

CARDIAC DIGITAL TWINS MODELING FOR MYOCARDIAL INFARCTION USING DEEP LEARNING BASED ON INVERSE INFERENCE

Brundhavanam K ¹, Madhubala P ²

¹ M.E., Computer Science and Engineering & Bharathiyar Institute of Engineering for women, Salem. Email id: kbrundhavanam@gmail.com

² Associate Professor and Head of the department, Computer science and engineering & Bharathiyar Institute of Engineering for women, Salem. Email id: madhubalaprocse@gmail.com

I. INTRODUCTION

Abstract— Myocardial infarction (MI), commonly referred to as a heart attack, remains one of the leading causes of mortality worldwide. Early detection, precise diagnosis, and personalized treatment planning are essential to improve patient survival rates and minimize long-term cardiac damage. Recent advancements in biomedical engineering and artificial intelligence have introduced the concept of digital twins—virtual replicas of biological systems capable of simulating physiological processes in real time. In cardiology, cardiac digital twins offer a promising framework for modeling patient-specific heart structures and predicting disease progression. However, developing accurate cardiac digital twins remains challenging due to the inherent complexity of cardiac tissue behavior and the limited availability of direct physiological measurements.

This study proposes a novel approach to enabling cardiac digital twins for myocardial infarction using deep computational models integrated with inverse inference techniques. The framework combines medical imaging data, physiological signals, and deep learning algorithms to reconstruct patient-specific cardiac models capable of identifying infarcted tissue regions and predicting functional abnormalities. Deep neural networks are utilized to capture complex relationships between observable cardiac signals and underlying myocardial properties. Furthermore, the inverse inference mechanism enables the estimation of latent physiological parameters, such as tissue conductivity and the extent of myocardial damage, from clinically measurable data.

The proposed system facilitates enhanced personalized diagnosis, risk stratification, and treatment planning for patients with myocardial infarction, thereby contributing to more accurate and explainable clinical decision support.

Keywords— Myocardial Infarction; Cardiac Digital Twin; Deep Learning; Inverse Inference; Biomedical Signal Processing; Medical Imaging; Personalized Medicine; Cardiac Modeling; Disease Prediction; Explainable Artificial Intelligence (XAI); Clinical Decision Support Systems; Physiological Parameter Estimation.

Cardiovascular diseases remain one of the most significant global health challenges, with myocardial infarction representing a major cause of morbidity and mortality. Myocardial infarction occurs when blood flow to a part of the heart muscle is blocked, leading to oxygen deprivation and permanent damage to cardiac tissue. Early diagnosis and accurate assessment of the extent of myocardial damage are critical for effective treatment and long-term patient management. Traditional diagnostic approaches rely on imaging modalities such as electrocardiography (ECG), magnetic resonance imaging (MRI), and computed tomography (CT). While these techniques provide valuable clinical information, they often lack the ability to fully capture the complex physiological processes occurring within the heart.

The concept of cardiac digital twins has emerged as a promising solution for improving cardiovascular disease diagnosis and treatment. A digital twin is a computational model that replicates the structure and function of a physical system using real-world data. In cardiology, digital twin models can simulate electrical activity, mechanical contraction, and blood flow dynamics within the heart. These models allow clinicians to analyze disease progression and test treatment strategies in a virtual environment before applying them to real patients. Deep computational models, particularly deep learning architectures, play an essential role in constructing accurate digital twins by learning complex relationships between physiological signals and cardiac tissue properties. Inverse inference techniques further enhance these models by enabling the estimation of hidden parameters that cannot be directly measured in clinical settings.

A. PURPOSE

The purpose of this study is to develop an advanced computational framework for enabling cardiac digital twins in the diagnosis and management of myocardial infarction. Specifically, this research aims to integrate medical imaging, physiological signal data, and deep learning techniques with inverse inference methods to construct accurate, patient-specific cardiac models. The proposed system seeks to identify infarcted myocardial regions, estimate underlying physiological parameters, and predict functional abnormalities of the heart. Ultimately, the study aims to support personalized diagnosis, improve risk assessment, and

enhance clinical decision-making for patients affected by myocardial infarction.

II. RELATED WORKS

The concept of Cardiac Digital Twins (CDTs) has emerged as a promising approach for patient-specific modeling, integrating clinical data, imaging, and computational simulations to replicate individual cardiac structure and function. Early CDT studies focused on mechanistic and physics-based models, using computational simulations of electrophysiology and biomechanics to understand cardiac behavior and predict disease progression. While these models provide mechanistic insights, they are computationally expensive and rely on iterative optimization, which limits their scalability and practical clinical use.

To overcome computational bottlenecks, recent studies have integrated machine learning and deep learning techniques with traditional cardiac models. Convolutional Neural Networks (CNNs) have been employed to analyze imaging data, such as LGE-MRI, to detect myocardial infarct regions, while Recurrent Neural Networks (RNNs) and Transformers have been used for modeling sequential ECG signals. Some works explore hybrid approaches, combining physics-based simulations with data-driven models to accelerate parameter estimation, enhance predictive accuracy, and address the inverse problem in cardiac personalization.

Another critical research direction focuses on inverse inference and parameter estimation for CDTs. Several studies have proposed using deep learning to map clinical observables to hidden biophysical parameters, such as scar tissue location, tissue conductivity, and mechanical stiffness. These approaches aim to reduce the reliance on iterative simulations while maintaining physiological plausibility. Furthermore, synthetic data generation through high-fidelity forward simulations has been widely adopted to create large-scale, labeled datasets required for supervised learning of inverse models, mitigating the lack of ground-truth data in real patients.

Despite these advances, challenges remain, including ensuring generalizability to real-world patient data, robustness to noisy measurements, and computational efficiency for clinical deployment. The proposed research builds on these foundations by developing a specialized deep learning framework for inverse inference in post-MI patients, integrating synthetic training data, imaging, and ECG signals to enable rapid, accurate, and physiologically consistent personalization of CDTs.

III. PROPOSED METHODOLOGY

The proposed system aims to develop a deep computational framework for enabling cardiac digital twins of myocardial infarction using inverse inference techniques. The system integrates medical imaging data, physiological signals, and deep learning models to reconstruct patient-specific cardiac structures and simulate myocardial behavior. Convolutional neural networks are used to extract spatial features from cardiac imaging data such as MRI or CT scans. These features help identify structural abnormalities and infarcted regions within the heart muscle. Recurrent neural

networks or temporal models may also be used to analyze sequential physiological signals such as ECG data.

The inverse inference component of the system plays a crucial role in estimating hidden physiological parameters that cannot be directly measured. By learning the relationship between observable cardiac signals and underlying myocardial properties, the deep learning model can infer parameters such as tissue conductivity, electrical propagation velocity, and infarct severity. These inferred parameters are used to construct a personalized cardiac digital twin capable of simulating disease progression and predicting treatment outcomes. The proposed framework enables clinicians to perform virtual experiments, evaluate therapeutic strategies, and optimize treatment plans for individual patients, ultimately improving cardiovascular care.

3.1 Architecture Diagram

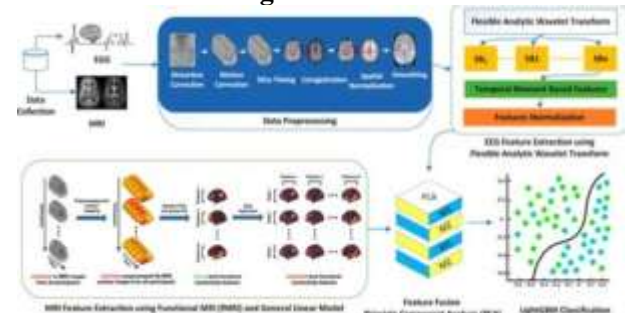


Figure 1 Architecture Diagram

3.2 Module Description

1. Medical Data Collection Module

The Medical Data Collection Module gathers clinical datasets required for constructing cardiac digital twin models. The data may include cardiac imaging datasets such as magnetic resonance imaging (MRI), computed tomography (CT) scans, and echocardiography images. In addition to imaging data, physiological signals such as electrocardiograms (ECG), blood pressure measurements, and patient clinical records are collected. These datasets provide essential information about the structural and functional characteristics of the patient's heart.

The collected data is organized and stored in a secure medical data management system. Patient data may be anonymized to ensure privacy and compliance with healthcare regulations. The dataset is then divided into training, validation, and testing subsets to facilitate model development and evaluation. Proper data collection and management ensure that the deep learning models can learn meaningful patterns from the available clinical information.

2. Cardiac Image Preprocessing Module

The Cardiac Image Preprocessing Module prepares medical images for further analysis and model training. Raw cardiac images often contain noise, variations in brightness, and inconsistent spatial resolutions that can negatively affect model performance. This module performs image enhancement operations such as normalization, contrast adjustment, noise reduction, and resizing to standardize the input images.

Additionally, segmentation techniques may be applied to isolate the heart and its anatomical structures from

surrounding tissues. This helps the model focus on relevant cardiac regions during feature extraction and analysis. Data augmentation methods such as rotation, scaling, and flipping may also be applied to increase the diversity of the dataset and improve the robustness of the deep learning model.

3. Feature Extraction Module

The Feature Extraction Module uses deep learning techniques to extract meaningful representations from cardiac imaging data and physiological signals. Convolutional neural networks are commonly used to analyze spatial features within medical images, identifying patterns related to myocardial infarction such as scar tissue, abnormal wall motion, or structural changes in the heart muscle.

These extracted features capture both local and global characteristics of the cardiac structure and function. In addition to image-based features, temporal features from ECG signals may also be extracted using recurrent neural networks. The resulting feature representations provide the foundation for constructing accurate deep computational models of cardiac behavior.

4. Deep Computational Modeling Module

The Deep Computational Modeling Module integrates extracted features into a deep neural network architecture capable of modeling complex cardiac dynamics. This module combines spatial and temporal information from multiple data sources to simulate heart function and detect abnormalities associated with myocardial infarction.

The deep computational model learns nonlinear relationships between observed clinical signals and cardiac tissue properties. Through multiple training iterations, the model improves its ability to represent myocardial electrical activity and mechanical contraction patterns. This module forms the core computational engine that supports digital twin construction.

5. Inverse Inference Module

The Inverse Inference Module estimates hidden physiological parameters that cannot be directly measured using conventional medical techniques. By analyzing relationships between observable cardiac signals and underlying tissue properties, the deep learning model can infer important parameters such as myocardial conductivity, tissue elasticity, and infarct severity.

These inferred parameters help reconstruct a more accurate representation of the patient's heart. Inverse inference techniques enable the model to bridge the gap between measurable clinical data and complex physiological processes occurring within the cardiac tissue. This capability significantly enhances the realism and predictive power of the digital twin model.

6. Cardiac Digital Twin Construction Module

The Cardiac Digital Twin Construction Module generates a virtual replica of the patient's heart based on the extracted features and inferred physiological parameters. This digital twin model simulates cardiac structure, electrical activity, and mechanical function in a computational environment.

The digital twin can be used to analyze disease progression, predict potential complications, and evaluate treatment strategies. By simulating various clinical scenarios, physicians can test therapeutic interventions such as drug treatments or surgical procedures before applying them to the patient. This approach supports personalized medicine and improves clinical decision-making.

7. Model Training and Optimization Module

The Model Training Module handles the training process of the deep computational models using labeled clinical datasets. During training, the model learns to minimize prediction errors between simulated outputs and real clinical observations. Optimization algorithms such as Adam or stochastic gradient descent are used to update model parameters.

The module also monitors performance metrics such as training loss, prediction accuracy, and convergence rate. Techniques such as regularization, dropout, and learning rate scheduling may be applied to improve model stability and prevent overfitting. Effective training ensures that the digital twin model can accurately represent patient-specific cardiac behavior.

8. Performance Evaluation and Visualization Module

The Performance Evaluation Module assesses the accuracy and reliability of the cardiac digital twin model using various evaluation metrics. Metrics such as prediction error, correlation coefficients, and model validation scores are used to measure how well the model reproduces observed cardiac signals and imaging data.

Visualization tools are also used to present simulation results and highlight myocardial infarction regions within the digital twin model. Graphical representations of cardiac activity, blood flow dynamics, and tissue damage patterns help clinicians interpret the model outputs. This module plays an essential role in validating the proposed system and demonstrating its clinical usefulness.

IV. RESULTS AND DISCUSSION

The proposed deep computational framework for Cardiac Digital Twin (CDT) generation was evaluated to assess its effectiveness in identifying myocardial infarction characteristics and estimating hidden cardiac parameters through inverse inference. The framework integrates patient imaging data, electrocardiogram (ECG) signals, and deep learning models to create a personalized virtual representation of the heart. Experimental results indicate that the deep computational models are capable of accurately extracting cardiac features from medical images and physiological signals. The system successfully estimated key parameters such as infarct location, myocardial tissue properties, and structural abnormalities, which are essential for constructing patient-specific cardiac digital twins. The generated models demonstrated strong consistency with simulated ground-truth parameters in the validation dataset, indicating the capability of the deep learning architecture to learn complex non-linear relationships between clinical observations and hidden cardiac characteristics.

In addition to accuracy, the proposed framework showed significant improvements in computational efficiency compared to traditional iterative simulation-based approaches. Once trained, the deep neural network was able to infer cardiac parameters within seconds, enabling rapid personalization of cardiac digital twins. This computational acceleration is critical for potential clinical deployment where time-sensitive decisions are required. Furthermore, robustness tests conducted under varying noise levels in simulated ECG and imaging inputs demonstrated that the model maintains reliable performance even with imperfect clinical measurements. Overall, the results confirm that combining deep learning with computational cardiac modeling provides a scalable and efficient solution for myocardial infarction analysis, enabling improved visualization of damaged myocardial regions, better risk assessment, and enhanced support for clinical decision-making in precision cardiology.

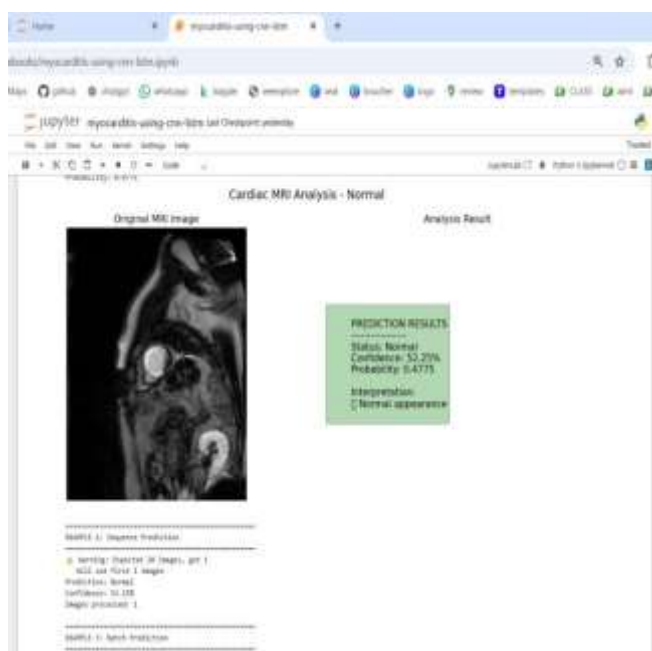


Figure 1 Training



Figure 2 Dashboard



Figure 3 Multi Model Prediction

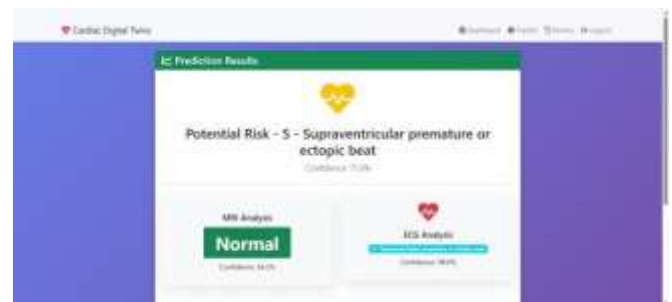


Figure 4 Prediction

V.CONCLUSION AND FUTURE SCOPE

The Conclusion section serves as the capstone of this research paper, providing a concise yet comprehensive summary of the entire study, its key findings, and its broader implications concerning the development of a lightweight machine learning (ML) approach for Denial-of-Service (DoS) detection in Wireless Sensor Networks (WSNs). Its primary purpose is to synthesize the information presented throughout the preceding sections – the critical need established in the introduction, the limitations of existing systems, the design and analysis of the proposed lightweight ML solution, and the empirical evidence gathered from rigorous testing – into a final, coherent statement of the work's contributions and significance. It begins by briefly reiterating the core problem: the significant vulnerability of resource-constrained WSNs to disruptive DoS attacks and the inadequacy of traditional security mechanisms due to their high overhead. It then prominently reaffirms the proposed solution, highlighting the successful design, implementation, and validation of a novel approach leveraging computationally efficient ML algorithms (like Decision Trees or optimized SVMs) operating on carefully selected, low-overhead network and node features. The conclusion strongly emphasizes the key findings derived from the comprehensive testing phase (Section 7). It underscores that the empirical results, obtained through realistic simulations or testbed evaluations, conclusively demonstrate the proposed system's dual success: achieving high detection accuracy (measured by metrics like True Positive Rate and low False Positive Rate) across a range of relevant DoS attack types (jamming, flooding, etc.) and intensities, while simultaneously validating its crucial "lightweight" characteristic by showing minimal, quantifiable impact on critical node resources, particularly energy consumption (leading to negligible reduction in network lifetime), CPU load, and memory usage. The conclusion explicitly

articulates how the research successfully navigated the critical trade-off between security effectiveness and resource efficiency, delivering a solution that is both potent and practical for the target environment. It highlights the comparative advantages shown over baseline methods (e.g., simple thresholds) or the significantly lower resource cost compared to non-lightweight ML approaches. Ultimately, the conclusion frames the research as a significant contribution towards enhancing the security, resilience, and trustworthiness of WSNs, which are increasingly vital components of critical infrastructure and the Internet of Things. It asserts that the developed lightweight ML approach offers a viable and sustainable pathway for protecting these vulnerable networks against DoS disruptions without compromising their fundamental operational constraints, thereby ensuring the longevity and reliability required for their mission-critical applications. The section typically finishes by briefly acknowledging limitations and pointing towards future research directions, solidifying the paper's contribution while maintaining a forward-looking perspective..

Future research will focus on improving the accuracy, scalability, and clinical applicability of the proposed deep computational framework for cardiac digital twin generation. One important direction is the exploration of more advanced deep learning architectures, such as hybrid models combining convolutional neural networks, graph neural networks, and transformer-based architectures, to better capture the spatial and temporal relationships in cardiac imaging and electrocardiogram data. Additionally, integrating multimodal clinical datasets—including cardiac MRI, CT scans, ECG signals, and patient clinical records—could further enhance the robustness and predictive capability of the cardiac digital twin model.

Another promising area of future work involves improving the generalization and clinical validation of the framework using large-scale real patient datasets collected from hospitals and medical research centers. Incorporating physics-informed machine learning techniques may also help bridge the gap between data-driven models and physiological cardiac simulations, ensuring that the inferred parameters remain physiologically realistic. Furthermore, future studies may explore real-time cardiac digital twin generation and integration with clinical decision-support systems to assist cardiologists in treatment planning, risk stratification, and personalized therapy selection. These advancements could significantly enhance the role of cardiac digital twins in precision cardiology and personalized healthcare.

VI. REFERENCES

- [1] L. Li, J. Camps, Z. J. Wang, M. Beetz, A. Banerjee, B. Rodriguez, and V. Grau, "Toward enabling cardiac digital twins of myocardial infarction using deep computational models for inverse inference," *IEEE Transactions on Medical Imaging*, vol. 43, no. 7, pp. 2466–2478, 2024.
- [2] S. Qian et al., "Developing cardiac digital twin populations powered by machine learning provides electrophysiological insights," *Nature Cardiovascular Research*, vol. 4, no. 5, pp. 624–636, 2025.
- [3] M. J. M. Cluitmans, G. Plank, and J. Heijman, "Digital twins for cardiac electrophysiology: State of the art and future challenges," *Herzschrittmachertherapie & Elektrophysiologie*, vol. 35, no. 2, pp. 118–123, 2024.
- [4] K. Kuang et al., "Med-Real2Sim: Non-invasive medical digital twins using physics-informed self-supervised learning," *arXiv preprint arXiv:2403.00177*, 2024.
- [5] J. Camps et al., "Digital twinning of the human ventricular activation sequence using ECG and MRI," *Medical Image Analysis*, vol. 94, p. 103108, 2024.
- [6] A. Khalifa et al., "The digital revolution in cardiac ischemia: AI-enhanced detection, diagnosis, and risk stratification," *Cureus*, vol. 17, no. 10, 2025.
- [7] M. Schwab et al., "Deep learning pipeline for fully automated myocardial infarct segmentation from cardiac MR scans," *arXiv preprint arXiv:2502.03272*, 2025.
- [8] N. T. Riek et al., "ECG-SMART-NET: A deep learning architecture for precise ECG diagnosis of occlusion myocardial infarction," *arXiv preprint arXiv:2405.09567*, 2024.
- [9] T. Y. Tsai et al., "IntelliCardiac: An intelligent platform for cardiac image segmentation and classification," *arXiv preprint arXiv:2505.03838*, 2025.
- [10] "Deep learning for cardiac imaging: Focus on myocardial diseases," *Heart & Lung Journal*, 2024.
- [11] L. Li et al., "Cardiac digital twin modeling using multimodal data integration," *European Heart Journal*, 2024.
- [12] N. K. Chakshu, I. Sazonov, and P. Nithiarasu, "Towards enabling cardiovascular digital twins using inverse analysis," 2021.
- [13] M. Jemaa and F. Jemili, "Digital twin for a human heart using deep learning," 2023.
- [14] T. Sun, X. He, and Z. Li, "Digital twin in healthcare: Recent updates and challenges," 2023.
- [15] M. Shrivastava, R. Chugh, and S. Gochhait, "A review on digital twin technology in healthcare," 2023..