Assessing the Impact of Signal Strength Variability on AI-based Heart Sound Analysis

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Abstract - Recent advances in machine learning and deep learning are fostering the adoption of AI in healthcare, notably in heart sound analysis. However, inconsistencies in the signal strength of clinical heart sound data pose a challenge, potentially compromising data reliability. This work investigates the influence of these signal fluctuations on the accuracy of AI-based heart sound identification, aiming to highlight critical insights for improving the robustness of AI applications in cardiac diagnostics.

I. Introduction

The advent of artificial intelligence (AI) in healthcare is anticipated to significantly enhance decision-making accuracy in diagnosis, treatment, and medication selection, while also mitigating operational burdens precipitated by staff shortages. Within this context, there is vigorous research underway focusing on diagnostic methodologies employing AI technology. A notable area of exploration is the utilization of machine learning for the identification and analysis of phonocardiograms.

In our work, we seek to align our verification data more closely with the heart sound data encountered in real-world medical settings by modulating the signal strength. This approach is designed to rigorously test the effectiveness of machine learning in the identification and classification of heart sounds, under conditions that more accurately reflect clinical environments. Our goal is to ascertain the robustness and reliability of machine learning applications in the nuanced realm of cardiac acoustics analysis.

II. How to create datasets of heart sound data

We detail the heart sound data utilized in this research and the methodology employed in creating the dataset.

Heart sound, in a clinical context, are typically categorized into three distinct types based on their rhythm and waveform characteristics: normal heart sound, abnormal heart sound, and murmurs. Normal heart sound exhibits regular rhythm and consistent waveforms, whereas abnormal heart sound is characterized by irregularities in waveform dimensions (both amplitude and duration) and rhythm inconsistencies. These irregular patterns often indicate various cardiac conditions, including hypertension, atherosclerosis of the aortic artery, and constrictive pericarditis.

Murmurs, on the other hand, present a more complex profile. Typically accompanied by additional acoustic phenomena—referred to clinically as 'murmurs'—these heart sounds display rapid fluctuations in their waveforms. Such patterns are commonly associated with specific heart ailments such as aortic valve stenosis, obstructive hypertrophic cardiomyopathy, and atrial septal defects. The intricate nature of these sounds makes their analysis particularly challenging. [2]

Fig. 1, 2, and 3 illustrate segments of phonocardiograms representing normal heart sound, abnormal heart sound, and murmurs, respectively. These visual aids facilitate a deeper understanding of the distinctions and nuances inherent in each heart sound category, underscoring the complexity of cardiac sound analysis.


Fig.1. phonocardiogram for normal heart sound

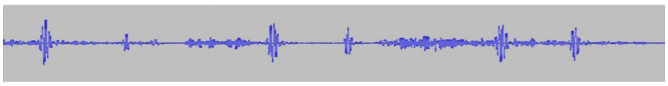
Fig.2. phonocardiogram for abnormal heart sound

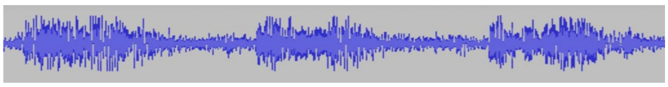
Fig.3. phonocardiogram for murmurs

This work details the creation of a validation dataset from WAV files, using a 48 kHz sampling rate for normal heart sound and 44.1 kHz for 51 types of abnormal heart sound and murmurs, each file lasting 25 to 114 seconds. Initially, we convert the heart sound data from WAV to CSV format, then apply downsampling and adjust the signal strength (illustrated in Fig. 4) by altering data values, creating datasets with 75%, 50%, and 25% signal strengths. We further process the data by segmenting it into one-second intervals. In downsampling, data with different numbers of data points per second are created, and this number of points is called the length of data.

We classify each by heart sound type and organizing them into training and test datasets. This methodology prepares the ground for comprehensive machine learning analyses, ensuring variations in heart sound characteristics are accurately represented.

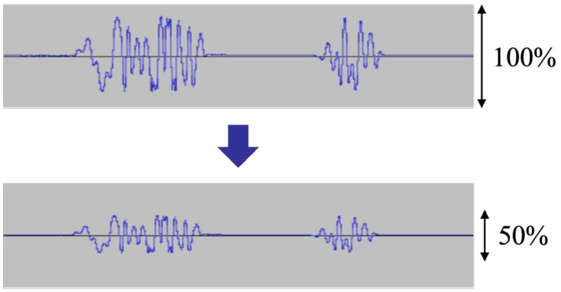

Fig.4. Heart sound with changes in signal strength from 100% to 50%

III. Optimizing length of data

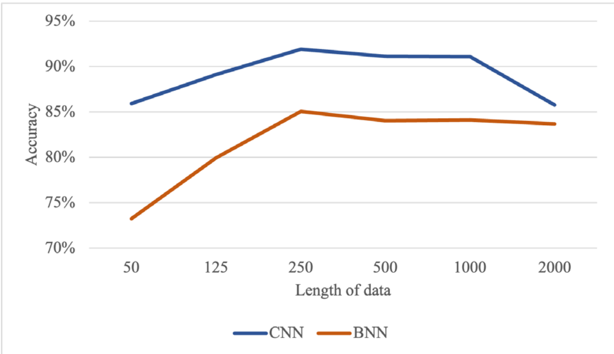

Fig.5. Accuracy for length of data

The performance of machine learning models is notably influenced by the quantity and duration of the data input. Consequently, this work emphasizes optimizing the dataset for machine learning by manipulating the length of heart sound data.

Fig. 5 demonstrates the identification accuracy correlated with each data length segment. It is important to note that the signal strength remained consistent throughout this particular phase of verification. The machine learning models deployed in this analysis include Convolutional Neural Networks (CNNs) and Binary Neural Networks (BNNs). [1]

The verification outcomes indicate a trend where a data length ranging from 250 to 1000 units yields higher accuracy. Conversely, excessively short or long data lengths contribute to a decline in accuracy. Based on the heart sound data examined in this context, we discerned that a data length of 250 units is optimally conducive to learning, offering the most reliable results for our machine learning models. This finding underscores the necessity of careful calibration of data parameters to enhance machine learning efficacy in medical diagnostics.

IV. Verification for strength of signal

We generate datasets derived from heart sound data, adjusting the signal strength across the entire dataset to 75%, 50%, and 25%, respectively. We then proceeded to compare the accuracy rates of classifying heart sound into three categories: normal heart sound, abnormal heart sound, and murmurs, utilizing machine learning techniques.

For this analysis, we employed machine learning models such as Convolutional Neural Networks (CNNs) and Binary Neural Networks (BNNs). [1] We standardized the data length at 250 units, based on optimal results gleaned from previous verifications. The dataset comprised 1,519 training samples and 731 test samples. Table 1 presents the verification results corresponding to each signal strength level.

Our findings show that differences in classification accuracy across different signal strengths vary among machine learning models. The CNN model achieved an accuracy of 87% to 91% across signal strength, with a maximum accuracy deviation of 3.89%. On the other hand, the BNN model demonstrated stability and recorded an overall accuracy of 84%–85%, with a maximum deviation of accuracy rate of only 0.79%.

These results conclude that in the context of heart sound data analysis using machine learning, there is a significant relationship between machine learning models and signal strength and classification accuracy. When this happens, the consistency of performance varies depending on the machine learning model, and it is considered necessary to use the optimal machine learning model.

TABLE 1. ACCURACY FOR STRENGTH OF SIGNAL

Strength of signal [%]	CNN [%]	BNN [%]
100	91.78	85.04
75	91.57	84.61
50	90.10	84.69
25	87.89	85.40

V. Conclusion

Our study investigates the impact of signal strength on the performance of machine learning models in classifying heart sounds. By adjusting heart sound signal strength to 75%, 50%, and 25%, we evaluate the accuracy of Convolutional Neural Networks (CNNs) and Binary Neural Networks (BNNs) across 1,519 training and 731 test samples. The CNNs' accuracy varies between 87-91%, while BNNs show more stability with 84-85% accuracy. The findings underscore the importance of model selection, as signal strength influences classification accuracy in heart sound analysis.

References

[1] Itay Hubara, Matthieu Courbariaux, Daniel Soudry, Ran El-Yaniv, Yoshua Bengio, “Binarized Neural Networks”, Advances in Neural Information Processing Systems 29 (NIPS 2016)

[2] Yasser Zeinali, Seyed Taghi Akhavan Niaki, “Heart sound classification using signal processing and machine learning algorithms”, Machine Learning with Applications Volume 7, 15 March 2022, 100206