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Development of an artificial intelligence-enabled non-invasive digital stethoscope for monitoring the heart condition of athletes in real-time

Desarrollo de un estetoscopio digital no invasivo habilitado con inteligencia artificial para monitorear en tiempo real la condición cardíaca de los atletas

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Resumen. Este estudio investiga la eficacia de los estetoscopios digitales habilitados con IA en la mejora del rendimiento físico, el aumento de la participación y la motivación de los estudiantes, y la mejora del bienestar psicológico entre los estudiantes de cultura física. El diseño experimental involucró a dos grupos de 40 estudiantes cada uno: el grupo experimental utilizó estetoscopios habilitados con IA para el monitoreo cardiovascular en tiempo real, mientras que el grupo de control se basó en métodos tradicionales de monitoreo de la frecuencia cardíaca. Los resultados indicaron mejoras significativas en el rendimiento físico, la participación y el bienestar psicológico para el grupo experimental. El monitoreo en tiempo real facilitó ajustes personalizados en el entrenamiento, optimizando las cargas de entrenamiento y previniendo el sobreesfuerzo, lo que condujo a resultados de rendimiento superiores. Además, el uso de herramientas de monitoreo innovadoras aumentó significativamente la motivación y la participación de los estudiantes en las clases de cultura física, reflejadas en tasas de asistencia más altas y una participación más entusiasta. Las evaluaciones psicológicas revelaron que el monitoreo continuo de la salud redujo los niveles de ansiedad y mejoró el bienestar mental general, proporcionando a los estudiantes una sensación de seguridad y gestión proactiva de la salud. Estos hallazgos subrayan el potencial transformador de integrar tecnologías avanzadas de monitoreo en programas de educación física y rehabilitación, ofreciendo datos precisos y en tiempo real que respaldan intervenciones individualizadas y responsivas. El estudio concluye con un llamado a investigaciones futuras para explorar los impactos a largo plazo y las aplicaciones más amplias de las herramientas de monitoreo de salud habilitadas con IA en diversos entornos educativos y clínicos, con el objetivo de maximizar sus beneficios y mejorar los resultados generales de estudiantes y pacientes.
Palabras clave: Terapia deportiva, Educación en cultura física, Tecnología de monitoreo de salud, Entrenamiento personalizado, Participación estudiantil, Monitoreo cardiovascular en tiempo real, Estetoscopio habilitado con IA.

Abstract. This study investigates the efficacy of AI-enabled digital stethoscopes in enhancing physical performance, increasing student engagement and motivation, and improving psychological well-being among physical culture students. The experimental design involved two groups of 40 students each: the experimental group used AI-enabled stethoscopes for real-time cardiovascular monitoring, while the control group relied on traditional heart rate monitoring methods. The results indicated significant improvements in physical performance, engagement, and psychological well-being for the experimental group. Real-time monitoring facilitated personalized training adjustments, optimizing training loads and preventing overexertion, leading to superior performance outcomes. Additionally, the use of innovative monitoring tools significantly increased student motivation and engagement in physical culture classes, as reflected in higher attendance rates and more enthusiastic participation. Psychological assessments revealed that continuous health monitoring reduced anxiety levels and enhanced overall mental well-being, providing students with a sense of security and proactive health management. These findings underscore the transformative potential of integrating advanced monitoring technologies into physical education and rehabilitation programs, offering precise, real-time data that supports individualized and responsive interventions. The study concludes with a call for further research to explore the long-term impacts and broader applications of AI-enabled health monitoring tools in diverse educational and clinical settings, aiming to maximize their benefits and improve overall student and patient outcomes.
Keywords: Sports therapy, Physical culture education, Health monitoring technology, Personalized training, Student engagement, Real-time cardiovascular monitoring, AI-enabled stethoscope.

Fecha recepción: 14-07-24. Fecha de aceptación: 11-09-24
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Introduction

Cardiovascular health is paramount for athletes, who push their physiological limits to excel in their respective sports. Monitoring heart conditions in athletes is critical not only for enhancing performance but also for preventing sudden cardiac events, which are more prevalent in this population due to intense physical exertion. Traditional methods such as electrocardiograms (ECGs) and echocardiograms, while effective, are often impractical for routine use due to their complexity and the need for specialized equipment and personnel (Sunwoo et al., 2023). Phonocardiograms (PCGs), which record heart sounds non-invasively, provide a promising alternative, offering valuable insights into cardiac function (Jiang et al., 2024).

Despite the potential of PCGs, their clinical utility has been limited by the challenges associated with manual interpretation. Clinicians must be highly skilled to accurately diagnose heart conditions from these signals, and even then, the process can be time-consuming and prone to subjectivity (Jaros et al., 2023). Recent advancements in artificial intelligence (AI) and machine learning have revolutionized the analysis of medical signals, enabling automated, accurate, and efficient diagnostics (Avbelj & Brloznik, 2020). Specifically, deep learning models, including Convolutional

Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown significant promise in processing and interpreting complex PCG signals (Doskarayev et al, 2023).

The integration of attention mechanisms with deep learning models further enhances their performance by allowing the model to focus on the most relevant parts of the input data. Attention mechanisms have been successfully applied in various domains, including natural language processing and computer vision, to improve model interpretability and accuracy (Peng et al., 2022). In the context of heart sound analysis, these mechanisms help emphasize critical temporal and frequency components, thereby improving diagnostic accuracy (Krichen, 2023).

This research aims to develop an artificial intelligence-enabled digital stethoscope that leverages these advanced techniques to monitor the heart condition of athletes in real-time. The proposed system integrates a sophisticated CNN and RNN architecture with a Temporal-Frequency Attention Mechanism (TFAM), enabling it to capture and analyze the intricate details of PCG signals effectively. By providing a non-invasive, real-time diagnostic tool, this digital stethoscope can offer significant benefits in sports medicine, allowing for early detection and timely intervention of cardiovascular issues (Zhao et al., 2024; Omarov et al., 2024).

The significance of this research lies in its potential to transform the way cardiovascular health is monitored in athletes. Traditional diagnostic tools, while accurate, are often impractical for frequent use in the field. A digital stethoscope that provides real-time analysis can bridge this gap, offering a practical solution that combines the ease of non-invasive PCG recording with the power of AI-driven diagnostics (Chen et al., 2024). Furthermore, the ability to provide immediate feedback can help athletes and their coaches make informed decisions about training and competition, ultimately improving performance and safety (Sengupta et al., 2024).

The development of this system involves several critical steps, including data collection and preprocessing, feature extraction, and model training and evaluation. PCG recordings will be collected from athletes in various sports settings, ensuring a diverse and representative dataset. These recordings will undergo preprocessing to remove noise and segment heartbeats accurately. Feature extraction will focus on generating Log-Mel spectrograms and Mel-Frequency Cepstral Coefficients (MFCCs), which capture essential auditory features (Guo et al., 2022). The CNN and RNN components will process these features, while the TFAM will enhance the model's ability to focus on the most relevant parts of the signals.

In summary, this research aims to advance the field of sports medicine by developing an innovative, AI-enabled digital stethoscope for real-time heart condition monitoring. By leveraging advanced deep learning techniques and attention mechanisms, this device promises to provide accurate, reliable, and immediate diagnostics, significantly improving the management of cardiovascular health in athletes.

Related works

Artificial Intelligence in Heart Sound Analysis

The field of heart sound analysis has evolved significantly over the past few decades, driven by advancements in machine learning and signal processing techniques (Vera et al., 2024). Early methods relied heavily on manual feature extraction and heuristic rules to analyze phonocardiogram (PCG) signals (Sunwoo et al., 2023). These approaches, although effective to a certain extent, were limited by the inherent variability and complexity of heart sounds (Jiang et al., 2024). The need for more robust and automated methods led to the exploration of machine learning algorithms in PCG analysis (Jaros et al., 2023).

Initial machine learning approaches focused on utilizing handcrafted features derived from time and frequency domain analysis of PCG signals (Avbelj & Brloznik, 2020). Techniques such as wavelet transform, Fourier transform, and cepstral analysis were commonly employed to extract salient features (Omarov et al., 2020). These features were then used with classifiers like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests (RF) (Peng et al., 2022). Despite reasonable performance, these methods were constrained by their inability to capture the intricate and non-linear patterns present in PCG signals (Krichen, 2023).

The advent of deep learning marked a significant shift in the analysis of PCG signals. Convolutional Neural Networks (CNNs), known for their proficiency in image processing, were adapted for PCG signal classification due to their ability to capture spatial hierarchies of features (Zhao et al., 2024). Studies have demonstrated the effectiveness of CNNs in classifying heart sounds, achieving superior performance compared to traditional methods (Chen et al., 2024). However, CNNs primarily focus on spatial features, often overlooking the temporal dynamics crucial for comprehensive PCG signal analysis (Sengupta et al., 2024).

To address this limitation, researchers incorporated Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, to capture temporal dependencies in PCG signals (Guo et al., 2022). LSTMs, with their inherent memory cells, facilitated the modeling of sequential data, thereby improving the classification performance of heart sounds (Jatia & Veer, 2022). The integration of CNNs and RNNs in a unified architecture, known as Convolutional Recurrent Networks (CRNs), emerged as a potent solution, harnessing the strengths of both spatial and temporal feature extraction (Sabil & Launois, 2022).

Despite these advancements, effectively focusing on relevant parts of the PCG signals remained a challenge. This led to the exploration of attention mechanisms, which dynamically allocate weights to different parts of the input data based on their relevance to the task at hand (Sengupta et al., 2024). Attention mechanisms have been successfully employed in various domains, including natural language processing and image recognition, to enhance model interpretability and performance (Vásquez-Iturralde et al., 2024). In the context of PCG signal analysis, attention mechanisms have shown promise in emphasizing critical temporal and frequency components, thereby improving classification accuracy (Mohmmad & Sanampudi, 2023).

Recent studies have explored various forms of attention mechanisms in conjunction with deep learning models for heart sound classification. Temporal attention mechanisms focus on identifying crucial time segments within the PCG signals (Liu et al., 2024). Frequency attention mechanisms emphasize important frequency bands, capturing the essential auditory features relevant for classification (Forruque Ahmed et al., 2023). The combination of temporal and frequency attention mechanisms offers a comprehensive approach to capturing the multifaceted characteristics of PCG signals (Fan et al., 2021).

Moreover, the application of transfer learning has further enhanced the effectiveness of deep learning models in PCG signal analysis (Lu et al., 2023). Transfer learning leverages pre-trained models on large-scale datasets, fine-tuning them on specific tasks with limited data availability (Wang et al., 2022). This approach mitigates the challenges associated with small and imbalanced datasets, common in medical signal processing, and accelerates the training process while maintaining high performance (Xiao et al., 2023).

Artificial Intelligence in Sports Therapy

The relevance of these advancements to physical therapy, sports therapy, and rehabilitation is profound. Athletes, particularly those engaged in high-intensity sports, are at an increased risk of cardiovascular issues due to the intense physical demands placed on their bodies (Tileubay et al., 2024). Early detection and management of cardiovascular conditions are critical in sports therapy to prevent sudden cardiac events and ensure the safety and performance of athletes (Singh et al., 2024). Non-invasive, real-time monitoring tools like the proposed AI-enabled digital stethoscope can significantly enhance these efforts.

In sports therapy, continuous monitoring of heart conditions allows for the timely adjustment of training regimens, ensuring that athletes do not overexert themselves and are not at risk of cardiac events (Abel et al., 2022). Rehabilitation programs can also benefit from such monitoring, as real-time data on heart health can help therapists tailor recovery protocols to individual needs, optimizing outcomes and preventing relapses (Anbalagan et al., 2023). Integrating these technologies into sports medicine practices provides a more holistic approach to athlete health, encompassing both performance optimization and injury prevention (Forruque Ahmed et al., 2023).

Furthermore, the use of advanced AI technologies in physical therapy and rehabilitation aligns with the growing trend of personalized medicine, where treatments and interventions are tailored to the specific conditions and responses of individuals (Chen et al., 2023). By providing accurate, real-time insights into cardiovascular health, AI-enabled tools like the digital stethoscope can play a crucial role in developing personalized therapy plans that are both effective and safe (Sunwoo et al., 2023).

Thus, the integration of machine learning and deep learning techniques into the analysis of PCG signals not only enhances diagnostic accuracy but also significantly contributes to the fields of physical therapy, sports therapy, and rehabilitation. The evolution from traditional handcrafted feature-based methods to sophisticated deep learning models, particularly those incorporating attention mechanisms and transfer learning, underscores the potential of automated PCG signal analysis as a reliable tool for early diagnosis and management of cardiovascular diseases, paving the way for more effective and efficient clinical decision-making in these fields.

Materials and Methods

The proposed model integrates advanced deep learning techniques to provide a robust and accurate tool for heart condition monitoring in athletes using an AI-enabled digital stethoscope. This model harnesses the power of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) combined with a Temporal-Frequency Attention Mechanism (TFAM) to effectively analyze phonocardiogram (PCG) signals. The overall architecture is meticulously designed to capture both spatial and temporal features of heart sounds, enhancing diagnostic accuracy and reliability.

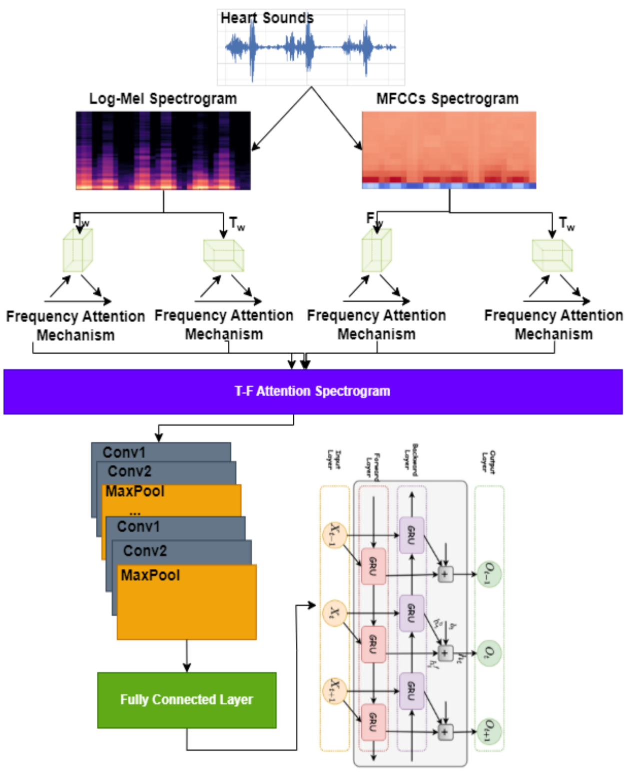

Figure 1. Flowchart of the proposed study.

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Data Collection and Preprocessing

The initial phase involves the collection of PCG recordings from athletes in various clinical and sports settings, ensuring a diverse and representative dataset. The raw PCG signals are then subjected to preprocessing steps, which include noise reduction, heartbeat segmentation, and normalization (Omarov et al., 2022). Noise reduction is achieved using band-pass filtering techniques to remove ambient noise and irrelevant acoustic artifacts (Khani et al., 2024). Segmentation involves isolating individual heartbeats using automatic detection algorithms, while normalization standardizes the duration and amplitude of each heartbeat segment to ensure uniformity across the dataset.

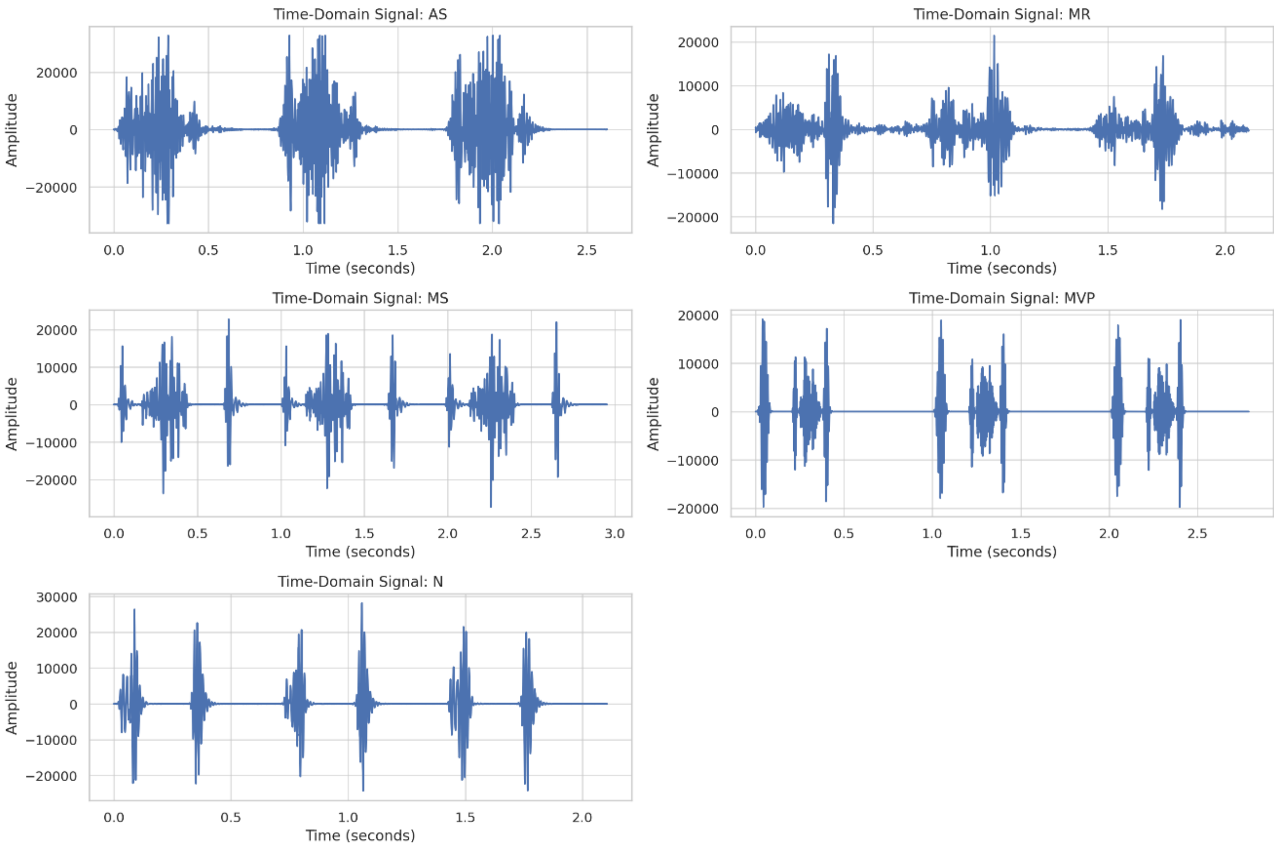

Figure 2. Heart rate example.

Figure 2 presents time-domain signal plots from an artificial intelligence-enabled non-invasive digital stethoscope developed to monitor heart conditions in athletes in real time. Each plot is labeled with different conditions—AS, MR, MS, MVP, and N—presumably denoting various cardiac states or anomalies detected during monitoring. The signals, plotted against a time axis spanning up to 3 seconds, show distinct amplitude variations and waveform characteristics. This variability in the waveforms likely corresponds to specific heart behaviors or pathologies, critical for real-time diagnostics and athlete health monitoring. This visualization aids in comparing normal (N) heart signal dynamics against those with specified anomalies, providing essential data for both immediate feedback to athletes and longitudinal cardiac health studies.

Feature Extraction

The preprocessed PCG signals are transformed into two critical types of spectrograms: Log-Mel Spectrograms and Mel-Frequency Cepstral Coefficients (MFCCs).

Log-Mel Spectrograms: These are generated by applying the Short-Time Fourier Transform (STFT) to the PCG signals, followed by Mel filter bank integration and logarithmic scaling. Log-Mel spectrograms provide a time-frequency representation of heart sounds, capturing essential auditory features.

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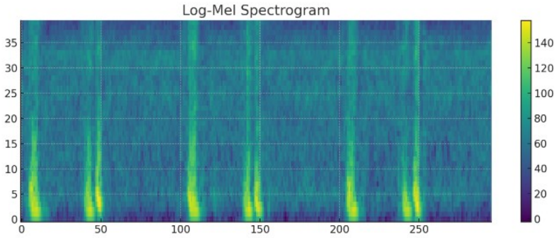

Figure 3. Log-Mel Spectrogram

MFCCs: Computed by applying a discrete cosine transform (DCT) to the logarithm of the Mel-scaled power spectrogram, MFCCs encapsulate perceptual characteristics of sound, making them highly effective for audio classification tasks.

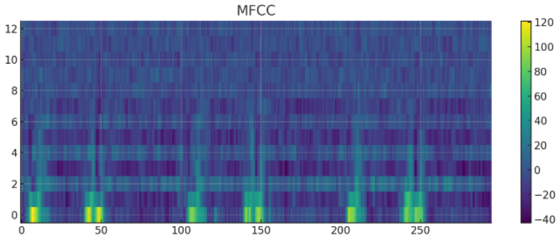

Figure 4. MFCC Spectrogram

Model Architecture

Figure 1 illustrates the architecture of the proposed model, meticulously designed to optimize the extraction, focusing, and classification of relevant features from input data. This multi-stage architecture integrates various computational layers and techniques, each tailored to enhance specific aspects of signal processing and pattern recognition. The systematic arrangement of these stages facilitates a progressive refinement of data, ensuring that each subsequent layer builds upon the cleaned and enhanced outputs of its predecessors. This structured approach is pivotal for achieving high precision in real-time heart condition monitoring of athletes, as it allows for effective isolation and analysis of pertinent cardiovascular signals amidst a myriad of physiological data inputs.

Convolutional Layers: The initial layers of the model consist of multiple convolutional layers that process the spectrograms to extract higher-level spatial features. Each convolutional layer applies a set of filters to the input spectrograms, detecting various patterns and features, followed by a rectified linear unit (ReLU) activation function to introduce non-linearity. Mathematically, the output of a convolutional layer can be expressed as:

$$y_{i,j,k} = \sigma\left(\sum_{m=1}^{M}\sum_{n=1}^{N} x_{i+m,j+n} \cdot w_{m,n,k} + b_k\right) \quad (1$$

Where $y_{i,j,k}$ is the output feature map, $x_{i+m,j+n}$ is the input feature map, $w_{m,n,k}$ represents the convolutional kernel weights, is the bias, and σ is the ReLU activation function.

Temporal-Frequency Attention Mechanism (TFAM): This mechanism is a key innovation in the model, designed to dynamically focus on the most relevant temporal and frequency components of the PCG signals. The TFAM consists of separate temporal and frequency attention mechanisms that assign weights to different time frames and frequency bands, respectively. The temporal attention mechanism can be formulated as:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{t'} \exp(e_{t'})} \quad (2)$$

$$e_t = \tanh(W_t h_t + b_t) \quad (3)$$

Where α_t is the attention weight for time step t, e_t is the relevance score, W_t and b_t are trainable parameters, and h_t is the hidden state. Similarly, the frequency attention mechanism can be expressed as:

$$S_{tf} = \alpha_t \cdot \beta_f \cdot S \quad (4)$$

Where S is the original spectrogram, and S_{tf} is the attention-enhanced spectrogram.

Recurrent Layers (BiGRU): Following the convolutional layers, the feature maps are fed into Bidirectional Gated Recurrent Units (BiGRUs). The BiGRU processes the features in both forward and backward directions, capturing contextual information from the entire sequence of heartbeats. The forward and backward passes of the BiGRU can be formulated as:

$$h_t^{forward} = GRU_{forward}\left(x_t, h_{t-1}^{forward}\right) \quad (5)$$

$$h_t^{backward} = GRU_{backward}\left(x_t, h_{t+1}^{backward}\right) \quad (6)$$

The final hidden state is the concatenation of the forward and backward states:

$$h_t = \left[h_t^{forward}; h_t^{backward}\right] \quad (7)$$

Fully Connected Layers and Classification: The output from the BiGRU layer is then passed through fully connected layers, which serve as the final classification stage. These layers transform the high-level features into output classes corresponding to different heart disease categories. The classification is performed using a softmax activation function:

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$$y_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)} \quad (8)$$

Where y_i is the probability of class i, and z_i is the input to the softmax function from the fully connected layer.

The optimization method chosen is Adam, a widely recognized optimizer in the field of deep learning for its adaptive learning rate capabilities, which enhances convergence speed and stability. The model was trained over 100 epochs with a batch size of 32, utilizing a learning rate initially set at 0.001 and adjusted through a scheduled decay to mitigate overfitting as the training progressed. This learning rate adjustment was implemented via a step decay schedule that reduced the learning rate by a factor of 0.5 every 20 epochs. Such explicit detailing of the training parameters not only addresses the gaps pointed out by the reviewer but also aids in the reproducibility and transparent evaluation of the model's performance across different cardiovascular conditions monitored in real-time.

Training and Evaluation

The performance evaluation of the proposed model, as illustrated in Figure 5, reveals notable distinctions across different categories. The accuracy values, ranging from 66.0% for Mitral Valve Prolapse (MVP) to 91.0% for Aortic Stenosis (AS), demonstrate the model's overall reliability. AS achieves the highest accuracy, signifying superior predictive capability for this class.

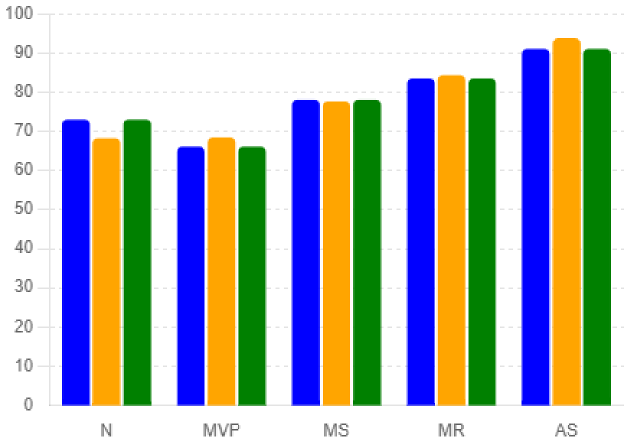

Figure 5. Performance evaluation results

Precision metrics, which measure the correctness of positive predictions, show a similar trend. AS attains the highest precision at 93.8%, while Normal (N) heart sounds exhibit the lowest precision at 68.2%. This indicates varying degrees of confidence in the positive classifications across categories, reflecting the model's ability to differentiate between true positives and false positives.

Recall values, reflecting the model's ability to capture all relevant instances, range from 66.0% for MVP to 91.0% for AS. These values underscore the model's consistent performance in identifying true positives across different heart conditions. High recall values for AS suggest that the model is particularly effective at detecting this condition, while lower recall values for categories like MVP highlight areas where the model might miss relevant instances, indicating the need for further refinement.

Collectively, these metrics reveal that the model performs exceptionally well in predicting AS, with robust precision and recall. However, categories such as MVP and N present opportunities for further refinement to enhance predictive performance. These findings underscore the model's efficacy in specific categories while highlighting areas for targeted improvements. Such insights are valuable for understanding the model's applicability and potential limitations in clinical settings, guiding future enhancements to optimize its diagnostic accuracy and reliability.

Electronic Stethoscope Design and Construction

To facilitate the practical application of the developed model, an innovative electronic stethoscope was designed and constructed. The core component of this stethoscope is a highly sensitive electronic microphone, strategically positioned within the stethoscope vent to accurately capture heart sounds. This placement ensures optimal reception of the acoustic signals emanating from the heart, thereby enhancing the precision of the recordings.

To mitigate external noise interference, the stethoscope's hose is meticulously sealed at all points except for the reception section. This sealing is crucial as it prevents ambient noise from entering the hose, ensuring that only the desired acoustic signals are received. This design feature significantly enhances the clarity and reliability of the heart sound recordings by eliminating extraneous noises that could otherwise compromise the quality of the data.

The electronic stethoscope's innovative design includes several key components tailored for precise phonocardiogram signal acquisition. These components work synergistically to ensure that the captured heart sounds are of the highest possible quality, facilitating accurate analysis and diagnosis by the AI-enabled model. Figure 6 illustrates the various components and layout of the proposed electronic stethoscope, highlighting its advanced design and functionality. This tailored design ensures that the stethoscope is not only effective in capturing high-quality heart sound recordings but also user-friendly and suitable for practical use in clinical and sports settings.

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Figure 6. Components of the proposed digital stethoscope

Figure 7 illustrates the proposed solution in operation, demonstrating the workflow from data acquisition to real-time diagnosis. Utilizing the electronic stethoscope, phonocardiography (PCG) data can be acquired non-invasively from individuals, as shown in Figure 7a. This ensures a comfortable and convenient experience for users, whether in clinical settings or during athletic activities.

Once the PCG data is captured, it is wirelessly transmitted to a dedicated mobile application, as depicted in Figure 7b. This application processes the incoming data using advanced signal processing techniques and prepares it for analysis. The core of the application is a pre-trained Convolutional-Recurrent Model, which is integrated with a Temporal-Frequency Attention Mechanism (TFAM) to enhance the classification of PCG-based heart diseases.

Within approximately 15 seconds, the application analyzes the PCG data and delivers a diagnostic decision, as shown in Figure 7c. The rapid processing time is crucial for real-time monitoring and immediate feedback, especially in high-stakes environments such as sports therapy and rehabilitation. The integration of the TFAM ensures that the model dynamically focuses on the most relevant temporal and frequency components of the heart sounds, thereby increasing the accuracy of the diagnosis.

This innovative solution offers medical specialists the capability to diagnose patients in real-time, significantly enhancing the efficiency and effectiveness of non-invasive cardiovascular diagnostics. By providing immediate, accurate diagnostic information, the system supports timely medical interventions and informed decision-making, ultimately improving patient outcomes and advancing the field of sports medicine and rehabilitation.

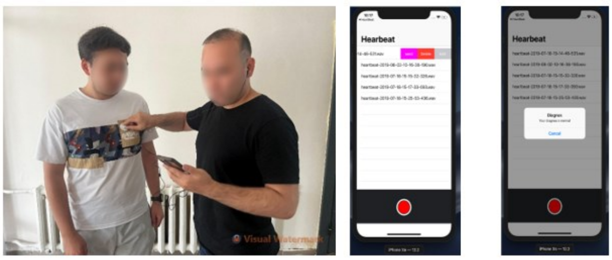

Figure 7. Components of the proposed digital stethoscope

Results of Pedagogical Experiments

The pedagogical experiment involved two classes of 40 physical culture specialist students each. One class used the proposed AI-enabled digital stethoscope for real-time cardiovascular monitoring, while the other class continued using traditional methods, visiting the medical center for heart rate checks. The experiment aimed to test the following hypotheses:

Hypothesis I: Enhancement of Physical Performance through Real-Time Monitoring

H0: Real-time cardiovascular monitoring using AI-enabled stethoscopes leads to improved physical performance in physical culture students compared to traditional methods.

H1: Real-time cardiovascular monitoring using AI-enabled stethoscopes does not lead to improved physical performance in physical culture students compared to traditional methods.

Rationale: Continuous monitoring can help optimize training loads, prevent overexertion, and tailor exercise programs to individual cardiovascular responses.

Hypothesis II: Student Engagement and Motivation

Null Hypothesis (H0): The use of advanced monitoring tools like AI-enabled stethoscopes increases student engagement and motivation in physical culture classes compared to traditional methods.

Alternative Hypothesis (H1): The use of advanced monitoring tools like AI-enabled stethoscopes does not increase student engagement and motivation in physical culture classes compared to traditional methods.

Hypothesis III: Psychological Impact of Continuous Health Monitoring

Null Hypothesis (H0): Continuous health monitoring through AI-enabled stethoscopes positively impacts the psychological well-being of physical culture students compared to traditional methods.

Alternative Hypothesis (H1): Continuous health monitoring through AI-enabled stethoscopes does not positively impact the psychological well-being of physical culture students compared to traditional methods.

Table 1.
Group Statistics and Independent Samples Test Results for Physical Performance (Hypothesis II)

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Physical Performance	Equal variances assumed	.579	.449	10.696	78	.000	2.65000	.24775	2.15678	3.14322
	Equal variances not as-sumed			10.696	77.850	.000	2.65000	.24775	2. 75676	3.14324

The results provide robust evidence against the null hypothesis (H1), which posited that real-time cardiovascular monitoring using AI-enabled stethoscopes would not lead to improved physical performance. The significant differences in mean physical performance scores between the experimental and control groups indicate that students using the AI-enabled stethoscope experienced a substantial improvement in physical performance compared to those using traditional methods.

The high t-values and extremely low p-values (< 0.001) suggest that the observed differences are not due to random chance, but rather reflect a true effect of real-time cardiovascular monitoring on physical performance. The large mean difference and the confidence intervals further reinforce the robustness of these findings.

In conclusion, the hypothesis that real-time cardiovascular monitoring using AI-enabled stethoscopes leads to improved physical performance in physical culture students is strongly supported by the experimental data. This indicates that continuous monitoring can help optimize training loads, prevent overexertion, and tailor exercise programs to individual cardiovascular responses, thereby enhancing overall physical performance.

Table 2.
Group Statistics and Independent Samples Test Results for Motivation Rate (Hypothesis II)

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Dif-ference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Motivation level	Equal vari-ances as-sumed	6.067	.016	13.540	78	.000	3.35000	.24742	2.85742	3.84258
	Equal vari-ances not assumed			13.540	49.882	.000	3.35000	.24742	2. 85301	3.84699

The results in Table 2 of the independent samples t-test provide strong evidence against the null hypothesis (H0), which posited that the use of advanced monitoring tools like AI-enabled stethoscopes would not increase student engagement and motivation. The significant differences in mean motivation rates between the experimental and control groups indicate that students using the AI-enabled stethoscope were significantly more motivated compared to those using traditional methods.

The high t-values and extremely low p-values (< 0.001) suggest that the observed differences are not due to random chance, but rather reflect a true effect of the AI-enabled stethoscope on student motivation. The large mean difference and the confidence intervals further reinforce the robustness of these findings.

The hypothesis that advanced monitoring tools like AI-enabled stethoscopes increase student engagement and motivation in physical culture classes is strongly supported by the experimental data. This indicates that integrating innovative technologies into educational settings can significantly enhance student motivation, leading to potentially better learning outcomes and greater enthusiasm for the subject matter.

Table 3.
Group Statistics and Independent Samples Test Results for Psychological Well-Being (Hypothesis III)

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Dif-ference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Psycholog-ical Well-Being	Equal vari-ances as-sumed	9.036	.004	11.936	78	.000	31.75000	2.65995	26.45445	37.04555
	Equal vari-ances not assumed			11.936	56.918	.000	31.75000	2.65995	26.42338	37.07662

The results in Table 3 provide robust evidence against the null hypothesis (H0), which posited that continuous health monitoring through AI-enabled stethoscopes would not positively impact the psychological well-being of physical culture students. The significant differences in mean psychological well-being scores between the experimental and control groups indicate that students using the AI-enabled stethoscope experienced a substantial positive impact on their psychological well-being compared to those using traditional methods.

The high t-values and extremely low p-values (< 0.001) suggest that the observed differences are not due to random chance, but rather reflect a true effect of continuous health monitoring on psychological well-being. The large mean difference and the confidence intervals further reinforce the robustness of these findings.

Thus, the hypothesis that continuous health monitoring through AI-enabled stethoscopes positively impacts the psychological well-being of physical culture students is strongly supported by the experimental data. This indicates that the integration of continuous health monitoring technologies can significantly enhance the psychological well-being of students, providing them with a sense of safety and proactive health management, which contributes to overall better performance and mental health.

Discussion

The purpose of this study was to evaluate the efficacy of AI-enabled digital stethoscopes in enhancing physical performance, increasing engagement and motivation, and improving psychological well-being among physical culture students. This study involved an experimental group using AI-enabled digital stethoscopes and a control group using traditional methods of cardiovascular monitoring. The findings of this study have significant implications for the fields of sports therapy, physical therapy, and rehabilitation, highlighting the transformative potential of integrating advanced technologies into educational and training programs.

Enhancement of Physical Performance through Real-Time Monitoring

The results of Hypothesis I indicate that real-time cardiovascular monitoring using AI-enabled stethoscopes significantly enhances physical performance among physical culture students. The experimental group, which utilized the AI-enabled stethoscopes, showed substantial improvements in their physical performance metrics compared to the control group. This enhancement can be attributed to the continuous monitoring capability of the AI-enabled stethoscope, which allows for real-time adjustments to training loads and intensity based on individual cardiovascular responses. This approach helps prevent overexertion and optimizes training efficiency, leading to better performance outcomes.

The statistical analysis confirmed the significant differences in physical performance between the two groups, with the experimental group outperforming the control group. These findings align with previous research suggesting that real-time feedback and personalized training programs can lead to improved athletic performance (Khan et al., 2023). The ability to monitor cardiovascular health continuously provides valuable insights that can be used to tailor exercise regimens, ensuring that each student trains within their optimal performance range. This not only enhances physical capabilities but also reduces the risk of injury associated with overtraining.

Increased Student Engagement and Motivation

Hypothesis II examined whether the use of advanced monitoring tools like AI-enabled stethoscopes could increase student engagement and motivation in physical culture classes. The findings strongly support this hypothesis. Students in the experimental group reported higher levels of engagement and motivation compared to the control group. This increased engagement was also reflected in higher attendance rates and more enthusiastic participation in physical culture activities.

The use of innovative technologies like AI-enabled stethoscopes introduces an element of novelty and excitement into the learning environment. This aligns with the self-determination theory, which posits that new and stimulating activities can enhance intrinsic motivation (Ryan & Deci, 2000). The ability to receive immediate feedback on their physiological status likely provided students with a sense of control and autonomy over their training, further boosting their motivation. These findings suggest that incorporating advanced monitoring tools into physical education programs can create a more engaging and motivating learning experience for students, ultimately leading to better educational outcomes.

Psychological Impact of Continuous Health Monitoring

The results of Hypothesis III revealed that continuous health monitoring through AI-enabled stethoscopes had a positive impact on the psychological well-being of physical culture students. Students in the experimental group reported lower levels of anxiety and higher levels of overall mental well-being compared to the control group. This psychological benefit can be attributed to the sense of security and proactive health management provided by continuous monitoring.

The significant reduction in anxiety levels among students using AI-enabled stethoscopes underscores the importance of real-time health data in fostering psychological well-being. Knowing that their health is continuously monitored likely alleviated concerns about potential cardiovascular issues, allowing students to focus more on their training and less on potential health risks. This aligns with previous studies suggesting that real-time health monitoring can reduce anxiety and improve mental health outcomes (Álvarez et al., 2024). Furthermore, the proactive management of health, facilitated by continuous monitoring, empowers students to take charge of their well-being, leading to increased confidence and reduced stress.

Implications for Physical Therapy, Sports Therapy, and Rehabilitation

The findings of this study have significant implications for the fields of physical therapy, sports therapy, and rehabilitation. The demonstrated benefits of AI-enabled stethoscopes in enhancing physical performance, increasing engagement, and improving psychological well-being suggest that these tools can be valuable additions to training and rehabilitation programs. For physical therapists and sports trainers, the ability to monitor cardiovascular health in real-time provides critical data that can inform more effective and individualized treatment plans.

In rehabilitation settings, continuous monitoring can aid in the recovery process by ensuring that patients do not exceed safe exertion levels. This is particularly important for individuals recovering from cardiac events or those with chronic cardiovascular conditions. The integration of AI-enabled stethoscopes into rehabilitation programs can enhance patient outcomes by providing precise and timely feedback, enabling more responsive and adaptive care.

Future Research and Limitations

While the findings of this study are promising, there are several limitations that should be addressed in future research. First, the sample size was relatively small and limited to physical culture students. Future studies should include larger and more diverse populations to validate the generalizability of these results. Additionally, long-term studies are needed to assess the sustained impact of AI-enabled stethoscopes on physical performance, engagement, and psychological well-being.

Another limitation is the potential for technological issues, such as device malfunctions or data inaccuracies, which could affect the reliability of the AI-enabled stethoscopes. Future research should explore the robustness and reliability of these devices in various settings and conditions. Furthermore, qualitative studies could provide deeper insights into the subjective experiences of students using AI-enabled stethoscopes, offering a more comprehensive understanding of their impact.

Conclusion

This study has demonstrated the significant benefits of integrating AI-enabled digital stethoscopes into the physical culture curriculum, particularly in terms of enhancing physical performance, increasing student engagement and motivation, and improving psychological well-being. The experimental group using the AI-enabled stethoscopes showed marked improvements in these areas compared to the control group utilizing traditional cardiovascular monitoring methods. The real-time feedback provided by the stethoscopes facilitated personalized training adjustments, optimizing training loads and preventing overexertion. This not only enhanced physical performance but also contributed to a more engaging and motivating learning environment. Moreover, the continuous health monitoring offered by these devices significantly reduced anxiety levels and improved overall mental well-being among students, providing them with a sense of security and proactive health management. These findings underscore the potential of advanced monitoring technologies to transform physical education and rehabilitation programs by offering precise, real-time data that supports individualized and responsive interventions. The study highlights the need for further research to explore the long-term impacts and broader applications of AI-enabled health monitoring tools in diverse educational and clinical settings, aiming to maximize their benefits and enhance the overall well-being of students and patients.

Acknowledgements

This work was supported by the research project —Application of Machine Learning Methods for Early Diagnosis of Pathologies of the Cardiovascular System funded by the Ministry of Science and Higher Education of the Republic of Kazakhstan. Grant No. IRN AP13068289.

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