of components of the log-mel spectrogram. More specifically, in our assumption, each filter is associated with a frequency characteristic. We process the output of the last 1D Conv-layer with a non-overlapping pooling layer of size 220, which is approximately equivalent to 10ms when the sampling rate is 22.05 kHz, resulting in an output matrix of size 64×150×1 corresponding to frequency×time×channel if the input segment is 1.5 seconds. From this point forward, WaveNet works similarly to MLNet trained with MFCC and/or log-mel features. We provide the detail configuration of WaveNet in section IV.

IV. EXPERIMENTS AND RESULTS

A. Experimental Data

Our experimental dataset contains three sound classes of the siren, vehicle horn, and noise. In collecting the dataset, we set several goals and requirements. Firstly, all data must be real-field recordings captured in road traffic or urban environments, rather than using simulated data. Secondly, the dataset must meet the need for quantity and diversity in building deep neural networks, so it should be adequately vast and varied in terms of sound's specification and recording conditions. To reach those two primary goals, we turn to four collection approaches: (1) we collect data from on-line resources which professionally provide audio/video clips of emergency vehicles, (2) integrating with published datasets which contain siren sounds and others related to urban soundscape, (3) directly capturing data while driving in Taiwan, (4) reproducing the sound class which is hard to collect a large amount.

For the first approach, thanks to the availability of videos on two Youtube channels including "TGG - Global Emergency Responses" [32] and "[rescue911.de] - Worldwide Emergency Responses" [33], which provide a large number of videos about emergency responses recorded all over the world, we have access to a diverse database of siren sounds of police cars, fire engines, fire ladder cars, ambulance cars, and police motorcycles. Notably, the channels' owners have captured videos from many areas, including in America (the USA, Canada, Cuba), in Europe (England, Germany, Scotland, Netherlands, Belgium), and Asia (Vietnam, Taiwan, Hong Kong, Singapore, Korea, Japan, and China). Besides, various siren types such as wail, yelp, and phaser horn are all included, and they can be operated solely or simultaneously. Also, they recorded data both inside and outside the cars traveling at various speeds so that the collected data also included Doppler Effect. For the second collection approach, we integrated our collected data with two datasets published in [16, 17], which respectively contain 8732 and 2000 environmental/urban sound clips. Next, we captured real siren, horns, and road noise in Taiwan's streets. Lastly, for vehicle horns, because the amount of this class is less than its two counterparts, we augmented the data by reproducing different recordings of horns and recording them at different scenarios, involving various distances and noise levels.

Table I. Summary of our experimental data.

Data Class	Data Sources			
	Our Collection	UrbanSound8K [16]	ESC-50 [17]	*Total (no. samples)*
Siren Sounds	7,773	929	40	8,742
Car Horns	7,083	429	40	7,552
Urban Noise	1,087	7,374	1,920	10,381
Total (no. sample)	15,943	8,732	2000	26,675
Total duration	17.7 hours	9.7 hours	2.8 hours	30.2 hours
Length of each clip	4 seconds	1-4 seconds	5 seconds	-
Sampling rate	44.1 kHz	8-192 kHz	44.1 kHz	-

To organize the experimental data, we randomly stored original recordings to 5 folds, in which each fold had a relatively equal amount of audio length across all three classes. We carefully conducted this five-fold separation in order to avoid the problem of overfitting when building the system using k-fold cross-validation because the recordings

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for training are entirely different from those for testing. For the data extracted from video clips [32, 33] and our real-field recordings, we split them into smaller non-overlapping 4-s clips, resulting in 15,943 data samples, as shown in Table I. By integrating with data of [16, 17] we end up with a dataset of 26,675 samples. Although [16, 17] contain small amount of horns and siren sounds, they provide the diversity for the noise class, many useful subsets of urban noise such as drilling, engine idling, jackhammer, street music [16], natural soundscapes, human-non-speech sounds, and exterior/urban noises [17] are available. On the other hand, our collected data provides a large number of horns and siren clips. From the figures in Table I, it is clear that our collected data complement the data from [16, 17] to create a relatively sizeable balanced dataset.

B. Experiment Setup

The experimental data was integrated from different sources, resulting in different properties among data samples, such as various sampling rates, one or two channels, and coding in different bit-depth. Thus, the preprocessing stage is required to standardize our data so that it benefits the experimental process. If an audio sample is stereophonic, we converted it into a monophonic signal by taking the average values of the signal amplitudes of each channel. Also, we resampled all recordings at a specific sampling rate. The resampling, monophonic conversion, and the extraction of spectrograms and MFCCs were conducted using Librosa [30], a python library for audio and music analysis.

In our experiments, we utilized a desktop PC built with 16 GB RAM, an Intel Core i7-9700K CPU (8 cores @3.60 GHz), and NVIDIA GeForce GTX 2080 Ti. The PC was running Ubuntu 18.04.2 LTS, and we used the TensorFlow deep learning framework to implement the network designs. The baseline setup for feature extraction parameters and the network hyper-parameters are listed as follows: sampling rate is 22.05 kHz; frame length of 23ms; the percentage of frame overlap is 50%; 50 training epochs; the initial learning rate is 0.001; and we trained the models with Adam optimizer, a variant of Stochastic Gradient Descent [35]. We evaluated the proposed models using the k-fold cross-validation scheme, and classification accuracy was the primary evaluation metric.

We conducted several experiments and reported the results in the next sections. We carried out an initial experiment to find appropriate parameters for later experiments. Then, we show the results of the proposed MLNet, WaveNet, and SirenNet. Also, we provide an analysis of experimental results and a comparison between this work and the prior works.

C. Initial Experiment

This initial experiment was a pilot investigation on the potential of end-to-end architecture, the efficiency of features aggregation, and suitable parameters, including input duration and sampling rate for the acoustic-based EVD. Consequently, we used the best parameters obtained from this experiment as the standard setup for the later experiments. Respectively, we call the WaveNet and MLNet with initial configurations as init-WaveNet and init-MLNet. We compared the accuracies of those networks according to different input lengths, including 0.25s, 0.5s, 1s, 1.5s, 2s, and 3s, to find the suitable one for classification. We did not consider the longer durations such as 4s, 5s for three main reasons: (1) in terms of real-life EVD application it is not practical to use such a long input because it obviously leads to prolonged response; (2) almost all samples of our experimental data are shorter than 4s, especially data from [16], the use of padding technique when building the model may cause the decrease in the accuracy, which has been shown in [31]; (3) it is computational expensive as it took too much time when we tried to train a WaveNet with input duration of 5s. In this experiment, we also considered different sampling rates (*SR*), in which the candidates for *SR* were 22,050 Hz, 16,000 Hz, and 8,000 Hz because these values of *SR* were commonly used in the field of audio recognition.

Table II. The configuration of the init-WaveNet. (*SR* = 22.05 kHz, and *L*-s = 1.5s)

Layer	Kernel size	Stride	Number of filters	Output shape (channel-last)
Input (*Raw data*)	-	-	-	(1, 33075, 1)
1D Conv1	(1, 8)	(1, 1)	64	(1, 33075, 64)
1D Conv2	(1, 8)	(1, 1)	64	(1, 33075, 64)
Pool1	(1, 220)	(1, 1)	-	(1, 150, 64)
Reshape	-	-	-	(1, 64, 150, 1)
2D Conv3	(4, 4)	(2, 2)	32	(1, 64, 150, 32)
2D Conv4	(4, 4)	(2, 2)	32	(1, 64, 150, 32)
Pool2	(2, 2)	(2, 2)	-	(1, 32, 75, 32)
Flatten	-	-	-	(1, 76800)
Fc1	-	-	512	(1, 512)
Fc2	-	-	64	(1, 64)
Output(#classes)	-	-	3	(1, 3)

For the initial configuration of WaveNet, we used two 1D Conv-layers with a filter size of 8 and stride of 1 for the raw feature extraction part, followed by two 2D Conv-layers with 4×4 receptive field and stride of 2×2, and two fully-connected layers in the classification part. The detail configuration of the init-WaveNet is presented in Table II. As we analyzed in section III.2.b, we considered the features extracted by 1D Conv-layers as time-frequency representation, so we reshaped and presented the output of those layers as (frequency, time, channel). Note that the network configuration and data processing technique were fixed for the whole initial experiment regardless of the change in sampling rate and input duration. The configuration of the init-MLNet is shown in Table III, in which we simplified the network with two 2D convolutional layers and two fully-connected layers. The output shape shown in Table II and Table III is in the case we apply the sampling rate of 22.05 kHz, and the input duration of 1.5 seconds.

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Table III. The configuration of the init-MLNet. *SR* = 22.05 kHz, *L-s* = 1.5s, and input is the combined feature.

Layer	Kernel size	Stride	Number of filters	Output shape (channel-last)
Input (*MFCC+log-mel*)	-	-	-	(1, 104, 65, 1)
2D Conv1	(4, 4)	(2, 2)	32	(1, 104, 65, 32)
2D Conv2	(4, 4)	(2, 2)	32	(1, 104, 65, 32)
Pool1	(2, 2)	(2, 2)	-	(1, 52, 32, 32)
Flatten	-	-	-	(1, 53248)
Fc1	-	-	512	(1, 512)
Fc2	-	-	64	(1, 64)
Output(#classes)	-	-	3	(1, 3)

Table IV. Performance of the init-WaveNet according to different sampling rates and input lengths.

Sampling rate	Input length (s)					
	0.25	0.5	1	1.5	2	3
22,050 Hz	91.76 (0.10)	92.19 (0.54)	92.89 (0.11)	93.99 (0.26)	94.70 (0.28)	94.79 (0.25)
16,000 Hz	88.95 (0.21)	90.84 (0.38)	92.31 (0.33)	93.89 (0.31)	94.41 (0.16)	94.69 (0.12)
8,000 Hz	89.20 (0.31)	90.71 (0.13)	92.87 (0.29)	93.91 (0.36)	94.73 (0.10)	94.28 (0.30)

Table V. Performance of init-MLNet and init-WaveNet according to different input lengths in case *SR* of 22.05 kHz.

Model (Feature)	Input length (s)					
	0.25	0.5	1	1.5	2	3
init-MLNet (log-mel)	78.58 (1.42)	80.54 (1.16)	85.24 (1.72)	91.18 (0.39)	92.15 (0.42)	92.56 (1.41)
init-MLNet (MFCC)	87.30 (0.54)	88.78 (0.63)	88.88 (0.77)	89.71 (0.67)	89.55 (0.98)	90.67 (0.61)
init-MLNet (MFCC+log-mel)	91.21 (0.55)	92.07 (0.53)	92.80 (0.49)	94.26 (0.51)	94.17 (0.36)	94.48 (0.96)
Init-WaveNet (Raw data)	91.76 (0.10)	92.19 (0.54)	92.89 (0.11)	93.99 (0.26)	94.70 (0.28)	94.79 (0.25)

The performance of the init-WaveNet with respect to different input durations and sampling rates are provided in Table IV. We performed 5-fold cross-validation in all experiments, so we provide the results with the average accuracy (%) and the standard deviation. From Table IV, we can see that with each input length of 1s, 1.5s, 2s, and 3s, the results of init-WaveNet for *SR* of 22.05 kHz are slightly higher than that of the two remaining sampling rates. However, for the shorter input durations of 0.25s and 0.5s, the init-WaveNet working with the *SR* of 22.05 kHz yielded much better performance compared to the results of experiments on the *SR* of 16 kHz and 8 kHz, by approximately 2.5% and 1.5% respectively. Thus, we decided to choose 22.05 kHz as the default sampling rate for the later experiments. In the following experiments, we tested MLNet trained on MFCC and/or log-mel features with the *SR* of 22.05 kHz. The experiment results are summarized in Table V.

For the input duration, as shown by statistics in Table IV and Table V, the accuracy generally tends to improve proportionally according to the increase in the length of the input waveform, this is true for all three values of sampling rates and both init-WaveNet and init-MLNet. We assume that the longer the original raw input, the more useful information provided to the network, resulting in better performance. However, the accuracy is at a high level when the input length ranges from 1.5s to 3s, and there is no significant gap in accuracy among this range. From this point of view, we choose the input length of 1.5s for system development due to the following reasons: (1) it still yields comparable accuracies compared with results of much longer input durations (2s and 3s); (2) we assume that such a duration is sufficient for representing the characteristics of siren sounds, especially two-tone siren and yelp siren which normally have the cycle of around 1s so that a sample of 1.5s can provide enough information for classifiers.

Results in Table V also show the efficiency of feature aggregation for init-MLNet; in other words, MFCC can complement the log-mel feature in acoustic-based EVD. Specifically, init-MLNet trained on the aggregated feature (MFCC+log-mel) yielded much better results than that of this model trained on a single feature, MFCC, or log-mel feature. For example, at the input length of 1.5s, the init-MLNet (MFCC+log-mel) reached an accuracy of 94.26%, which is much higher than that of init-MLNet (log-mel) and init-MLNet (MFCC), by 3.08% and 4.55%, respectively. Last but not least, the initial experiment also presents the potential of WaveNet. Across all input lengths, the performance of init-WaveNet was better than that of init-MLNet trained on MFCC or log-mel features, in which init-WaveNet yielded higher average accuracies and smaller standard deviations compared to that of init-MLNet, as shown in Table V. Considering the input length of 1.5s, init-WaveNet (raw data) yields an accuracy of 93.99%, which is respectively 2.81% and 4.28% higher than the results of MLNet (log-mel) and MLNet (MFCC).

D. Results and Analysis

1) The Proposed MLNet

It is essential to find a suitable number of convolutional layers and appropriate parameters for a network to maximize its performance. Thus, we conducted a series of experiments to investigate the influence of different numbers of 2D convolutional layers on the performance of the MLNet. As a result, we can choose a suitable architecture for the proposed MLNet applied to acoustic-based EVD. We consider the number of convolutional layers up to 6 because, with this configuration, the output of the last convolutional layer already reaches a small size. Also, since the amount of data for training is not large enough, the use of deeper architectures may lead to significant overfitting. Note that the standard configuration to all network versions is that we apply batch normalization to each layer to speed up the computational process, and we set a dropout of 0.5 for the fully-connected layers in order to avoid overfitting. In all convolutional layers, we use the receptive field of 4×4, and we set the stride step to 2×2. Table VI shows the list of layers, memory cost, and the number of parameters of MLNet models with 2, 3, 4, 5, 6 convolutional layers, respectively.

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Table VI. Parameters and memory cost of MLNet with the different numbers of 2D convolutional layers.

Layer	2 Conv-layers	3 Conv-layers	4 Conv-layers	5 Conv-layers	6 Conv-layers
	#Parameters (memory)	#Parameters (memory)	#Parameters (memory)	#Parameters (memory)	#Parameters (memory)
Input (104, 65, 1)	0 (6.7 K)	0 (6.7 K)	0 (6.7 K)	0 (6.7 K)	0 (6.7 K)
Conv 4×4 – 32	544 (216.3 K)	544 (216.3 K)	544 (216.3 K)	544 (216.3 K)	544 (216.3 K)
Conv 4×4 – 32	16.4 K (216.3 K)	16.4 K (216.3 K)	16.4 K (216.3 K)	16.4 K (216.3 K)	16.4 K (216.3 K)
Conv 4×4 – 64	-	32.8K (106.4 K)	32.8K (106.4 K)	32.8K (106.4 K)	32.8K (106.4 K)
Conv 4×4 – 64	-	-	65.6 K (106.4 K)	65.6 K (106.4 K)	65.6 K (106.4 K)
Conv 4×4 – 128	-	-	-	131 K (53.2 K)	131 K (53.2 K)
Conv 4×4 – 128	-	-	-	-	262 K (53.2 K)
Fc-512	27.2 M (512)	13.6 M (512)	13.63 M (512)	6.8 M (512)	6.8 M (512)
Fc-64	32.8 K (64)	32.8 K (64)	32.8 K (64)	32.8 K (64)	32 K (64)
Output-3	195 (3)	195 (3)	195 (3)	195 (3)	195 (3)
Total parameters	27.3 M	13.7 M	13.8 M	7.1 M	7.3 M
Total memory	440 K	546 K	653 K	705 K	759 K

Table VII presents the experimental results of models with respect to different numbers of convolutional layers. It can be seen from Table VII that MLNet working with aggregated feature (MFCC+log-mel) yields the highest average accuracy of 96.42% when it is configured with four convolutional layers, this result is higher than that of models with 2, 3, 5, and 6 convolutional layers by 2.16%, 1.73%, 1.33%, and 1.81%, respectively. It also indicates that using deeper architectures does not result in better performance. As a result of this investigation, we design our proposed MLNet with four convolutional layers and two fully-connected layers, as presented in Fig.3 and Table VI. Moreover, in terms of memory cost, it requires a small amount of memory (653 K) to train the proposed MLNet.

Table VII. The results of MLNet configured with different numbers of convolutional layers. (SR=22.05 kHz, *L-s* = 1.5s)

Models (Aggregated feature)	**Accuracy** (std. deviation)
MLNet with 2 Conv-layers	94.26 (0.51)
MLNet with 3 Conv-layers	94.69 (0.48)
MLNet with 4 Conv-layers	**96.42** (0.45)
MLNet with 5 Conv-layers	95.09 (0.32)
MLNet with 6 Conv-layers	94.61 (0.85)

Table VIII. The configuration of the WaveNet, including MLNet used as classification part. (SR = 22.05 kHz, and L-s = 1.5s)

	Layer	Kernel size	Stride	Number of filters	Output shape (channel-last)
Raw feature extraction	Input (*Raw data*)	-	-	-	(1, 33075, 1)
	1D Conv1	(1, 64)	(1, 1)	64	(1, 33075, 64)
	1D Conv2	(1, 64)	(1, 1)	64	(1, 33075, 64)
	Pool1	(1, 220)	(1, 1)	-	(1, 150, 64)
	Reshape	-	-	-	(1, 64, 150, 1)
Classification (MLNet)	2D Conv3	(4, 4)	(2, 2)	32	(1, 64, 150, 32)
	2D Conv4	(4, 4)	(2, 2)	32	(1, 64, 150, 32)
	Pool2	(2, 2)	(2, 2)	-	(1, 32, 75, 32)
	2D Conv5	(4, 4)	(2, 2)	64	(1, 32, 75, 64)
	2D Conv6	(4, 4)	(2, 2)	64	(1, 32, 75, 64)
	Pool3	(2, 2)	(2, 2)	-	(1, 16, 37, 64)
	Flatten	-	-	-	(1, 37888)
	Fc1	-	-	512	(1, 512)
	Fc2	-	-	64	(1, 64)
	Output(#classes)	-	-	3	(1, 3)

2) The proposed WaveNet

Recall that WaveNet has two parts, including a part for raw feature extraction using 1D-CNN and the other part for classification based on 2D-CNN, as shown in Fig. 2. Since we process the feature extracted from raw waveforms as time-frequency representation, we propose to directly use the proposed MLNet as a classification part of WaveNet. Consequently, in this experiment, we aim to find a suitable configuration for the feature extraction part of WaveNet, involving finding a suitable number of 1D Conv-layers and the appropriate filter size. We conducted experiments with the data of 1.5s length sampled at 22.05 kHz, and the networks were configured with 1, 2, 3, and 4 1D Conv-layers in the raw feature extraction part, respectively. Besides, the filter sizes of 4, 6, 8, 16, 32, 64, 128, and 256 were separately applied to each model. The number of 1D Conv-layers was limited to 4 also to avoid overfitting when training models with our moderate dataset. At each layer, we used 64 filters and stride step of 1. We set the pooling size of the max-pooling layer used at the *last* 1D Conv-layer to 220 so that we obtain the feature map of size 64×150×1 corresponding to time frequency×time×channel.

Table IX. The results of WaveNet with different numbers of 1D Conv-layers. (*SR*=22.05 kHz, *L*-s = 1.5s)

Filter size	Number of 1D convolutional layers			
	1 Conv-layer	2 Conv-layers	3 Conv-layers	4 Conv-layers
4	84.58 (4.17)	90.47 (2.46)	93.78 (0.45)	93.51 (0.68)
6	85.80 (2.30)	92.53 (1.87)	93.82 (0.74)	94.40 (0.37)
8	89.20 (0.97)	94.41 (0.68)	94.64 (0.78)	94.12 (1.05)
16	91.74 (0.65)	94.73 (0.54)	95.03 (0.26)	94.83(0.75)
32	92.20 (1.69)	95.37 (0.95)	**95.95 (0.50)**	**95.48 (0.33)**
64	94.88 (0.61)	**96.51 (0.31)**	95.47 (0.27)	95.38 (0.53)
128	**95.35 (0.41)**	95.50 (0.53)	94.57 (0.46)	93.81 (0.39)
256	94.49 (0.27)	94.67 (0.37)	90.96 (0.65)	90.59 (0.53)

We summarize the results of this investigation in Table IX. We found a common trend that across different numbers of 1D Conv-layers, the classification accuracies are improved when the filter size is increased up to a specific value. However, when the number of convolutional layers becomes more extensive, the models tend to reach

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the highest accuracy with the smaller filter sizes, and the accuracies start to drop when the models have significantly large filter sizes, of 128, 64, 32, and 32 respectively for models with 1, 2, 3, and 4 convolutional layers.

Another vital observation is that WaveNet configured with more 1D Conv-layers performs better than the network with a single-convolutional layer. More specifically, in the case of one layer, we achieve the highest accuracy of 95.35% when the filter size is 128. For the case of two and three layers, the accuracy reaches the highest values when the filter size is 64 (96.51%) and 32 (95.95%), alternatively. However, the deeper model with four Conv-layers yields lower accuracies compared to that of 2 and 3 Conv-layer models. We suppose that the convolutional operations of two and three Conv-layer models respectively with filter sizes of 64 and 32, can adequately extract the most useful features for classification, and when the model is deeper (four 1D Conv-layer), it starts to overfit.

As a result, we decided to configure the raw feature extraction part of the proposed WaveNet with two convolutional layers and the filter size of 64, as shown in Table VIII, and the remaining part of WaveNet is the proposed MLNet. Notably, with the same configuration of two 1D Conv-layers and the filter size of 8, the model using MLNet for classification yields a higher accuracy of 94.41% by 0.42% compared to the result (93.99%) of the model with the initial configuration (init-WaveNet). This fact indicates that the idea of processing features extracted by 1D-CNN as time-frequency format and classify them by MLNet is practically efficient.

3) Results of the proposed Ensemble Model (SirenNet) and Analysis

Next, we evaluated the performance of the proposed SirenNet (Fig. 2) to prove the complementary relationship between the raw features and handcrafted features, including MFCC and log-mel spectrogram. For every sample, we calculated the predictions of each network stream (MLNet and WaveNet). After that, we averaged the softmax outputs from these two streams to obtain the final classification result. We summarize the results of SirenNet in Table X and a confusion matrix in Table XI, in which Table X also provides information about the model's loading time and inference time. From the statistics of Table X, it is clear that SirenNet achieved a promising accuracy of 98.24%, which is higher than the results of WaveNet and MLNet by 1.75% and 1.85%, separately. This result indicates that raw features learned by WaveNet have the capability of complementing MFCC and log-mel features in acoustic-based emergency vehicle detection. Also, with such a high accuracy, the SirenNet is auspiciously applied to real-world applications, which is one of the significant contributions of this work. For the utilization time, we can see that the time cost of MLNet (11 ms) and WaveNet (14 ms) are almost comparable and acceptably low. In the case of ensemble architecture, although the time cost of this model (27 ms) almost doubles that of the single networks, the inference time of SirenNet is still short enough for real-time operation of the EVD system.

Table X. Results of the SirenNet and comparison to single networks.

Model	Accuracy (%)	Model loading time (s)	Inference time (s)
SirenNet (Raw data, MFCC+log-mel)	98.24 (0.36)	0.805	0.027
WaveNet (Raw data)	96.51(0.31)	0.389	0.011
MLNet (MFCC+log-mel)	96.42 (0.45)	0.415	0.014

From the confusion matrix in Table XI, we can see the detail about the rates of correct prediction and misclassification across three sound classes. The misclassification rates between siren sounds and vehicle horns are meager, which is 0.44%, and 0.11%, respectively. This result shows the advantage of SirenNet since there is little probability of predicting the sound of ordinary vehicles as siren sounds of emergency vehicles and vice versa. Meanwhile, the significant misclassifications were made between sirens or horns with noise, in which 1.35% of sirens and 1.67% of horns are predicted as noise, this could be resulting in by the recordings of sirens and horns with heavy noise.

Table XI. Normalized confusion matrix obtained by testing the SirenNet on the dataset of 1.5s length.

True Class	Predicted Class		
	Sirens	Horns	Noise
Sirens	0.9854	0.0011	0.0135
Horns	0.0044	0.9789	0.0167
Noise	0.0104	0.0074	0.9822

We also evaluated the efficiency of the proposed SirenNet, WaveNet, and MLNet when they worked with data samples shorter than 1.5s. We summarize the results of this evaluation in Table XII. Notably, the proposed models show excellent performances, even working with short input durations of 1s, 0.5s, and even 0.25s. Across those three cases of input length, the optimized WaveNet and MLNet yielded much higher accuracies compared to the results of networks with *initial* configurations and trained with longer input length of 1.5s; this also results in high accuracies of the ensemble model (SirenNet). The results of SirenNet are 97.74%, 97.42%, and 96.89% respectively for input lengths of 1s, 0.5s, and 0.25s. It is clear that even with concise recordings such as 0.25 second where the performances of single networks start to degrade significantly, 92.20 % for WaveNet and 94.47% for MLNet (MFCC+log-mel), the SirenNet still yields a high accuracy of 96.98%, only 1.35% lower than the result of experiment on the data of six times longer (1.5s). This result further confirms the efficiency of the proposed SirenNet.

Table XII. Results of the proposed models on different input durations.

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Model	Input Length (s)			
	1.5	1	0.5	0.25
SirenNet (Raw data, MFCC+log-mel)	98.24 (0.36)	97.74 (0.79)	97.42 (0.39)	96.89 (0.57)
WaveNet (Raw data)	96.51 (0.31)	95.59 (0.32)	94.43 (0.51)	92.20 (0.65)
MLNet (MFCC+log-mel)	96.42 (0.45)	95.49 (0.16)	95.37 (0.46)	94.47 (0.59)

At last, we compared the results of our work with that of several existing related works listed in the literature review section. Some works based on microcontrollers [11-13] and circuit design [14, 15] only reported the possibilities of siren detection systems, and they did not evaluate the system's accuracy on an extensive dataset, so we only focused on the comparison with works based on machine learning or deep learning approaches. Table XIII shows the comparison between our works and prior works [4, 8, 10, 34] based on methodology and prediction accuracy. In terms of feature for classification, to the best of our knowledge, this work is the first one investigating the use of raw waveform for acoustic-based EVD. Equally important, the proposed WaveNet yielded promising results (96.51%), which is even better than the results of related works, 94% [34] and 83% [8] in the works of L. Marchegiani et al., and below 90% in [4, 10]. For the use of MFCC, log-mel spectrogram, we can see that our proposal of aggregating MFCC and the log-mel feature is also useful, as the result of MLNet (96.42%) is higher than result of [34] (94%) and much higher than that of [4, 8, 10]. Finally, the proposed ensemble model (SirenNet) achieved the highest accuracy (98.24%) among all models. The performance of SirenNet is 4.24% higher than the model in [34] and much higher than the results of the remaining models.

Table XIII. Comparison of classification accuracy with other systems.

Work	Feature	Model/Method	Accuracy (%)
L. Marchegiani et al. [34], 2018	Spectrogram (log-mel)	CNN	94.00
L. Marchegiani et al. [8], 2017	Spectrogram	K-NN	83.00
J. Schroder et al. [10], 2013	Hand-labeled PBMs MFCC Spectrogram	Part-based Models (PBMs) HMM	86.00 (PBMs) 80.00 (HMM+MFCC) 74.00 (HMM+log-mel)
J.J. Liaw et al. [4], 2013	Longest Common Subsequence (LCS)	LCS Comparison	85.00
This work	Raw data	1D-CNN (WaveNet)	96.51
This work	MFCC+Spectrogram	2D-CNN (MLNet)	96.42
This work	Aggregated features: Raw data, MFCC, Spectrogram	CNN (SirenNet)	98.24

VI. CONCLUSION & FEATURE WORK

In this work, we introduced a deep-learning model (SirenNet) based on convolutional neural networks for siren-sound-based emergency vehicle detection. The proposed SirenNet is composed of two single CNN-based networks, including an end-to-end network (the WaveNet), which works with raw waveform input, and the MLNet trained on well-known handcrafted features (MFCC, and log-mel spectrogram). We conducted all experiments on an extensive data set, including our collection of 17.7 hours of recordings and 12.5 hours of recordings from Urbansound8k and ESC-50 datasets. The use of an end-to-end architecture and the combination of MFCC and log-mel features for acoustic-based EVD are first investigated in this work, and those schemes brought about promising results, in which the WaveNet and MLNet respectively yielded accuracies of 96.51% and 96.42%. The ensemble architecture (SirenNet) further boosted the classification accuracy to reach the highest value of 98.24%. Those experimental results showed the efficiency of our proposed models and proved the complementary relationship between features automatically extracted from raw waveforms and handcrafted features. Also, the SirenNet requires a short inference time of 27 ms, which is well acceptable for real-time detection. The results of this work lay a good foundation for future development and applications.

Although we have achieved promising results in this work, future work is still needed to improve the detection performance and to meet the need for reliable and convenient emergency vehicle detection systems. For example, the primary focus in our future work could be the localization of siren sources so that the detection system could also provide information about the direction of the emergency vehicles to drivers.

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