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A.B. Baimussayeva[1], N.D Torebay[2], S.S. Karzhaubekova[1], S.D.Kurakbayeva[1], Zh.Zh. Azhibekova[3*]

[1]M.Auezov South Kazakhstan University, Shymkent, Kazakhstan
[2]Central Asian Innovative University, Shymkent, Kazakhstan
[3]Asfendiyarov Kazakh National Medical University, Almaty, Kazakhstan
e-mail: azhibekova.z@kaznmu.kz

REAL -TIME DETECTION OF CARDIAC PATHOLOGIES USING AN INTELLIGENT DIGITAL STETHOSCOPE

Abstract

The paper analyzes how the demands of the medical industry and technological advancements have combined to drive significant innovation in diagnostic tools over the past few years. This study aims to present the development and validation of a real-time digital stethoscope capable of detecting cardiovascular abnormalities from phonocardiograms. The proposed CNN–BiLSTM architecture allows for efficient extraction of spatial and temporal features from spectrograms of cardiac signals. This approach provides accurate signal classification and improves the quality of diagnosis. In addition to accurately recording heart sounds, the device simultaneously analyzes acoustic characteristics to detect possible conditions. This is accomplished using modern signal processing methods. Early testing in a cohort of 200 patients validated the clinical potential of this approach, demonstrating 94.5% diagnostic accuracy in distinguishing between pathological and normal cardiac murmurs. This reduces delays associated with manual interpretation and facilitates timely treatment. Given that it would make vital cardiac diagnostics accessible, the device is likely to be most useful in areas with limited resources. The device can be applied in various clinical settings. The results demonstrate the importance of digital technology in integrating conventional medical equipment, opening the door to a new era of high-quality, easily accessible patient care.

Keywords: digital stethoscope, CNN–BiLSTM, artificial intelligence, machine learning, real-time, biomedical signal processing, phonocardiography.

А.Б. Баймусаева[1] Н.Д. Төребай[2], С.С. Каржаубекова[1], С.Д. Куракбаева[1], Ж.Ж. Ажибекова[3]
[1]М.Әуезов атындағы Оңтүстік Қазақстан университеті, Шымкент қ., Қазақстан,
[2]Орталық Азия инновациялық университеті, Шымкент қ., Қазақстан,
[3]С. Ж. Асфендияров атындағы Қазақ ұлттық медицина университет, Алматы қ., Қазақстан

ИНТЕЛЛЕКТУАЛДЫ САНДЫҚ СТЕТОСКОППЕН ЖҮРЕК ПАТОЛОГИЯЛАРЫН НАҚТЫ УАҚЫТ РЕЖИМІНДЕ АНЫҚТАУ

Аңдатпа

Ғылыми зерттеу жұмысында медицина саласының талаптары мен технологиялық жетістіктері ретінде соңғы жылдары диагностикалық құралдардарға жасанды интеллект әдістерін қосу арқылы автоматтандырылған жүйеге қол жеткізу процессі қарастырылған. Бұл зерттеудің мақсаты - жүрек-қан тамырларының жұмысындағы қиындықтарды фонокардиограммалардан анықтай алатын нақты уақыт режиміндегі сандық стетоскопты жасау және тексеру ұсынылған. Жүрек дыбыстарын дәл жазумен қатар, құрылғы бір уақытта пайда болатын акустикалық сипаттамаларды талдайды. Ұсынылған CNN–BiLSTM архитектурасы жүрек сигналдарының спектрограммаларынан кеңістіктік және уақыттық ерекшеліктерін тиімді түрде алуға мүмкіндік береді. Бұл тәсіл сигналдың дәл жіктелуін қамтамасыз етеді және диагностика сапасын жақсартады. Бұл заманауи сигналды өңдеу әдістерін қолдану арқылы жүзеге асырылады. 200 пациенттен тұратын топқа ерте тестілеуді жүргізу арқылы бұл тәсілдің клиникалық бейімділігін анықтап, патологиялық және қалыпты жүрек шуылдарын ажыратуда 94,5% диагноз дәлдігін көрсетті. Бұл қолмен енгізуде кездесетін кідірістерді азайтады және адамдардың уақтылы ем алу процессін жеңілдетеді. Бұл маңызды жүрек диагностикасына қол жетімді ететінін ескере отырып, құрылғы ресурстары шектеулі аймақтарда пайдалана алу дәлдігін арттырады.

Зерттеу қорытындылары сандық технологияның дәстүрлі медициналық жабдықтарды интеграциялау үшін қаншалықты маңызды екенін толық ашып көрсетеді, бұл жоғары сапалы, оңай қолжетімді пациенттерге күтім жасаудың жаңа дәуіріне жол ашады деп қарастырылған.

Түйін сөздер: сандық стетоскоп, CNN–BiLSTM, жасанды интеллект, машиналық оқыту, нақты уақыт режимінде, биомедициналық сигналдарды өңдеу, фонокардиография.

А.Б. Баймусаева[1] Н.Д. Төребай[2], С.С. Каржаубекова[1], С.Д. Куракбаева[1], Ж.Ж. Ажибекова[3]
[1]Южно-Казахстанский университет имени М.Ауэзова, г.Шымкент, Казахстан,
[2]Центрально-Азиатский инновационный университет, г.Шымкент, Казахстан[3] Казахский
[3]Национальный медицинский университет имени С. Д. Асфендиярова, г.Алматы, Казахстан

ВЫЯВЛЕНИЕ ПАТОЛОГИЙ СЕРДЦА В РЕЖИМЕ РЕАЛЬНОГО ВРЕМЕНИ С ПОМОЩЬЮ ИНТЕЛЛЕКТУАЛЬНОГО ЦИФРОВОГО СТЕТОСКОПА

Аннотация

В исследовательской работе рассматривается процесс создания автоматизированной системы путем внедрения методов искусственного интеллекта в диагностические инструменты в последние годы как требование и технологический прогресс в медицинской сфере. Целью данного исследования является разработка и тестирование цифрового стетоскопа реального времени, способного выявлять сердечно-сосудистые заболевания по фонокардиограммам. Помимо точной записи сердечных звуков, устройство одновременно анализирует появляющиеся акустические характеристики. Предложенная архитектура CNN–BiLSTM позволяет эффективно извлекать пространственные и временные характеристики из спектрограмм сердечных сигналов. Такой подход обеспечивает точную классификацию сигналов и повышает качество диагностики. Это достигается за счет использования современных методов обработки сигналов. Проведя предварительное тестирование на группе из 200 пациентов, была определена клиническая осуществимость данного подхода, показавшая диагностическую точность 94,5% в различении патологических и нормальных сердечных шумов. Это сокращает задержки, возникающие при ручном вводе, и облегчает процесс своевременного лечения пациентов. Это повышает точность устройства в регионах с ограниченными ресурсами, поскольку делает доступной важную кардиологическую диагностику. Результаты исследования подчеркивают важность цифровых технологий для интеграции традиционного медицинского оборудования, что, как ожидается, положит начало новой эре высококачественной и легкодоступной медицинской помощи пациентам.

Ключевые слова: цифровой стетоскоп, CNN–BiLSTM, искусственный интеллект, машинное обучение, в реальном времени, обработка биомедицинских сигналов, фонокардиография.

Introduction

The heart, considered one of the most vital organs in the human body, functions as a continuous pump that enables blood circulation and supports the essential functions of all systems. The complex operation of the heart's valves and muscular structures may fail, leading to various cardiac diseases that significantly affect an individual's health [1,2].

Auscultation, the method of listening to bodily sounds, especially those of the heart, has historically been a vital technique for physicians, providing essential insights into the operation of this crucial organ. Nonetheless, traditional stethoscopes, despite their considerable utility in medical practice, have significant limitations. Their effectiveness primarily depends on the physician's expertise and intuition, which entails the risk of subjective interpretation and the potential to neglect minor acoustic anomalies [3].

Since the beginning of the 21st century, the amalgamation of technology and medicine has intensified. The proliferation of accurate, replicable digital devices has broadened diagnostic opportunities, facilitating the advancement of traditional methodologies [4]. Phonocardiograms have become highly pertinent as audiovisual recordings of heart sounds and noises, facilitating a detailed auditory representation of cardiac function that surpasses the capabilities of conventional auscultation with a standard stethoscope [5].

Nonetheless, despite the wealth of information contained in phonocardiograms, the principal challenge remains their complex interpretation. The manual analysis of phonocardiographic signals requires substantial time and significant expertise from a specialist [6]. A pressing need exists for automated, accurate, and, importantly, real-time analytical methods that can merge the extensive nature of phonocardiographic data with the effectiveness of traditional diagnostics [7]. This requirement is especially relevant because of the shortage of skilled cardiologists and limited access to specialized medical services.

This article introduces the development of a real-time digital stethoscope to address the previously mentioned challenges. The apparatus documents, analyzes, and interprets cardiac sounds, providing diagnostic information instantaneously during the assessment. This device represents both a technological advancement and a modern trend in medicine: the amalgamation of human expertise and digital technology. The following sections analyze the theoretical foundations of the development, the operational mechanisms, and empirical evidence supporting the effectiveness of the proposed solution in cardiological diagnostics.

Research Methodology

The proposed methodology for analyzing and classifying cardiac acoustic signals is described.

The proposed approach consists of several stages: data collection, preprocessing, feature extraction, classification, and decision making. The general workflow of the system is shown in Figure 1.

Figure 1. Heart sound processing and diagnosis process based on CNN–BiLSTM

The general workflow of the proposed methodology is shown in the figure. The system consists of several main stages: data collection, preprocessing, feature extraction, classification, and decision making.

In the first stage, cardiac acoustic signals are collected using an electronic stethoscope and converted to digital format. In the next stage, the signals undergo preprocessing, which includes noise reduction, filtering, and segmentation. These operations allow improving signal quality and increasing the signal-to-noise ratio (SNR).

In the third stage, time and frequency features are extracted from the processed signals. These features are designed to effectively convey important information to the model.

In the next stage, the obtained features are classified using a hybrid CNN–BiLSTM model. This model allows for the simultaneous analysis of spatial and temporal dependencies.

At the final stage, the system makes a diagnostic decision based on the results obtained. In addition, the parameters used during the training of the model (number of epochs, batch size, and optimizer type) are separately displayed.

a) Characteristics of cardiac auscultations

The primary heart sounds, S1 and S2, primarily occupy the upper frequency range of the phonocardiogram spectrum and are best captured with the diaphragm of a stethoscope during auscultation. The primary heart sound (S1), associated with the closure of the atrioventricular valves, typically exhibits a frequency range of 50 to 60 Hz. The second heart sound (S2), linked to the closure of the semilunar valves, typically occurs within the 80 to 90 Hz frequency range. The third heart sound (S3) is characterized by reduced amplitude and occurs in early diastole. It typically occurs in the 20-30 Hz frequency range and may be more challenging to discern due to its subtle characteristics.

The fourth heart sound (S4), which occurs at the end of diastole, is readily detectable with a stethoscope and typically manifests at frequencies below 20 Hz [8].

Although the tones S1 and S2 are generally easily discernible, their intensity may vary. In specific clinical situations, the intensity of these sounds may be reduced owing to preexisting cardiac impairments. The frequency characteristics of the S1 and S2 tones are not strictly fixed and may fluctuate in accordance with the heartbeat. The difficulties in differentiating cardiac sounds have prompted scholars to develop more accurate analytical methods for their assessment [9].

Figure 2 presents a comprehensive classification and functional characteristics of cardiac sounds and murmurs [10]. Certain cardiovascular conditions are generally associated with specific heart sounds. Some atypical heart murmurs manifest as high-frequency anomalies following the initial acoustic indicators of tricuspid stenosis. The ejection sound (ES) is a recognized murmur that arises at the onset of systole, caused by the swift closure of the semilunar valves at the beginning of systolic function.

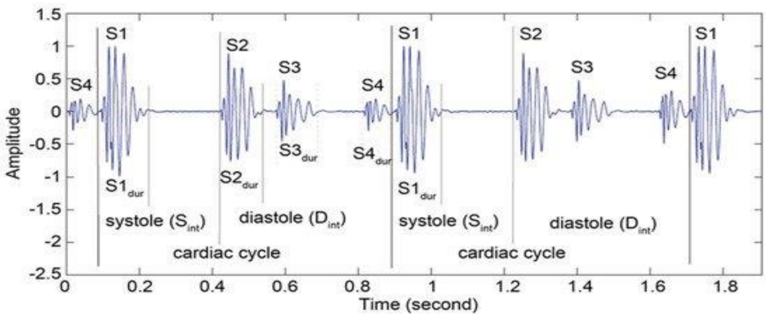

Figure 2. Heart sounds.
Configuration of the proposed electronic stethoscope

Figure 3 illustrates a conceptual diagram of the developed stethoscope, incorporating machine learning technologies for heart-sound assessment. Cardiac acoustic impulses are initially captured using a stethoscope. They then proceed to the analog processing unit, where amplification, filtering, and digital conversion occur. The obtained digital data is transmitted to the computing module for further analysis. The analog component of the system must provide a high signal-to-noise ratio, effectively minimize common-mode interference, and decrease baseline drift and signal saturation, which is crucial for the accurate and reliable acquisition of heart sounds. In the initial amplification phase, subtle heart sounds recorded by the microphone are augmented to improve their clarity and suitability for subsequent analysis (Figure 2).

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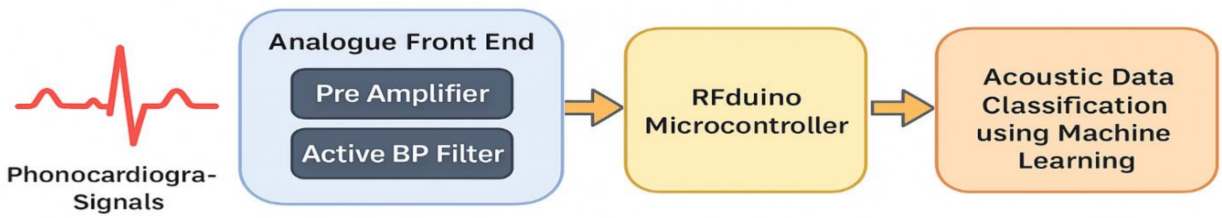


Figure 3. Proposed heart disease detection system diagram

Figure 4 illustrates a computerized heart-monitoring system using an electronic stethoscope. The system architecture encompasses data collection, pre-processing, and waveform analysis. The preprocessing phase converts heart-acoustic signals from the electronic stethoscope to a digital format. After noise suppression and removal of external interference, the cardiac signal waveform is normalized and segmented.

Subsequently, analytical instruments extract characteristics and categorize patterns. The approach centers on clinically relevant diagnostic findings derived from medical markers. This section describes the specifics and sub-phases of each primary component of this architecture.

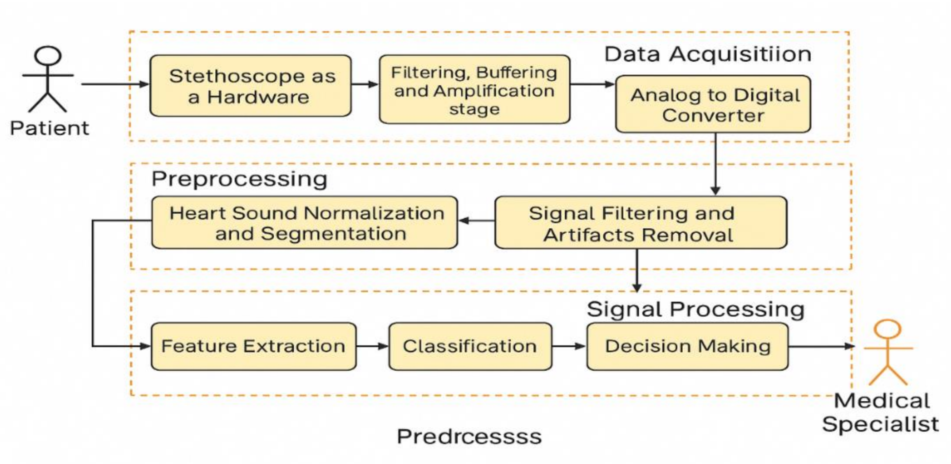


Figure 4. Framework for the registration and processing of cardiac sounds, followed by analysis

b) Acquisition of Heart Sounds

In the initial stage of cardiac sound acquisition, an automated audio signal is generated to reflect cardiac function, laying the foundation for subsequent computational processing steps.

The patient's heart sounds are recorded using a digital stethoscope, as depicted in Figure 5. The design of this device may include a digital acoustic system, a piezoelectric sensor, or a pneumatic receiving mechanism. The device subsequently converts the heart's electrodynamic activity into auditory representations.

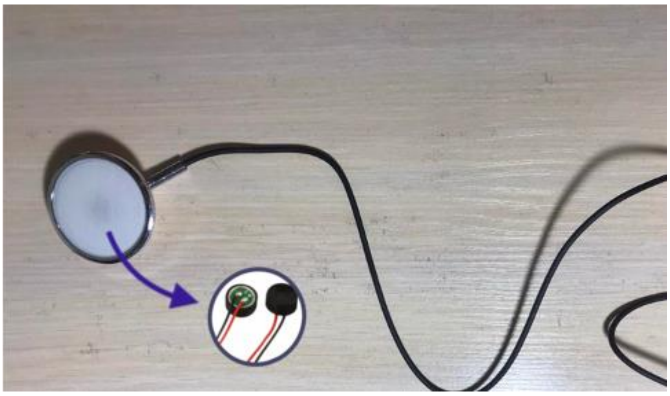


Figure 5. Electronic sensor stethoscope

Signal amplification and filtration are essential stages in every data transmission system. Low-pass filters are utilized to reduce interference from external electrical sources. An anti-aliasing filter is utilized to avert spectral aliasing and prevent distortion during signal digitization. A bandpass filter is utilized in specific implementations, tuned to the frequency range that captures the primary components of heart sounds. This facilitates accurate evaluation of the required bandwidth and reduces the likelihood of distortion caused by frequency overlap. Following the amplification phase, the signal is directed to the analog-to-digital converter, where it is converted into digital format. This module ensures accurate signal digitization, with conversion settings configurable in advance by the device developer [11]. Increased sampling rates and bit depth improve the accuracy of digital data representation while also enhancing the efficient use of bandwidth and energy resources.

c) Data Collection

At this stage, the digitized cardiac acoustic signals undergo noise reduction, calibration, and segmentation [12]. A noise reduction module is used to reduce noises in the signals. A digital filtering architecture is typically utilized to separate the target signal from background noise, restricting the processing to the relevant frequency range. Modern noise-reduction methods can significantly improve the signal-to-noise ratio (SNR), thereby facilitating more accurate identification of informative segments in the signal.

Calibration and rhythmic segmentation. Divergences in signal recording sites and equipment settings may result in inconsistencies in the configuration of the obtained acoustic data. The signals are calibrated to the reference scale to equalize variations, thereby minimizing variability caused by data-source heterogeneity and preventing distortion of amplitude characteristics. The auditory sequence is segmented rhythmically, enabling the subsequent stage of processing: the extraction of cardiac signal components and the identification of diagnostically pertinent characteristics.

d) Processing Module for Cardiac Acoustic Signals

Currently, the primary activities performed are feature extraction and classification.

Signal processing involves converting analog data into a digital format suitable for detailed analysis and subsequent therapeutic application. The gathered attributes are used within a classification framework that enhances data interpretation and supports medical decision-making in diagnosis and treatment planning.

Central processing units are fundamental components of devices that process digital inputs and perform calculations.

Our investigation revealed that the primary focus is on three crucial phases of automated detection of various cardiac abnormalities and auditory disorders:

e) Compilation of cardiac auscultation data and development of sensor systems.

f) Diminution of noise and segmentation of cardiac acoustic signals.

g) Accurate feature extraction achieved through independent assessment of cardiac sounds.

In this research work, a hybrid CNN–BiLSTM model is proposed for classifying cardiac acoustic signals. This model combines the advantages of Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks, which allows for efficient detection of spatial and temporal features.

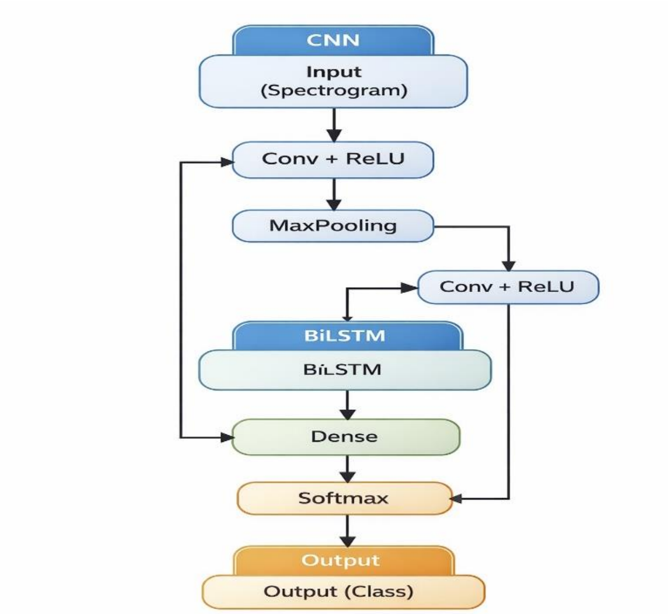


Figure 6. Cardiac signal classification model using CNN–BiLSTM

The figure shows a neural network that processes cardiac signals in the form of a spectrogram. First, CNN layers extract important features, then BiLSTM analyzes temporal dependencies. Finally, the signal is classified into a specific class using Dense and Softmax layers.

The CNN part is designed to automatically extract local patterns and frequency features from input signals or their spectrogram representations:

$$y_i = f\left(\sum_{j=1}^{n} w_j \, x_{i+j-1} + b\right) \quad (1)$$

Where:
x – input signal
w – filter (kernel)
b – bias
f – activation function
This reduces the need for manual feature extraction and increases the efficiency of the model.

The BiLSTM layer allows for the detection of temporal dependencies. Unlike conventional LSTM, BiLSTM processes the signal in two directions (forward and backward) which allows for a better understanding of complex temporal structures:

$$h_t, C_t = LSTM(x_t, h_{t-1}, C_{t-1}) \quad (2)$$

Where:
x_t – current input data,
h_{t-1} – previous hidden state,
C_{t-1} – previous memory state,
h_t – current hidden state,
C_t – updated memory state.
The features obtained from the CNN layers are fed to the BiLSTM network, after which the final classification is performed using Fully Connected Layers.

Results of the study

Hardware. The rapid advancement of mobile technologies presents new opportunities to enhance conventional medical practices. Possible applications include mobile devices for clinical data acquisition, the distribution of diagnostic information to healthcare providers, researchers, and patients, online surveillance of patient vital signs, and the delivery of immediate responses to medical emergencies. The proposed architecture is simple and comprises merely three essential components: a stethoscope, a customized mobile application, and an effective hardware device. An electronic sensor for capturing acoustic impulses is optimally positioned within the stethoscope chamber. To minimize external interference, all other openings of the tube are hermetically sealed, except for the sound inlet.

Figure 7 illustrates the primary components of the proposed electronic stethoscope.

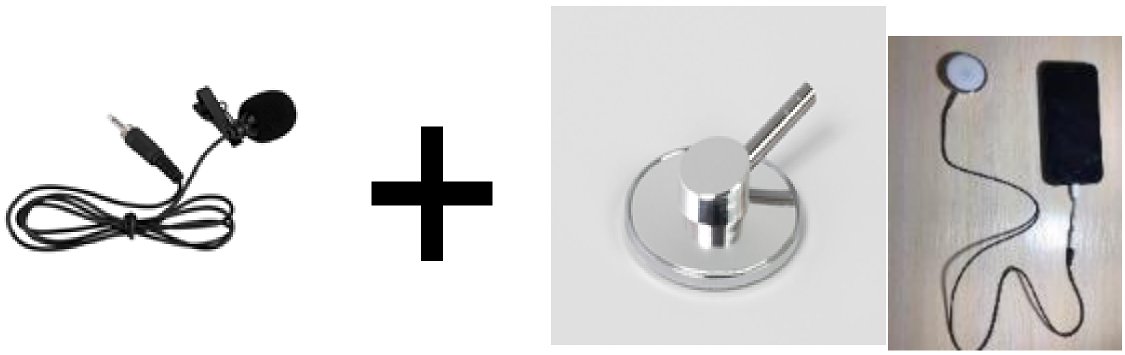


Figure 7. Electronic sensor stethoscope

Figure 8 illustrates the methodological framework for detecting cardiac irregularities on a mobile device after acoustic cardiac signals are collected with a stethoscope. The initial phase involves a comprehensive analysis of audio data collected with a stethoscope. The next phase utilizes an advanced algorithm designed to identify and eliminate background noise.

A refined classification method is utilized to examine the purified and organized signals [8-11]. The final stage of analysis identifies critical diagnostic indicators that form the basis for an initial evaluation of cardiac health, providing a thorough overview of possible heart conditions.

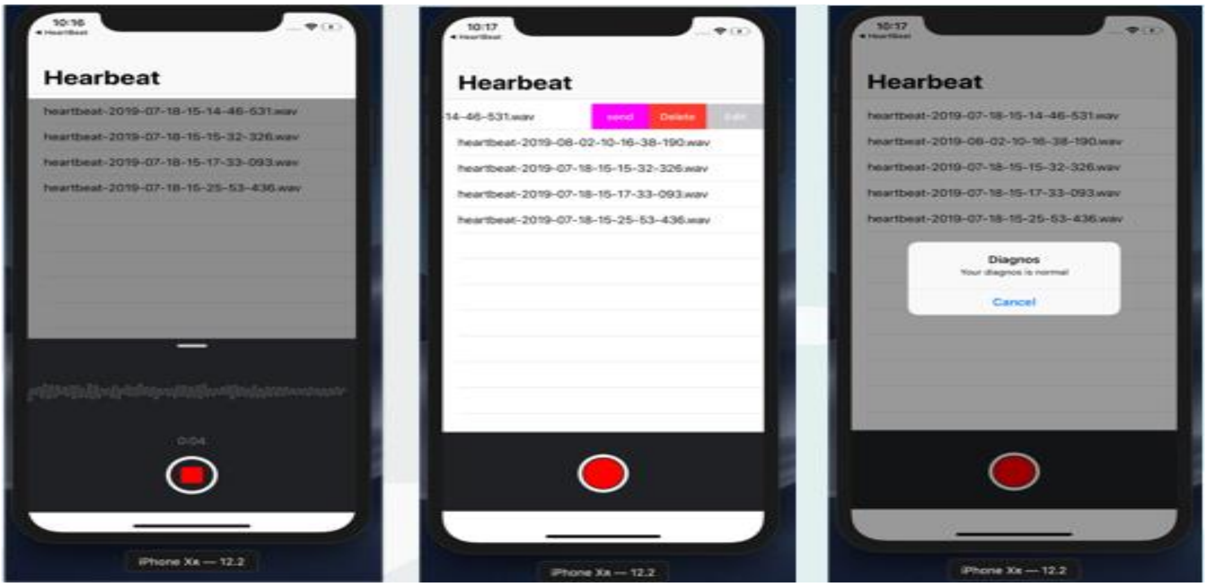
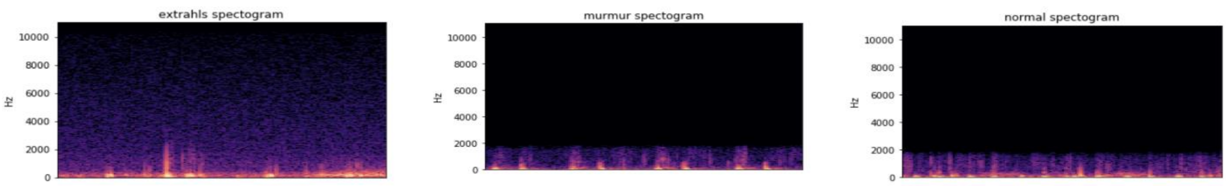


Figure 8. Heartbeat abnormality detection process

Software

Figure 9 illustrates diverse acoustic profiles of cardiac activity, encompassing normal sounds indicative of a healthy heart; murmurs, which are supplementary acoustic phenomena resulting from circulatory abnormalities and characterized by distinct oscillations; additional tones, which are unintended acoustic signals; and artifacts, which are various atypical sound manifestations captured during the recording process



Extrahls type Murmur type Normal type

Figure 9. Analysis of cardiac acoustic waves in temporal and spectral domains

Figure 8 illustrates the training and validation techniques employed to identify irregular cardiac cycles. This image illustrates the accuracy of training and validation throughout 300 iterations. Figure 10-11 depicts the fluctuations of loss across the training and validation phases. Significantly, after around 100 iterations, the loss for both training and validation phases begins to exhibit a propensity to stabilize.

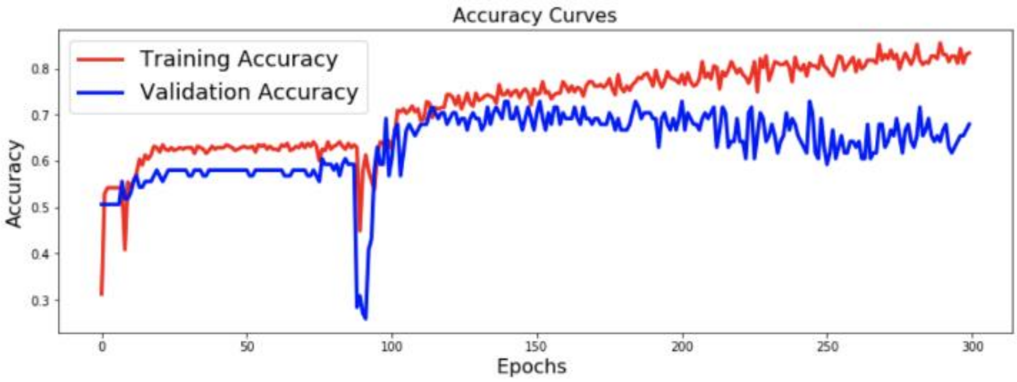


Figure 10. Using a Machine Learning Model for the Detection of Abnormal Heartbeats

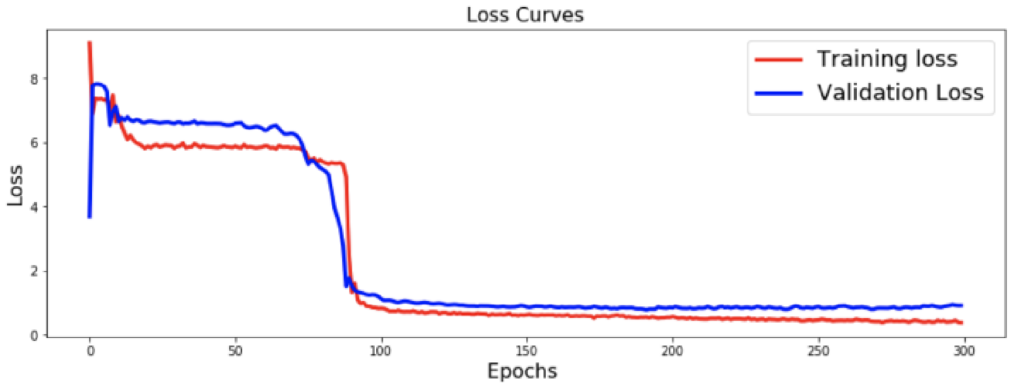


Figure 11. Comparative assessment of training and validation losses during model training

Figure 12 illustrates the error matrix derived from the classification of heart audio signals acquired using a digital stethoscope in the context of the planned study on real-time phonocardiogram-based cardiac diagnosis. The matrix illustrates the efficacy of the categorization model across five types of heart sounds: artifacts, additional heart sounds, extrasystoles, heart murmurs, and normal heart sounds.

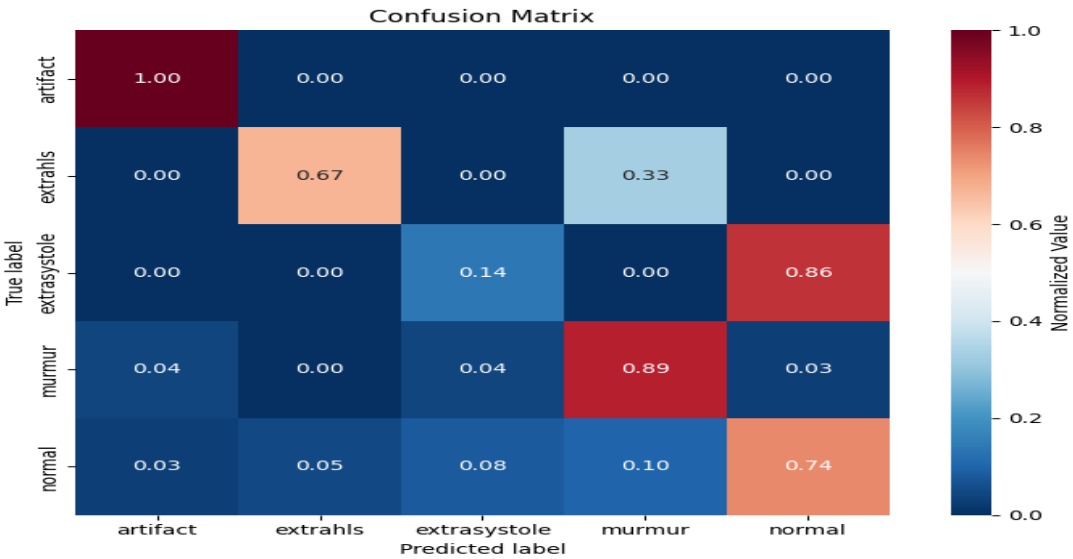


Figure 12. Confusion matrix for different types of heart sound classification

For recognition accuracy testing, the diagonal parts of the matrix show the fraction of true positives for each category. Thus, the model identified artifacts with 100% accuracy, demonstrating the algorithm's remarkable sensitivity to non-pathological noise. Extrasystoles were diagnosed with 86% accuracy, and normal heart sounds were recognized with 74% accuracy.

Pathological signs, including extra cardiac sounds and murmurs, complicate classification. In particular, 33% of extra heart sounds and 23% of heart murmurs were misdiagnosed. This shows that the acoustic qualities of small diseases are similar to those of normal heart sounds and highlights the limits of the feature-extraction and categorization system.

The findings suggest improving feature extraction and classification algorithms to more accurately diagnose minor illnesses. These regions need more research and improvements to improve the model's accuracy, reduce misclassifications, and improve clinical reliability.

Discussion

Despite the high overall accuracy of 94.5%, the lower results for individual classes are explained by the use of different evaluation metrics. Specifically, the accuracy for normal signals is 74%, while for extrasystoles it is 86%. While overall accuracy describes the proportion of correctly classified samples for the entire dataset, the metrics for individual classes indicate sensitivity or intra-class accuracy values, which are determined based on the diagonal elements of the confusion matrix.

Although the model demonstrates high overall performance, there are differences in the recognition performance of certain classes. This is explained by the similarity of the acoustic characteristics of the signals and the imbalance of classes in the datasets.

Conclusion

This paper reports a study on the development and evaluation of an intelligent system for diagnosing heart disorders by analyzing real-time phonocardiograms recorded with a digital stethoscope. The swift advancement of mobile technologies offers numerous opportunities for incorporating methods for collecting, processing, and evaluating medical data directly into clinical practice. The suggested device architecture is straightforward and comprises three essential components: an electronic stethoscope with an integrated sensor, a mobile application, and a compact processing module.

These findings underscore the need for improved acoustic feature extraction techniques and classification algorithms, particularly for identifying subtle or uncommon clinical diseases. The use of more complex neural network topologies and the augmentation of the training dataset to address clinical heterogeneity appear to be potential avenues for further investigation.

The proposed device has potential as an auxiliary diagnostic instrument that can enhance the accuracy and efficiency of primary cardiac evaluations, particularly in remote monitoring and mobile healthcare contexts.

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