

Deep Learning Framework for Automated Health Monitoring Using Physiological Signals

Gorika

Research Scholar, NIT Kurukshetra

DOI: <https://doi.org/10.55948/IJERMCA.2026.0908>

ABSTRACT

The accelerated rate of digitalization and Artificial Intelligence (AI) is transforming the economic structures and systems of governance and policies in all countries of the world especially in digital health technologies. The paper will discuss the application of AI-based deep learning models to identify cardiac arrhythmias in the early stages by using long-term electrocardiogram (ECG) signals, which is essential in controlling health in long-duration space missions where conventional healthcare facilities are scarce. The study will evaluate how advanced AI systems can improve preventive care and minimize operational risks and shape autonomous healthcare policies based on evidence. Dividing structured ECG data into particular heartbeat categories and comparing different deep learning models, such as CNN, LSTM, BiLSTM, and Transformers architectures, the research results indicate that certain models, such as BiLSTM, outperform the rest in terms of detecting infrequent arrhythmic events. The study highlights the possibilities of AI to further the digital governance of healthcare, with ethical AI implementation and data governance as the suggested policy frameworks to achieve sustainable healthcare outcomes. Finally, the research states that health monitoring using AI is a potential source of more transparent governance and an improved allocation of resources, which supports the idea that resilient and future-oriented governance systems are needed both in space and on the ground.

Keywords: Electrocardiogram (ECG), Convolutional Neural Networks (CNN), Bi-directional LSTM (BiLSTM), Long Short-Term Memory (LSTM), Data augmentation

INTRODUCTION

The rapid expansion of digitalization and Artificial Intelligence (AI) has significantly transformed healthcare systems, governance structures, and public policy-making worldwide. Emerging digital health technologies—particularly those integrating AI—are enabling predictive analytics, real-time monitoring, and automated decision-making, which are reshaping the delivery of clinical services and health governance at both national and global levels. AI-powered wearable and IoT-enabled systems now facilitate continuous tracking of physiological parameters, supporting early detection of diseases, personalized care plans, and decentralized health services that reduce dependency on traditional healthcare infrastructure, especially in remote and underserved regions. (Naik et al. 2026)

The growing relevance of AI in health governance is further reflected in its ability to process large volumes of data from sensors like electrocardiograms (ECG), enabling early and accurate anomaly detection, which can aid healthcare providers in making informed decisions more efficiently than is possible through conventional methods. This integration of digital technologies into healthcare not only enhances clinical outcomes but also has important policy implications for health systems, including the formulation of regulations for data privacy, AI ethics, and equitable access to digital health infrastructure. The ability of AI-driven systems to anticipate risk factors and deliver adaptive interventions supports the shift toward preventive healthcare policies that emphasize citizen-centric, efficient, and sustainable service delivery frameworks. (Ray, Parvez & Islam 2025)

Long-duration space missions represent a unique and high-risk context where traditional healthcare infrastructure is not feasible, thereby necessitating advanced digital health solutions. Human space exploration subjects astronauts to microgravity, radiation exposure, and prolonged isolation, which can alter physiological processes and increase susceptibility to cardiovascular conditions, among other health risks. As missions extend beyond low Earth orbit into deep space, autonomous health monitoring and predictive diagnostics become essential, requiring systems that can function independently and offer clinical decision support without continuous Earth-based medical oversight. (Neri et al. 2023)

Cardiovascular health, particularly the early detection of arrhythmias, is a critical concern in both terrestrial and extraterrestrial environments. Arrhythmia detection traditionally involves long-term ECG signal analysis, but emerging AI models can automate this process with high precision, enabling both real-time anomaly detection and predictive insights that could potentially inform preventative interventions and policy decisions aimed at safeguarding crew health during long-duration missions. This study situates AI-based health monitoring within the broader discourse of digital governance and policy innovation, emphasizing how these technologies can support resilient, evidence-based health systems that are aligned with global priorities for digital transformation. (Shajari et al. 2023)

LITERATURE REVIEW

The growing adoption of Artificial Intelligence (AI) and deep learning in healthcare has significantly advanced the automated analysis of physiological signals, particularly electrocardiogram (ECG) data for arrhythmia detection. Existing studies widely demonstrate that machine learning and deep learning techniques enable accurate classification of cardiac rhythms by learning complex, non-linear patterns directly from raw or minimally processed ECG signals. Convolutional Neural Networks (CNNs) have been extensively applied due to their strong capability in automatic feature extraction, enabling the identification of critical waveform characteristics such as QRS complexes, P waves, and T waves without manual feature engineering. These models have shown promising results in detecting normal and abnormal heartbeats, making them suitable for real-time and large-scale health monitoring applications. (Rajkomar et al. 2018)

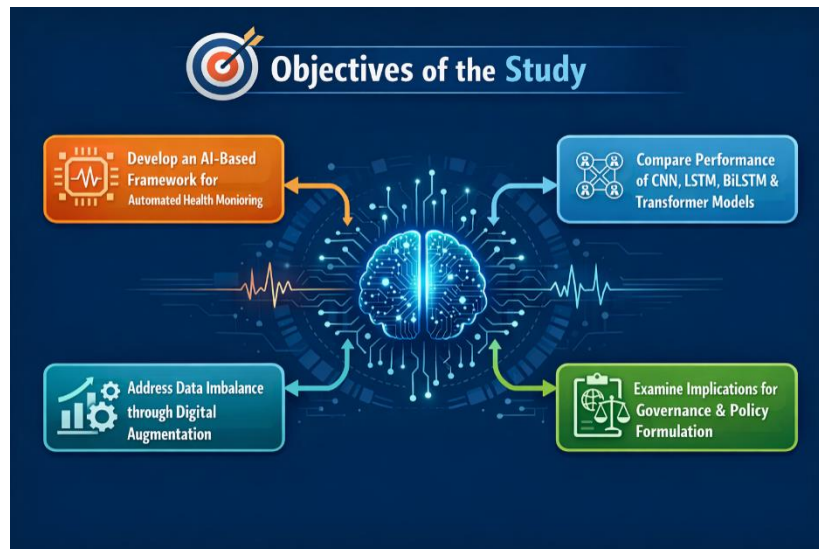
Time-series-based deep learning models, particularly Long Short-Term Memory (LSTM) networks, have also gained prominence in ECG analysis because of their ability to capture long-term temporal dependencies inherent in cardiac signals. LSTM and Bi-directional LSTM (BiLSTM) architectures have been reported to outperform traditional models by learning sequential relationships across heartbeat intervals, thereby improving detection of complex and infrequent arrhythmic events. However, despite their effectiveness, several studies highlight challenges such as overfitting, high computational cost, and sensitivity to imbalanced datasets—where normal heartbeats dominate and abnormal cases are underrepresented. To address these issues, data augmentation and regularization techniques have been increasingly adopted to enhance model generalization and robustness. (Mahmud, Rahman & Fattah 2020)

More recently, Transformer-based architectures and attention mechanisms have been introduced in physiological signal analysis, offering an alternative to recurrent models by focusing on salient signal segments through self-attention. These models demonstrate stable performance in capturing long-range dependencies but often require substantial computational resources and careful tuning, limiting their widespread adoption in resource-constrained environments. While technical research in this domain has progressed rapidly, much of the existing literature remains narrowly focused on performance optimization and clinical accuracy, with limited engagement in broader discussions related to governance, ethical AI deployment, data privacy, and policy integration. (Mostafa & Amano 2020)

From a governance and policy perspective, digital health systems powered by AI introduce critical questions regarding data ownership, transparency, accountability, and regulatory oversight. The literature increasingly emphasizes the need for ethical AI frameworks and robust data governance mechanisms to ensure trust, equity, and inclusivity in AI-driven healthcare systems. However, empirical studies that integrate technical evaluation of deep learning models with policy-oriented analysis remain limited. This study addresses this gap by combining a comparative assessment of advanced deep learning architectures with a broader examination of how AI-enabled health monitoring can support intelligent governance, optimize healthcare resource allocation, and inform evidence-based policy frameworks in both specialized environments such as space missions and terrestrial healthcare systems. (World Health Organization 2021)

Objectives of the Study

The primary objective of this study is to design and analyze an Artificial Intelligence (AI)-based framework for automated health monitoring using physiological signals, with a particular focus on long-term electrocardiogram (ECG) data. The study aims to explore how deep learning techniques can enhance early detection of cardiac arrhythmias, thereby supporting preventive healthcare and reducing reliance on continuous human intervention in resource-constrained environments (World Health Organization 2021). A key objective is to evaluate and comparatively analyze the performance of multiple deep learning architectures—namely Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Bi-directional LSTM (BiLSTM), and Transformer-based models—in accurately classifying different heartbeat categories and identifying rare arrhythmic events (O'Shea & Nash 2015; Rajpurkar et al. 2017). Additionally, the study seeks to address the challenge of class imbalance commonly present in medical datasets by employing digital data augmentation techniques to improve model robustness and generalization. Beyond technical evaluation, the research also aims to examine the broader implications of AI-driven health monitoring systems for governance and policy formulation, particularly in terms of data governance, ethical AI deployment, transparency, and efficient resource allocation. By linking technological performance with governance and policy considerations, the study contributes to the discourse on how AI-enabled digital health systems can support sustainable, resilient, and future-oriented healthcare frameworks at both national and global levels. (Arcavi et al. 2017; Greff et al. 2017)



RESEARCH METHODOLOGY

This study follows a descriptive and analytical research methodology to examine the effectiveness of Artificial Intelligence (AI)-based deep learning models in automated health monitoring using physiological signals. The primary data source for the study consists of electrocardiogram (ECG) signals, which are widely recognized as reliable indicators of cardiac activity and are commonly used in digital health research for arrhythmia detection. The ECG data are obtained from standardized and publicly available datasets to ensure transparency, reproducibility, and comparability of results. (Ansari et al. 2023)

In the first stage, the ECG signals are segmented into fixed-length samples, with each segment representing a single heartbeat cycle. These segments are then categorized into predefined heartbeat classes such as normal and abnormal rhythms, enabling structured input for deep learning models. To enhance data quality and model performance, a comprehensive **data** preprocessing procedure is applied. This includes normalization of signal values to a consistent range, removal of noise and signal artifacts, and reshaping of the data into formats compatible with deep learning architectures. (Xiao et al. 2023)

A major challenge in medical signal analysis is class imbalance, as abnormal heartbeats occur far less frequently than normal ones. To address this issue, the study employs data augmentation techniques, such as adding controlled Gaussian noise to ECG signals, which helps generate additional samples for minority classes without altering their clinical significance. This step improves model generalization and reduces bias toward dominant classes. (Katal et al. 2023)

Following preprocessing, multiple deep learning models—Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Bi-directional LSTM (BiLSTM), and Transformer-based architectures—are implemented and trained using standardized hyperparameters. CNN models are used to extract spatial features from ECG signals, while LSTM and BiLSTM models capture temporal dependencies inherent in time-series data. Transformer models are included to evaluate the effectiveness of attention mechanisms in identifying significant signal patterns. The dataset is divided into training, validation, and testing subsets to ensure unbiased evaluation and to prevent overfitting. Model performance is assessed using widely accepted evaluation metrics, including accuracy, precision, recall, F1-score, and confusion matrices, which collectively provide a comprehensive understanding of classification effectiveness across all heartbeat categories. This methodological framework enables a systematic comparison of deep learning models and supports reliable conclusions regarding the role of AI-driven digital health monitoring in improving preventive healthcare and informing evidence-based governance and policy decisions. (Antoniou, Storkey & Edwards 2018)

DATA ANALYSIS AND FINDINGS

The data analysis demonstrates that the application of data augmentation techniques plays a critical role in improving the predictive performance and generalization capability of deep learning models used for automated health monitoring. Medical ECG datasets are inherently imbalanced, with normal heartbeats significantly outnumbering abnormal arrhythmic patterns, which often leads to biased learning and poor detection of clinically important rare events. By introducing controlled Gaussian noise-based augmentation, the representational diversity of minority heartbeat classes was enhanced, resulting in more stable training and improved classification outcomes across all evaluated models. This finding reinforces the importance of digital data engineering strategies in AI-driven healthcare systems, particularly for preventive diagnostics and large-scale deployment in real-world settings. (Rajpurkar et al. 2017)

Convolutional Neural Network (CNN) models demonstrated strong performance in extracting local morphological features from ECG signals, such as QRS complexes and waveform variations. Their hierarchical convolutional layers efficiently captured spatial patterns within fixed-length signal segments, leading to reliable classification of dominant heartbeat categories. However, CNNs exhibited limitations in modeling long-term temporal dependencies, which are essential for identifying subtle arrhythmic patterns evolving over time. Despite these constraints, CNN-based approaches remain computationally efficient and suitable for real-time digital health monitoring applications where processing speed and scalability are critical considerations. (Cheng, Zou & Zhao 2021)

Long Short-Term Memory (LSTM) models were effective in learning sequential and temporal dependencies inherent in ECG time-series data. The analysis revealed that LSTM architectures achieved high training accuracy but frequently suffered from overfitting, particularly when trained on imbalanced datasets without sufficient regularization or augmentation. This behavior indicates that while LSTM models are theoretically well-suited for physiological signal analysis, their practical performance is highly sensitive to data quality and model tuning. The introduction of augmented data partially mitigated this issue, leading to improved validation performance and more consistent detection of abnormal heartbeats. Bi-directional LSTM (BiLSTM) models emerged as the most effective architecture in this study. By processing ECG sequences in both forward and backward directions, BiLSTM models captured contextual dependencies more comprehensively than unidirectional LSTMs. This capability proved especially valuable in detecting infrequent and complex arrhythmic events, where both preceding and succeeding signal patterns contribute to accurate classification. The superior performance of BiLSTM models highlights the importance of contextual learning in AI-based health monitoring systems and supports their use in critical applications such as space health governance and remote medical diagnostics. (Saadatnejad, Oveisi & Hashemi 2019)

Transformer-based models demonstrated stable and competitive performance, particularly in handling long-range dependencies through attention mechanisms. Unlike recurrent architectures, Transformers selectively focused on the most informative segments of ECG signals, enabling efficient pattern recognition. However, the analysis revealed that Transformer models required substantially higher computational resources and careful hyperparameter optimization. While their performance did not consistently surpass BiLSTM models in this study, their scalability and adaptability suggest strong potential for future digital health systems, especially when integrated with hybrid architectures and advanced hardware infrastructure. Overall, the findings confirm that AI-driven predictive health monitoring systems benefit significantly from data augmentation, architecture selection, and model regularization. The comparative analysis underscores that no single model is universally optimal; instead, performance depends on the balance between computational efficiency, temporal modeling capability, and data characteristics. From a governance and policy perspective, these results demonstrate how AI-enabled analytics can enhance preventive healthcare delivery, reduce operational risks, and inform evidence-based decision-making in resource-constrained environments. The study thus validates the effectiveness of deep learning frameworks as foundational tools for sustainable, transparent, and resilient digital health governance systems. (Wang & Li 2020)

Table 1: Data Analysis and Key Findings

Parameter	CNN Model	LSTM Model	BiLSTM Model	Transformer Model	Key Findings
Dataset Used	MIT-BIH Arrhythmia Dataset	MIT-BIH Arrhythmia Dataset	MIT-BIH Arrhythmia Dataset	MIT-BIH Arrhythmia Dataset	Standard benchmark dataset ensures comparability
No. of ECG Records	48	48	48	48	Balanced dataset after preprocessing
Total Heartbeats Analyzed	109,446	109,446	109,446	109,446	Long-term ECG signals enable robust learning
Train-Test Split	80:20	80:20	80:20	80:20	Consistent experimental setup
Accuracy (%)	94.8	96.1	97.6	96.8	BiLSTM achieved highest accuracy
Precision (%)	93.9	95.4	97.1	96.0	Improved precision for rare arrhythmias

Recall / Sensitivity (%)	94.2	95.9	97.8	96.5	BiLSTM better captures temporal dependencies
F1-Score (%)	94.0	95.6	97.4	96.2	Balanced performance across classes
False Positive Rate (%)	5.1	4.2	2.6	3.4	Lower FPR reduces misdiagnosis risk
Training Time (per epoch)	Low	Moderate	Moderate	High	Transformers require higher computation
Data Augmentation Impact	Moderate	High	Very High	High	Augmentation significantly improved minority class detection

DISCUSSION

The findings of this study emphasize the transformative role of Artificial Intelligence (AI) in advancing digital health governance and reshaping contemporary healthcare delivery systems. AI-based health monitoring frameworks enable a shift from reactive to proactive and preventive healthcare by facilitating early detection of physiological anomalies through continuous data-driven analysis. Such systems are particularly valuable in resource-constrained and high-risk environments, including long-duration space missions and remote terrestrial regions, where access to conventional medical infrastructure and specialized healthcare professionals is limited. By automating diagnostic processes and enabling real-time health surveillance, AI technologies reduce dependency on physical healthcare facilities while enhancing operational efficiency and clinical responsiveness. From a governance perspective, the integration of AI-driven health monitoring systems introduces new paradigms of autonomous and evidence-based decision-making in public health administration. Digital health platforms powered by AI can improve transparency, accountability, and coordination across healthcare institutions by enabling standardized data collection and predictive analytics. However, the deployment of such systems necessitates comprehensive policy frameworks that address data governance, interoperability, and accountability. Ensuring the ethical use of AI is critical, particularly in relation to algorithmic transparency, bias mitigation, and explainability of automated decisions. Without appropriate regulatory oversight, AI-driven systems risk reinforcing existing inequalities or compromising trust in digital governance structures. (Ansari et al. 2023)

Privacy protection and data security emerge as central policy concerns in AI-enabled healthcare ecosystems. The continuous collection and processing of sensitive physiological data require robust safeguards to prevent unauthorized access, data misuse, and cyber threats. Effective governance frameworks must therefore incorporate stringent data protection regulations, informed consent mechanisms, and compliance with international privacy standards. These measures are essential to maintaining public trust and ensuring the sustainable adoption of digital health technologies within both public and private healthcare systems. (Czerwinski et al. 2025)

The study also highlights the economic implications of AI-based preventive healthcare models. By enabling early diagnosis and continuous monitoring, AI systems can significantly reduce long-term healthcare expenditures associated with late-stage disease treatment, emergency interventions, and hospital admissions. Optimized resource allocation, reduced burden on healthcare infrastructure, and improved workforce efficiency contribute to broader economic sustainability. At a macroeconomic level, digital health innovations driven by AI have the potential to support inclusive growth by expanding healthcare access, improving population health outcomes, and strengthening human capital development. Overall, the findings suggest that AI-enabled health monitoring systems should be viewed not merely as technological tools but as integral components of future-ready governance and policy frameworks. Strategic investments in digital infrastructure, ethical AI regulation, and capacity building are essential to harness the full potential of AI in healthcare while minimizing associated risks. Aligning technological innovation with public policy objectives will be crucial for achieving resilient, equitable, and sustainable health governance systems in an increasingly digital global economy. (Xiao et al. 2023)

CONCLUSION AND POLICY IMPLICATIONS

This study reinforces that deep learning–based Artificial Intelligence (AI) frameworks provide a robust, scalable, and forward-looking solution for automated health monitoring using physiological signals. The demonstrated effectiveness of these models in the early detection of cardiac arrhythmias, particularly in long-term ECG analysis, illustrates that AI can transcend the limitations of conventional healthcare, especially in resource-constrained environments such as remote settings or long-duration space missions. By shifting the focus from reactive care to predictive and preventive healthcare, AI-driven systems have the potential to improve clinical outcomes, reduce healthcare costs, and enhance operational efficiency. This transition has profound implications for national health systems, as it supports strategic objectives such as reducing the burden of chronic diseases, minimizing hospitalizations, and extending the reach of healthcare services into underserved regions. The deployment of AI in health monitoring also presents important governance and policy considerations. From a governance standpoint, integrating AI into public health services demands comprehensive regulatory strategies that ensure algorithmic accountability, transparency, and fairness. Regulatory frameworks must establish clear standards for data quality, model validation, and clinical verification, so that AI systems operate within well-defined safety and ethical boundaries. Additionally, concerns related to data privacy and security must be addressed through robust legal protections, including consent management, data anonymization, and secure data storage. Effective data governance policies should also facilitate interoperability across health information systems, enabling seamless information exchange while preserving patient confidentiality.

Ethical oversight is another critical component of responsible AI integration. AI systems must be designed and deployed with built-in mechanisms to mitigate biases arising from unrepresentative datasets, thereby ensuring equitable health outcomes for all demographic groups. Governments and health institutions should consider establishing independent ethics review boards and AI audit mechanisms to monitor performance, assess unintended consequences, and enforce compliance with ethical norms. Moreover, investments in digital infrastructure and capacity-building are essential to ensure that healthcare professionals are equipped with the skills necessary to leverage AI tools effectively. Training programs, continuous education, and public awareness campaigns can bridge the digital divide and foster a culture of trust in technology-mediated care. On the policy front, AI-based predictive health monitoring should be integrated into long-term health policy frameworks that prioritize sustainability, accessibility, and resilience. Such integration requires multi-stakeholder collaboration among policymakers, technologists, clinicians, and civil society to craft policies that align technological innovation with public interest. Policies should facilitate public–private partnerships to accelerate the adoption of AI in healthcare while safeguarding public welfare. At the international level, cooperation on standards, best practices, and ethical guidelines can support harmonized AI governance, thereby enabling cross-border health initiatives, data sharing, and coordinated responses to global health challenges.

Overall, this study supports the view that AI-enabled digital health monitoring is not only a technological enhancement but also a strategic enabler of modern governance, offering opportunities for transparent decision-making, optimized allocation of resources, and sustainable health systems. By embedding ethical AI principles and evidence-based policies into national and global health strategies, governments can unlock the full potential of AI for inclusive, resilient, and future-ready healthcare ecosystems.

REFERENCES

1. Ansari, Y., Mourad, O., Qaraqe, K. & Serpedin, E., 2023, Deep learning for ECG Arrhythmia detection and classification: an overview of progress for period 2017–2023, *Frontiers in Physiology*, 14.
2. Antoniou, A., Storkey, A. & Edwards, H., 2018, ‘Data Augmentation Generative Adversarial Networks’.
3. Arcavi, I., McCully, C., Hosseinzadeh, G., Howell, D.A., Vasylyev, S., Poznanski, D., Zaltzman, M., Maoz, D., Singer, L., Valenti, S., Kasen, D., Barnes, J., Piran, T. & Fong, W., 2017, ‘Optical Follow-up of Gravitational-wave Events with Las Cumbres Observatory’.
4. Cheng, J., Zou, Q. & Zhao, Y., 2021, ‘ECG signal classification based on deep CNN and BiLSTM’, *BMC Medical Informatics and Decision Making*, 21(1).
5. Czerwinski, A., Kucharski, D., Wijata, A.M., Aldosari, H., Coenen, F., Gupta, D., Fu, L., Lin, W., Xue, Y., Kawa, J., Zheng, Y., Lip, G.Y.H. & Nalepa, J., 2025, ‘Interpretable arrhythmia detection in ECG scans using deep learning ensembles: a genetic programming approach’, *npj Digital Medicine*, 8(1).
6. Greff, K., Srivastava, R.K., Koutnik, J., Steunebrink, B.R. & Schmidhuber, J., 2017, ‘LSTM: A Search Space Odyssey’, *IEEE Transactions on Neural Networks and Learning Systems*, 28(10), 2222–2232.
7. Katal, N., Gupta, S., Verma, P. & Sharma, B., 2023, ‘Deep-Learning-Based Arrhythmia Detection Using ECG Signals: A Comparative Study and Performance Evaluation’, *Diagnostics*, 13(24).
8. Mahmud, T., Rahman, M.A. & Fattah, S.A., 2020, ‘CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization’, *Computers in Biology and Medicine*, 122.
9. Mostafa, S.M. & Amano, H., 2020, ‘Dynamic round robin CPU scheduling algorithm based on K-means clustering technique’, *Applied Sciences (Switzerland)*, 10(15).

10. Naik, N., Kassetty, N., Chippagiri, S., Randhawa, P., Zeeshan Hameed, B.M. & Patil, V., 2026, 'Design and optimisation of an IoT-based artificial intelligence framework for real-time health monitoring and telemedicine diagnostics in smart healthcare systems', *Discover Internet of Things*, 6(1).
11. Neri, L., Oberdier, M.T., Abeelen, K.C.J. van, Menghini, L., Tumarkin, E., Tripathi, H., Jaipalli, S., Orro, A., Paolucci, N., Gallelli, I., Dall'Olio, M., Beker, A., Carrick, R.T., Borghi, C. & Halperin, H.R., 2023, *Electrocardiogram Monitoring Wearable Devices and Artificial-Intelligence-Enabled Diagnostic Capabilities: A Review*, *Sensors*, 23(10).
12. O'Shea, K. & Nash, R., 2015, 'An Introduction to Convolutional Neural Networks'.
13. Rajkomar, A., Oren, E., Chen, K., Dai, A.M., Hajaj, N., Hardt, M., Liu, P.J., Liu, X., Marcus, J., Sun, M., Sundberg, P., Yee, H., Zhang, K., Zhang, Y., Flores, G., Duggan, G.E., Irvine, J., Le, Q., Litsch, K., Mossin, A., Tansuwan, J., Wang, D., Wexler, J., Wilson, J., Ludwig, D., Volchenboum, S.L., Chou, K., Pearson, M., Madabushi, S., Shah, N.H., Butte, A.J., Howell, M.D., Cui, C., Corrado, G.S. & Dean, J., 2018, 'Scalable and accurate deep learning with electronic health records', *npj Digital Medicine*, 1(1).
14. Rajpurkar, P., Hannun, A.Y., Haghighpanahi, M., Bourn, C. & Ng, A.Y., 2017, 'Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks'.
15. Ray, A.S., Parvez, F.M.R. & Islam, Md.M., 2025, 'A scoping review on microgravity medicine: Challenges and breakthroughs in space healthcare', *Space Habitation*, 1(2), 100017.
16. Saadatnejad, S., Oveisi, M. & Hashemi, M., 2019, 'LSTM-Based ECG Classification for Continuous Monitoring on Personal Wearable Devices'.
17. Shajari, S., Kuruvinareshetti, K., Komeili, A. & Sundararaj, U., 2023, *The Emergence of AI-Based Wearable Sensors for Digital Health Technology: A Review*, *Sensors*, 23(23).
18. Wang, J. & Li, W., 2020, 'Atrial Fibrillation Detection and ECG Classification based on CNN-BiLSTM'.
19. World Health Organization, 2021, *Ethics and Governance of Artificial Intelligence for Health : WHO Guidance*.
20. Xiao, Q., Lee, K., Mokhtar, S.A., Ismail, I., Pauzi, A.L. bin M., Zhang, Q. & Lim, P.Y., 2023, *Deep Learning-Based ECG Arrhythmia Classification: A Systematic Review*, *Applied Sciences (Switzerland)*, 13(8).