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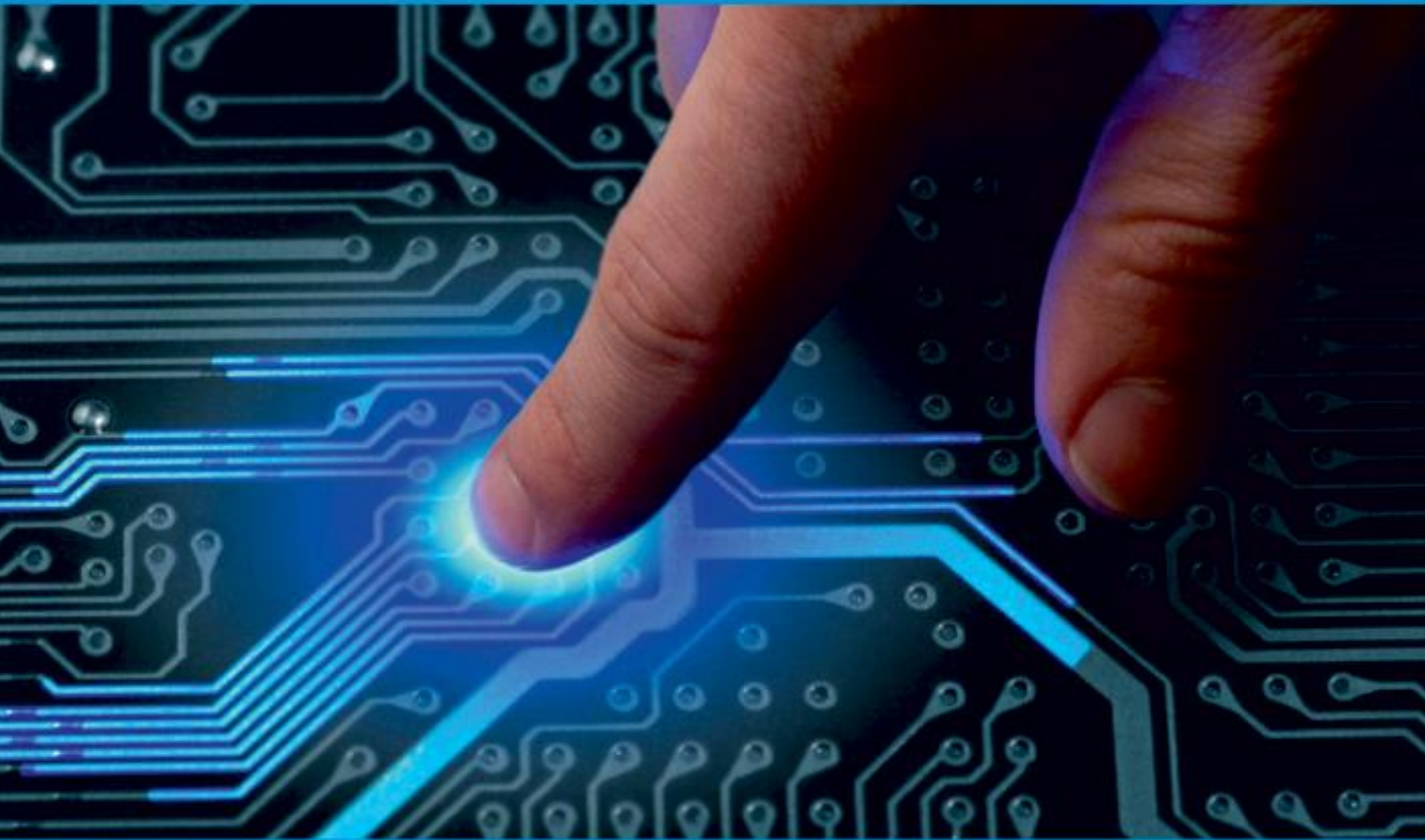

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An End-to-End Deep Learning Framework for Real-Time Denoising of Heart Sounds for Cardiac Disease Detection in Unseen Noise

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ABSTRACT: The automated classification of heart sounds plays a significant role in the diagnosis of cardiovascular diseases (CVDs). With the recent introduction of medical big data and artificial intelligence technology, there has been an increased focus on the development of deep learning approaches for heart sound classification. However, despite significant achievements in this field, there are still limitations due to insufficient data, inefficient training, and the unavailability of effective models. With the aim of improving the accuracy of heart sounds classification, an in-depth systematic review and an analysis of existing deep learning methods were performed in the present study, with an emphasis on the convolutional neural network (CNN) and recurrent neural network (RNN) methods developed over the last five years. This paper also discusses the challenges and expected future trends in the application of deep learning to heart sounds classification with the objective of providing an essential reference for further study.

KEYWORDS: CVDs; CNN; deep learning; heart sounds classification; RNN

I. INTRODUCTION

In recent times, unmanned aerial vehicles (UAVs), widely recognized as drones, have become an area of substantial interest. Without a pilot on board, UAVs can be operated from miles away with the help of a remote controller. Initially, their applications were limited to military sectors [1]. Military UAVs are used in warfare, surveillance, air strikes, investigations, etc. [2]. However, drones are now being utilized for a diverse range of applications that extend beyond the military, making them a valuable tool in many different industries. For example, governments use UAVs for forestry surveillance [2], disaster management, remote sensing, etc. Companies such as Amazon, UPS Inc., and many others are using them for their product delivery services, etc. In agriculture, drones are being used for spraying fertilizers and insecticides and crop monitoring. Firefighters, healthcare services, and hobbyists are utilizing drones for rescue missions, ambulance services, and recreational photography. UAVs are now widely employed beyond military applications; rather, they are an inherent part of our society. Most UAVs registered in the United States serve recreational purposes, over 70%, while the rest are used for commercial application.

The increased number of drone users raises concerns for privacy and security. The deployment of civilian drones in national airspace has raised concerns about unauthorized and unskilled pilots intruding into restricted zones and disrupting flight systems. Limited regulations during drone purchases can contribute to this issue. For example, a few years ago, a civilian drone crashed into an army chopper [8]. The most concerning issue is about exploiting UAVs for terrorist attacks and illegal surveillance [6]. To prevent the mentioned occurrences, an anti-UAV system capable of detecting, identifying, and neutralizing unauthorized UAVs capturing information utilizing different sensors is desired. Besides, UAV and UAV flight controllers, Bluetooth, and WIFI also use the 2.4 gigahertz (GHz) band. Detecting UAVs among these signals is a very challenging task as those types of signals have become more common in any infrastructure in the present day. Identification and classification involve identifying the model of the received radio frequency (RF) signal.

The neutralization involves raising alarms or bringing down the unauthorized UAV or tracking the source of the UAV controller signal. Several works have explored methods of detecting drones using various technologies, including radar,

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audio, video, thermal imaging, and RF. Radar-based techniques rely on the principle of using electromagnetic backscattering to detect and identify aerial objects by analyzing their radar cross-section (RCS) signature [10]. Due to their smaller size, detecting drones using RCS analysis can be more challenging when compared to airships. In audio-based techniques, a microphone is used to collect the audio fingerprint of the engine and propellers [6,10]. The video surveillance camera is used to monitor areas with the help of computer vision from the visual feature objects (e.g., UAVs). In the thermal-imaging-based system, the thermal signature of the UAV emitted from the engine is used for detection. In RF-based systems, RF signals are intercepted and analyzed for identification and detection. The advantage of the RF-based detection technique is that it can work regardless of any weather condition, as well as day or night. Therefore, RF-based surveillance system has become more promising than other existing systems in recent times. However, one of the major challenges of RF-based sensing is the presence of other 2.4 GHz signals like WIFI and Bluetooth.

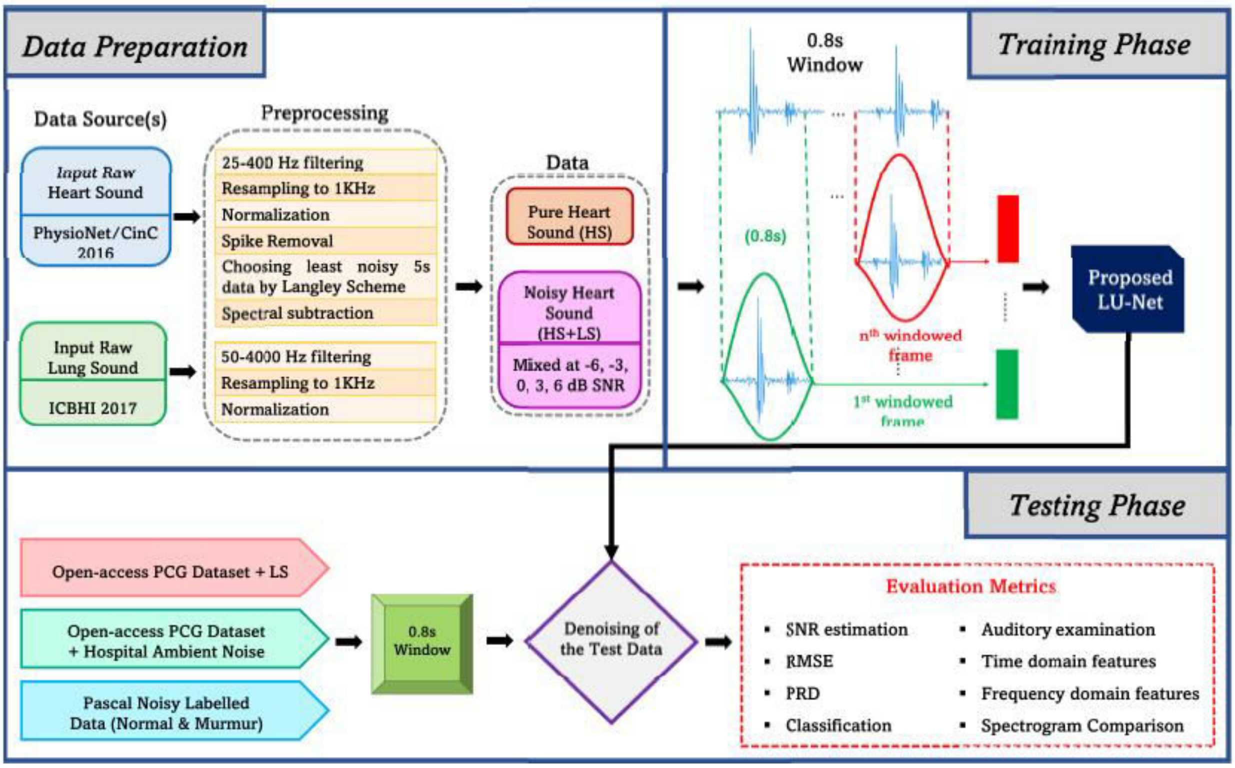

Fig 1: An End-To-End Deep Learning Framework For Real-Time Denoising

Machine learning (ML) and deep learning (DL) techniques have revolutionized many areas such as image segmentation and disease detection [13]. With the development of DL algorithms, deep-learning-assisted drone-detection techniques have become popular in the literature. A deep neural network (DNN) was integrated to classify multirotor UAVs with audio signals in. The authors have evaluated different architectures such as recurrent neural network (RNN), convolutional neural network (CNN), and convolutional recurrent neural network (CRNN) and compared the performances of these models against late fusion methods, which performed better than existing solo network architectures. A weight-optimized long short-term memory (LSTM) model was proposed to classify drones using radar cross-section (RCS) signatures at millimeter-wave (mm wave). Due to the optimization, the computational overhead was reduced by denying the flow of the gradient through the hidden states of the LSTM layers. Furthermore, adaptive learning rate optimization was also introduced. Previously, signatures of RCS were converted into images that required more computation. The LSTM-ALRO model introduced in this work yielded better results than existing image-based deep learning models. However, the impediments of the audio and radar-based techniques are that they are highly sensitive to noise and their performance suffers with the increase in range. Moreover, radar-based techniques are not effective with smaller drones. The RF-based technique using deep learning for classifying multiple drones was presented in. The authors proposed a supervised deep learning algorithm to perform the detection and classification tasks. They have used short-term Fourier transform (STFT) for preprocessing RF signals. STFT was first used in this work to perform preprocessing of the data, which was fundamental to the increased performance of their algorithm.

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II. RELATED WORK

With increasing industrialization, urbanization, and globalization, cardiovascular diseases (CVDs) are posing a serious threat to human health, causing the death of increasing numbers of people globally. Approximately 17.9 million people died from CVDs in 2016, accounting for 31% of all global deaths. Of these deaths, 85% resulted from heart attack and stroke. CVDs exert a heavy burden on the finances of sufferers in low- and middle-income countries, and early detection and diagnosis are very significant to reducing the mortality rate. Cardiac auscultation is a simple, essential, and efficient method for examining CVDs and has a history of more than 180 years. It is crucial to the early diagnosis of CVDs because of its noninvasiveness and good performance for reflecting the mechanical motion of the heart and cardiovascular system. However, cardiac auscultation requires substantial clinical experience and skill, and the human ear is not sensitive to sounds within all frequency ranges. The use of computers for the automatic analysis and classification of heart sound signals promises to afford substantial improvements in this area of human health management.

A heart sound is a kind of physiological signal, and its measurement is known as phonocardiography (PCG). It is produced by the heart systole and diastole and can reflect physiological information regarding body components such as the atria, ventricles, and large vessels, as well as their functional states [3]. In general, fundamental heart sounds (FHSs) can be classified as the first heart sounds and the second heart sounds, referred to as S1 and S2, respectively. S1 usually occurs at the beginning of isovolumetric ventricular contraction, when the already closed mitral and tricuspid valves suddenly reach their elastic limit due to the rapid pressure increase within the ventricles. S2 occurs at the beginning of the diastole when the aortic and pulmonic valves close.

It is important to segment the FHSs accurately and locate the state sequence of S1, the systole, S2, and the diastole. **Figure 1** illustrates a PCG process with simultaneous electrocardiogram (ECG) recording and the four states of the PCG recording: S1, the systole, S2, and the diastole. The correspondence between the QRS waveform of the ECG and the heart sound signal is used to locate the S1 and S2 locations. FHSs provide important initial clues for heart disease evaluation in the process of further diagnostic examination. It is very important to extract the features from all parts of the FHS for quantitative analysis in the diagnosis of cardiac diseases. Within this framework, automatic heart sounds classification has attracted increased attention over the past few decades.

III. METHODOLOGY

This section describes the identification and detection of UAS signals along with Bluetooth and WIFI signals utilizing the proposed architecture using the CardRF dataset. The complete architecture of the proposed system for the UAS signal. The samples sourced from the RF database are preprocessed, and additive white Gaussian noise (AWGN) is incorporated into the samples to generate noisy samples of different SNRs. Each requisite step of UAS signal detection and identification is illustrated in a detailed manner in the following sections.

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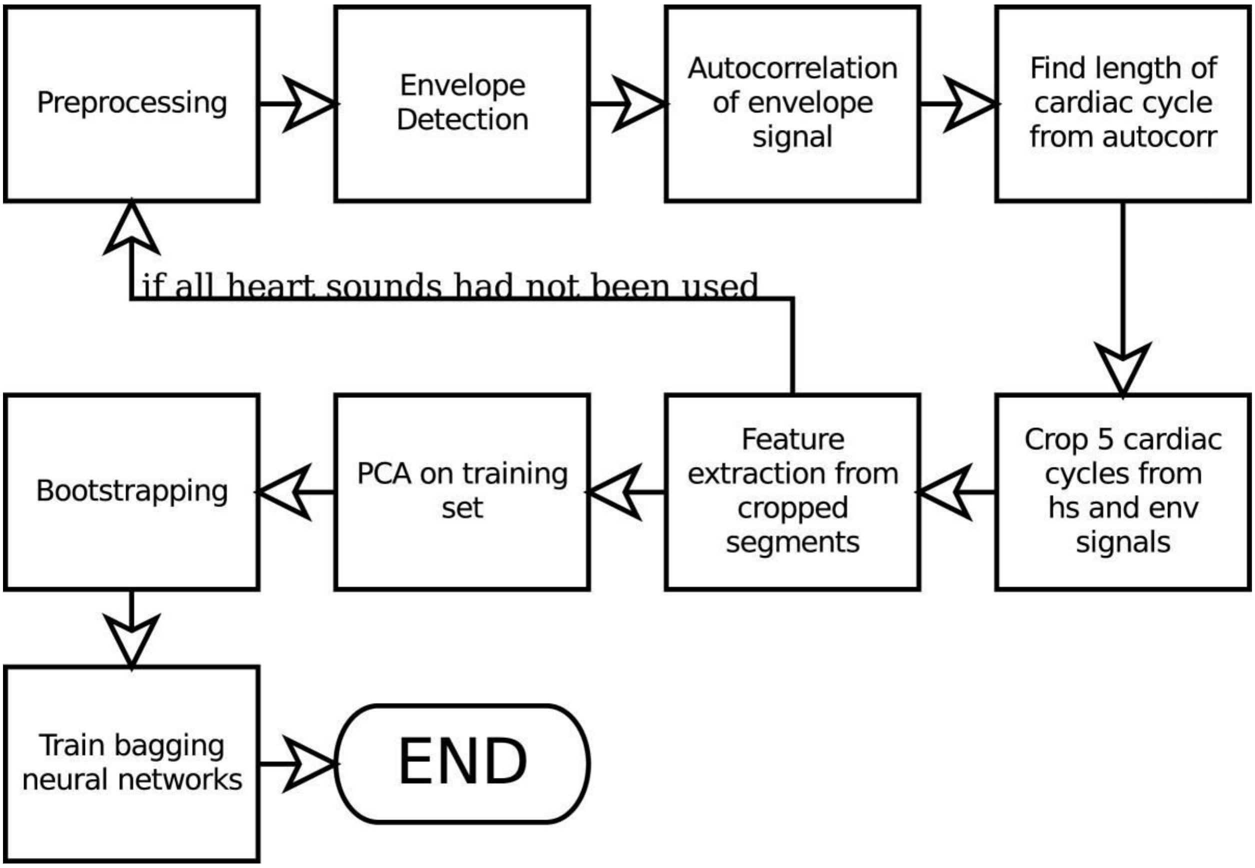

Fig 2: Work Flow

The heart sounds acquisition process is easily affected by environmental interferences such as interference due to friction between the equipment and human skin, electromagnetic interference, and random noises such as breath sounds, lung sounds, and environment sounds. The heart sound signals are usually coupled with these interference signals, and this necessitates the elimination of the out-of-band noise. The denoising significantly influences the segmentation, feature extraction, and final classification performances. The commonly used denoising methods are wavelet denoising, empirical mode decomposition denoising, and digital filter denoising. Based on prior knowledge of heart sound signals, the construction of a wavelet basis function for heart sound signals is a new research direction in the area of heart sounds feature extraction.

The aim of the segmentation is the division of the PCG signals into four parts or segments: the first heart sounds (S1), systole, second heart sounds (S2), and diastole. Each segment contains efficient features that contribute to distinguishing the different categories of heart sounds. However, the duration of the heart beat cycle, the number of heart sounds, and the types of heart murmurs vary between individuals, and this causes the inaccurate segmentation of PCG signals. The segmentation of the FHSs is thus an essential step in automatic PCG analysis. The most commonly used heart sounds segmentation methods in recent years include envelope-based methods, ECG or carotid signal methods, probabilistic model methods, feature-based methods, and time–frequency analysis methods. The utilized algorithms are based on the assumption that the diastolic period is longer than the systolic period. In fact, this assumption is not always true for an abnormal heart sound, especially in infants and cardiac patients.

IV. RESULT ANALYSIS

In most studies on traditional machine learning methods for heart sounds classification, a segmentation algorithm was used to identify the locations of the S1, S2, systole, and diastolic phases. Based on these locations, the time-domain, frequency-domain, and statistical features were extracted from the segmented heart sounds. The typical traditional machine learning approach for the automatic segmentation and classification of heart sounds was proposed by Pedro Narváez. In this work, the empirical wavelet transform (EWT) and the normalized average Shannon energy (NASE)

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were used to automatically identify cardiac cycles and locate the segments of the S1, systole, S2 and diastole in a recording. This method has given better results than other machine learning methods such as discrete wavelet transform, Butterworth or Chebyshev filters and empirical mode decomposition (EMD). However, in the segmented heart sounds classification, the process of heart sounds classification is more complicated and increases the complexity of the computation. Conversely, in unsegmented heart sounds classification, a small segment of the heart sounds is directly converted into representation features, without the need of the computational cost for substantial feature engineering. The classification performance is also comparable with that of methods that utilize heart sounds segmentation.

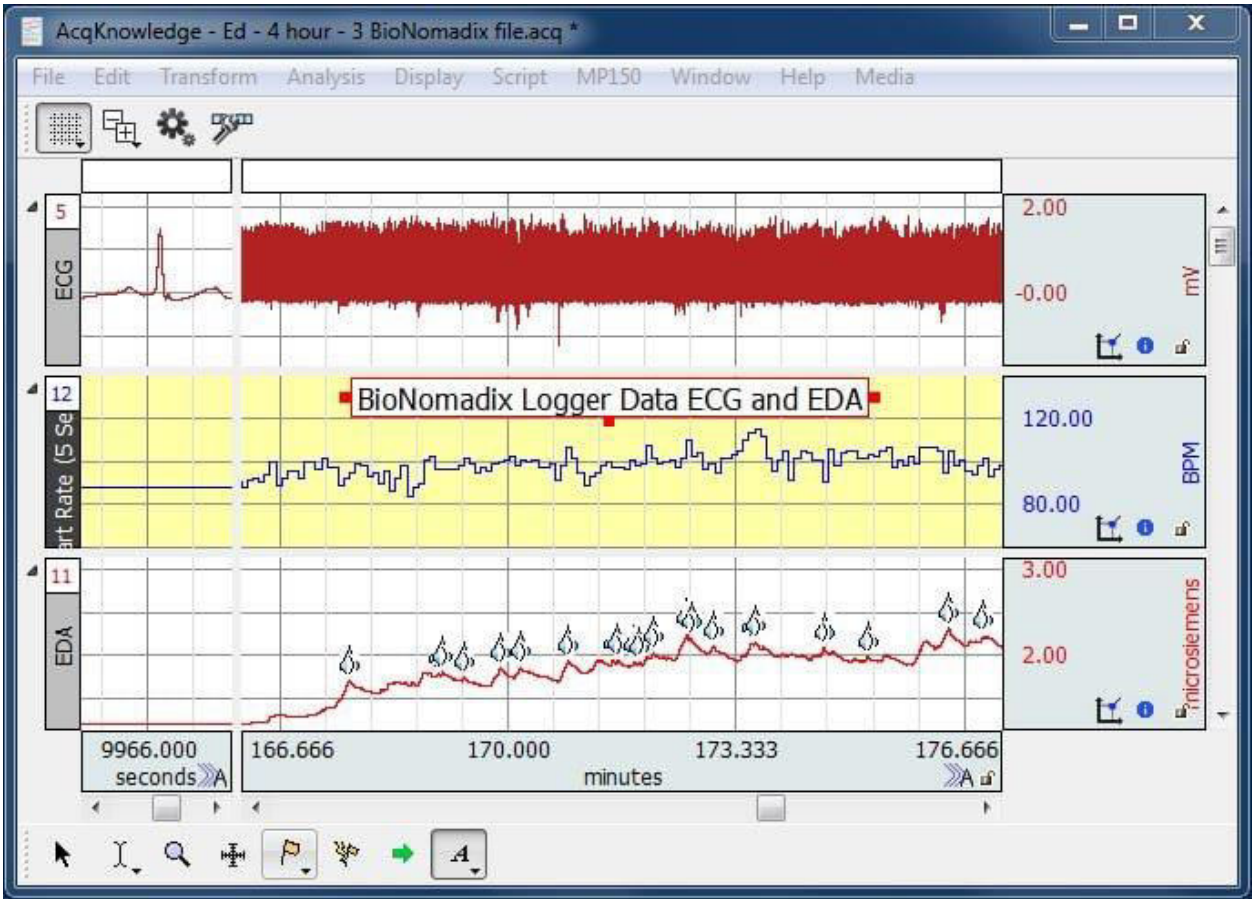

Fig 3: Result analysis

Traditional machine learning methods for heart sounds classification generally use small-scale training data, and the feature learning is based on prior knowledge of the data. They thus mostly rely on learned distributed discriminative features. However, the essence of deep learning is to build a neural network with multiple hidden layers and to hierarchically fine-tune all the model parameters from the bottom to the top through massive data training. Strong generalized and abstraction features are extracted step-by-step from the low-level features of the raw data, and the prediction is made easier through the use of end-to-end networks, resulting in improved classification accuracy. Unlike traditional machine learning methods, the single architecture of a deep learning method can be used for joint feature extraction, feature selection, and classification. Deep learning is thus very effective for heart sounds classification while eliminating the need for the complicated feature engineering required by traditional machine learning.

V. CONCLUSIONS

In this article, we have utilized an end-to-end deep learning architecture for detecting and identifying UAV signals based on their RF signature. We have considered both UAV and UAV controller signals for our classifier. The communications of the UAV and the flight controller are established at the 2.4 GHz frequency band. Other devices, such as Bluetooth and WIFI signals, also operate in the same range, so we have considered both of these signals as

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well. Our proposed model is trained on signals from different noise levels, and it can classify signals from unknown SNRs as well, which makes our proposed model more effective. Our proposed model does not require any feature-extraction techniques, which makes it computationally efficient. The raw RF signals, after being normalized, are fed into the network model for training. The model is trained with the data from 0 dB to 30 dB SNR. The average accuracy of the model is 97.53%. Furthermore, the network is evaluated on the data from unseen noise levels to evaluate the performance of the classifier. The overall accuracy for the detection task on unseen data is above 94%. We have obtained an overall accuracy above 76% for specific device identification tasks because of the higher misclassification rate from the same makers. The classification accuracy greatly improves when devices from the same manufacturers are clustered together. The model yields an accuracy of 84% on average when classifying the RF signature of the manufacturers. Finally, we have compared our work with the existing framework and found that the performance of our model, despite having no feature-extraction steps, is more stable across different SNRs.

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