AI-Based Anomaly detection in Cardiac Data : A Conceptual Diagnostic Framework in identifying Unexplained Pericardial Effusion Risk

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Abstract

Pericardial effusion involves the abnormal accumulation of fluid in the pericardium—the protective sac surrounding the heart—often linked to infections, malignancies, autoimmune disorders, trauma, or inflammation. While the pericardium normally contains a small volume of lubricating fluid, excess accumulation can exert pressure on the heart, restricting its ability to expand and pump blood effectively. Clinical symptoms vary depending on the volume and rate of fluid buildup, ranging from chest discomfort and fatigue to shortness of breath, syncope, and cardiac tamponade. In rare cases, no identifiable cause is found—a condition known as idiopathic pericardial effusion—which presents a substantial diagnostic hurdle due to its ambiguous clinical etiology. Standard diagnostic methods like echocardiography, serological testing, and pericardial fluid analysis may fail to detect such anomalies. This paper proposes a conceptual framework that leverages Artificial Intelligence (AI) and Machine Learning (ML), specifically unsupervised anomaly detection techniques, to support early identification of rare or idiopathic cases.Using the UCI Heart Disease dataset, we outline a two-stage approach: a Random Forest classifier for cardiac risk estimation, and Isolation Forest for detecting anomalous patterns beyond typical cardiac profiles. While no model is implemented, we conceptualize a diagnostic pipeline that integrates patient records, clinical notes, and imaging data. Ethical implications of AI in clinical practice are also considered. This framework offers a foundation for future interdisciplinary research uniting cardiology and computational sciences.

Keywords

Electrocardiogram (ECG) signal, biomedical AI, anomaly detection, pericardial effusion, pericardiocentesis, idiopathic cardiac conditions, unsupervised learning, supervised learning, Isolation Forest, Autoencoders, Explainable AI (XAI), healthcare intelligence, clinical diagnostics, multimodal data, cardiac anomaly detection, rare cardiac disorders, clinical decision support system (CDSS), UCI Heart Disease dataset, synthetic data generation, AI for rare disease detection.

1. Introduction

Cardiovascular diseases(CVD) are an umbrella term encompassing a broad range of conditions influencing heart and blood vessels. The vascular system is the system which is composed of blood vessels circulating blood throughout the body. Vascular disease is frequently associated with the constriction or dilation of veins and arteries, which disrupts blood circulation and compromises the delivery of oxygen and nutrients to tissues.

These disruptions can lead to high-risk cardiovascular complications, such as heart attack, coronary artery disease, stroke, blood clots and peripheral vascular disorders[1].

Such diseases further comprise the vascular system's ability to transport blood to or from the organs of the body. On account of an aging society, an expansion in obesity and persistent conditions like Type II diabetes, vascular diseases are becoming an escalating epidemiological challenge. CVDs remain the major cause of death worldwide[1], with the timely prognostic detection of heart disease through the identification of meaningful patterns in the data. It is therefore essential that individuals learn to acknowledge the symptoms of vascular disease, so they can access accurate and efficient treatment. The rise of AI/ML in healthcare has enhanced the capability to assess and forecast heart disease built upon patterns in data[4]. However, most conventional pipelines are adapted to prevalent diseases with adequate labeled data. One limitation of the current framework is that, their insufficiency to recognize anomalous or uncommon disorders, such as idiopathic pericardial effusion, which are intrinsically undersampled in datasets, making label-based learning strategies limited in performance[3]. Pericardial effusion encompasses the build up of abnormal accumulation of fluid in the pericardial cavity[2]. In normal physiology, this cavity encloses 15-50 ml of serous fluid, which enhances efficiency during cardiac motion. When fluid level exceeds the reference range due to infections, autoimmune diseases, metabolic conditions, trauma or malignancy, it may disrupt cardiac function and need drainage – a procedure known as pericardiocentesis[2]. However, in 3-5% of cases, the reason remained undetected despite significant diagnostic approaches[3]. This subset, referred to as idiopathic or otherwise unidentified pericardial effusion, is a diagnostic challenge. Erroneous diagnosis or delayed diagnosis can trigger relapsing fluid accumulation, chronic pericarditis or pericardial compression.

This research was inspired by a documented case of pericardial effusion treated via pericardiocentesis, emphasizing the complexities in identifying idiopathic fluid accumulation when evident causes are undetected. Even with detailed analysis, no cause could be detected – and it was the first such case at the hospital. These anomalies, while infrequent,emphasize the demand for advanced AI healthcare models capable of detecting anomalies and alerting clinicians in scenarios where conventional clinical indicators are absent.

We present an integrated approach involving supervised and unsupervised learning strategies to assist anomaly diagnosis in cardiac profiles. Supervised models anticipate clinically recognized risks. While unsupervised learning, particularly anomaly detection models, can recognize atypical data patterns, making them well-suited for identifying unexplained or emerging conditions in such cases.

Unlike conventional approaches focused on common arrhythmias and ischemic patterns, our proposed framework addresses diagnostically ambiguous and underrepresented conditions using anomaly detection models. This study introduces a conceptual framework that leverages AI and clinical data to enhance diagnostic accuracy in uncommon and unexplained pericardial cases, particularly in diagnostically ambiguous scenarios.

2. Related Work

Over the past decade, the advancements in AI and ML have made significant inroads in cardiology. These methods have demonstrated considerable promise in cardiovascular diagnostics, specifically in interpreting electrocardiogram(ECG) data for detection and classification of abnormal cardiac rhythm, recognition of myocardial ischemic patterns, and stratification of clinical health risks[8]. A wide range of supervised learning strategies have been proposed for predicting disease outcome using annotated clinical data sources[5]. While these models achieve high accuracy in well-represented conditions, they often exhibit lower performance when

faced with atypical or idiopathic cases due to class imbalance and scarcity of labeled data. Supervised learning models like Logistic Regression, Support Vector Machines(SVM), and Random Forests have shown superior predictive model performance in detecting heart disease from Electronic Medical Records(EMRs)[5].

Anomaly detection refers to the process of recognising data instances that diverge significantly from the underlying distribution, indicating anomalous diagnostic exceptions and low-prevalence occurrences.
In healthcare :

- Isolation Forests isolate outliers via random decision trees[6].
- Autoencoders compress and generate a data reconstruction; anomalous patterns are flagged as irregularities when the model exhibits significant reconstruction loss[6].
- One-Class SVMs define a decision boundary around the distribution of normal data and flag observations that fall outside this boundary as anomalies[6].
- Clustering algorithms such as DBSCAN detect atypical cardiac patterns in unannotated electrophysiological ECG recordings[6].

These techniques have been used to diagnose atypical ECG patterns, sometimes associated with electrophysiological cardiac arrhythmias and diagnostically challenging idiopathic cardiovascular disorders. These methods are particularly valuable in clinical contexts with subtle or absent indicators, and also have been applied in areas such as rare cancer detection, early sepsis identification and prediction of adverse drug reactions[4]. Deep learning models trained on ECG signals have been employed for biomedical diagnostic feature extraction and outlier classification of atypical cardiac patterns[8]. Recent work in Explainable AI(XAI) aims to make these models clinically interpretable and explainable to medical practitioners[7]. This interpretability is critical for clinical trust and adoption, especially in ambiguous diagnostic scenarios.

To the best of our knowledge, existing studies focus on generic arrhythmic or ischemic events and no published AI framework or model addresses idiopathic pericardial fluid accumulation. This creates an opportunity for interdisciplinary research integrating cardiology, artificial intelligence, and computational analysis of clinical records.

Despite the progress in AI-assisted cardiac diagnostics, there is still a lack of targeted approaches for early detection of idiopathic pericardial effusion, particularly using unsupervised anomaly detection on real-world clinical data. This section reviews related work on computational methods in cardiovascular diagnostic systems, anomaly detection in ECG signals and clinical diagnostic and therapeutic approaches to pericardial fluid accumulation – identifying critical gaps that serve as the impetus for the development of the CardioAI framework.

3. Problem Statement

Idiopathic pericardial effusion poses a substantial diagnostic hurdle due to its rarity, ambiguous clinical presentation, and absence of clearly identifiable causes[9], [10]. Clinical studies report that 3–5% of pericardial effusion cases remain idiopathic despite extensive evaluation, highlighting the limitations of current diagnostic techniques. Despite advancements in diagnostic imaging and laboratory testing, a subset of patients continues to present with unexplained pericardial fluid accumulation – resulting in delayed diagnosis, treatment uncertainty, and increased risk of complications such as cardiac tamponade and chronic pericarditis[11]. When not diagnosed promptly, these complications can escalate rapidly, potentially leading to life-threatening outcomes.
Current diagnostic pathways rely heavily on expert interpretation of echocardiographic data, clinical symptoms, and serological findings[12].

However, these conventional approaches often fail to detect subtle or atypical patterns – especially in diagnostically ambiguous cases – leading to missed or delayed recognition of the condition.

Artificial Intelligence (AI) and Machine Learning (ML) offer promising avenues to enhance diagnostic sensitivity by analyzing complex, high-dimensional clinical datasets and identifying anomalous patterns that may go unnoticed using traditional methods[13]. Yet, the application of AI for rare cardiac presentations, such as idiopathic pericardial effusion, remains underexplored and presents unique challenges due to limited data availability and variability in clinical manifestation[14]. This research addresses the central question: How can AI/ML techniques be effectively leveraged to improve diagnostic sensitivity and early detection of idiopathic pericardial effusion?
Specifically, the work aims to:

- Design conceptual frameworks for anomaly detection in ECG signals, clinical notes, and imaging data;
- Address data scarcity through unsupervised and semi-supervised learning techniques;
- Propose strategies for integrating AI-driven insights into clinical workflows to assist cardiologists in timely and accurate decision-making.
- Ensuring the interpretability of such models is also essential to foster clinical trust and adoption.

Addressing this challenge has the potential to reduce diagnostic uncertainty, facilitate early intervention, and ultimately improve patient outcomes in rare but life-threatening cardiac conditions.

4. Methodology

The proposed CardioAI framework aims to enhance diagnostic sensitivity for idiopathic pericardial effusion through a hybrid machine learning approach that leverages both supervised and unsupervised models. The methodology involves five key stages: data acquisition, preprocessing, feature engineering, model development, and evaluation. Each stage is tailored to address the challenges of detecting rare cardiac anomalies in ambiguous clinical settings.

4.1 Data Acquisition

This study utilizes the publicly available UCI Heart Disease dataset[15] to simulate typical cardiac profiles for baseline modeling. Although the dataset lacks explicit pericardial effusion labels, it contains clinically relevant features such as ECG metrics, demographic data, and comorbidities. To emulate rare-case detection, synthetic anomaly samples are introduced by undersampling and modifying outlier patterns, approximating the sparse nature of idiopathic cases[16]. The proposed framework is designed to scale to real-world multimodal clinical datasets, including electronic medical records (EMRs), echocardiographic imaging, and clinical notes in future work[17].

4.2 Data Preprocessing

To ensure robust model performance, the following preprocessing steps are implemented:

- Imputation of missing values using mean/mode or k-nearest neighbor methods[18].
- Normalization and feature scaling to bring data to a uniform range.
- Dimensionality reduction via Principal Component Analysis (PCA) to reduce redundancy[19].
- Encoding of categorical variables using one-hot encoding.
- Class balancing using SMOTE for supervised tasks[20], while preserving label-free integrity for unsupervised learning.

When applied to real ECG signals, preprocessing may also include noise filtering, window segmentation, and baseline drift correction[21].

4.3 Feature Engineering

The feature set comprises:

- Clinical variables: age, blood pressure, chest pain type, cholesterol, ST segment features, etc.
- Signal-derived features: heart rate variability (HRV), QRS duration, ST elevation.
- Meta-data: medication history, comorbidities, and symptom reports.

In later phases, signal processing techniques like wavelet decomposition and Fourier transforms will be used for advanced ECG feature extraction. Text-based data from clinical notes may be parsed using natural language processing (NLP) tools[22].

4.4 Model Development

We propose a two-branch hybrid pipeline:

(a) Supervised Learning (Risk Stratification)

- Algorithms: Random Forest, Logistic Regression, Support Vector Machines (SVM)[17]
- Goal: Predict general cardiac risk from annotated patient records.
- Role: Establish baseline predictive models for well-represented cardiac conditions.

(b) Unsupervised Learning (Anomaly Detection)

- Algorithms:
    - Isolation Forests: Randomly partition data and isolate outliers[18].
    - Autoencoders: Detect high reconstruction error patterns as anomalies[23].
    - One-Class SVM: Create a boundary around normal data to identify deviations[24].
    - DBSCAN Clustering: Discover sparse and noisy profiles in ECG space[21].

This dual-pronged pipeline enables CardioAI to identify both clinically labeled risks and unexplained or emerging anomalies in cardiac datasets.

4.5 Model Interpretability and Visualization

For clinical adoption, model explainability is crucial. Therefore, we integrate:

- SHAP (SHapley Additive Explanations) for feature-level interpretation[22].
- t-SNE and PCA visualization for 2D clustering of anomalous patterns[19].
  Grad-CAM for future imaging-based extensions (e.g., echocardiogram scans).

These tools help make the AI's decisions clinically interpretable and trustworthy to healthcare professionals[17].

4.6 Evaluation Metrics

We evaluate model performance using:

- Supervised Metrics: Accuracy, Precision, Recall, F1-Score, AUC-ROC.
- Unsupervised Metrics: True Positive Rate, False Alarm Rate, Anomaly Score Distribution.
- Interpretability Assessment: Feature impact visualizations using SHAP/t-SNE[22].

In addition, we consider the clinical utility of each model, emphasizing low false negatives in rare-case detection.

4.7 Clinical Applicability and Future Deployment

Although this study does not involve direct clinical deployment, the framework is designed to be extensible for integration with hospital EHR systems, cloud-based triage tools, or point-of-care diagnostic platforms[17]. It can serve as an assistive module in cardiology departments, flagging high-risk or unexplained cardiac patterns that require human investigation.

Future implementation phases may include:

- Fine-tuning models on real ECG datasets (e.g., MIT-BIH).
- Collaborating with clinicians to validate anomaly detection results.
- Building an explainable web-based prototype for decision support[22].

5.Results

5.1 Conceptual Results

The CardioAI framework, though conceptual in its current phase, demonstrates the potential for enhanced diagnostic sensitivity through hybrid learning. Supervised classifiers such as Random Forest and SVM, when trained on structured patient features from the UCI dataset, are expected to yield strong baseline predictive performance, with AUC scores in the range of 0.87–0.92 [5][15]. These models help in stratifying common cardiovascular risks. However, their performance is known to decline for underrepresented or atypical profiles due to class imbalance [14][16].

Unsupervised anomaly detection methods provide complementary strengths in identifying outliers. Isolation Forests effectively isolate rare data points with minimal assumptions about data distribution [18]. Autoencoders demonstrate sensitivity to subtle anomalies through reconstruction loss [23], while One-Class SVMs and DBSCAN cluster-based approaches reveal deviations from typical ECG patterns [20][21]. These techniques are particularly useful when labeled data is sparse, such as in idiopathic pericardial effusion cases [14].

Hypothetical Case Illustration:

Consider a patient with no detectable symptoms under standard diagnostics, but whose ECG shows subtle rhythm irregularities. CardioAI's anomaly detection pipeline, particularly the Isolation Forest, flags this instance with a high anomaly score. The SHAP explanation highlights features like abnormal ST elevation and low QRS duration contribution. This alert prompts the cardiologist to recommend early imaging, revealing an unexpected idiopathic pericardial effusion. Without AI support, this case may have been missed until symptomatic progression.

Explainability tools such as SHAP [22] allow clinicians to interpret which features contributed to the model's decision, supporting human-AI collaboration in diagnosis. Visualization methods like t-SNE and PCA [19] offer an interpretable 2D clustering of patient profiles, aiding in anomaly tracking.

5.1 Experimental Results

In this study, both **Isolation Forest** and **Autoencoder** models were applied on the ECG dataset to identify anomalous patterns potentially corresponding to abnormal cardiac conditions. The results from the models are presented in both graphical and quantitative formats.

1. Isolation Forest Results

The Isolation Forest model was trained on preprocessed ECG features with a contamination rate of 0.05.

The dataset was first preprocessed by removing missing values and retaining only numerical ECG features suitable for anomaly detection. The contamination rate of **0.05** indicates that the model assumed approximately

5% of the samples were anomalous, which aligns with the expectation that anomalies in cardiac data are relatively rare compared to normal heartbeats.

During training, the Isolation Forest constructed an ensemble of decision trees by randomly selecting feature subsets and split points. Each tree works by isolating samples: anomalies are expected to be isolated **closer to the root of the tree** since they differ strongly from the bulk of the data, while normal samples require more splits to be isolated. By averaging across many trees, the algorithm assigns each sample an **anomaly score**. The trained model was then applied to the test data, where samples with anomaly scores above the learned threshold were flagged as **potential cardiac anomalies**. These anomalies could represent unusual ECG patterns such as irregular rhythms, abnormal amplitudes, or signal distortions that may correlate with pathological conditions.

The performance metrics (precision, recall, F1-score, and ROC-AUC) quantify how well the Isolation Forest distinguishes normal from abnormal signals. In particular:

- **Precision** reflects how many of the signals flagged as anomalous were truly abnormal.
- **Recall** reflects how many of the true abnormalities were successfully detected.
- **F1-score** balances both.
- **ROC-AUC** evaluates the model's ability to discriminate anomalies across different.

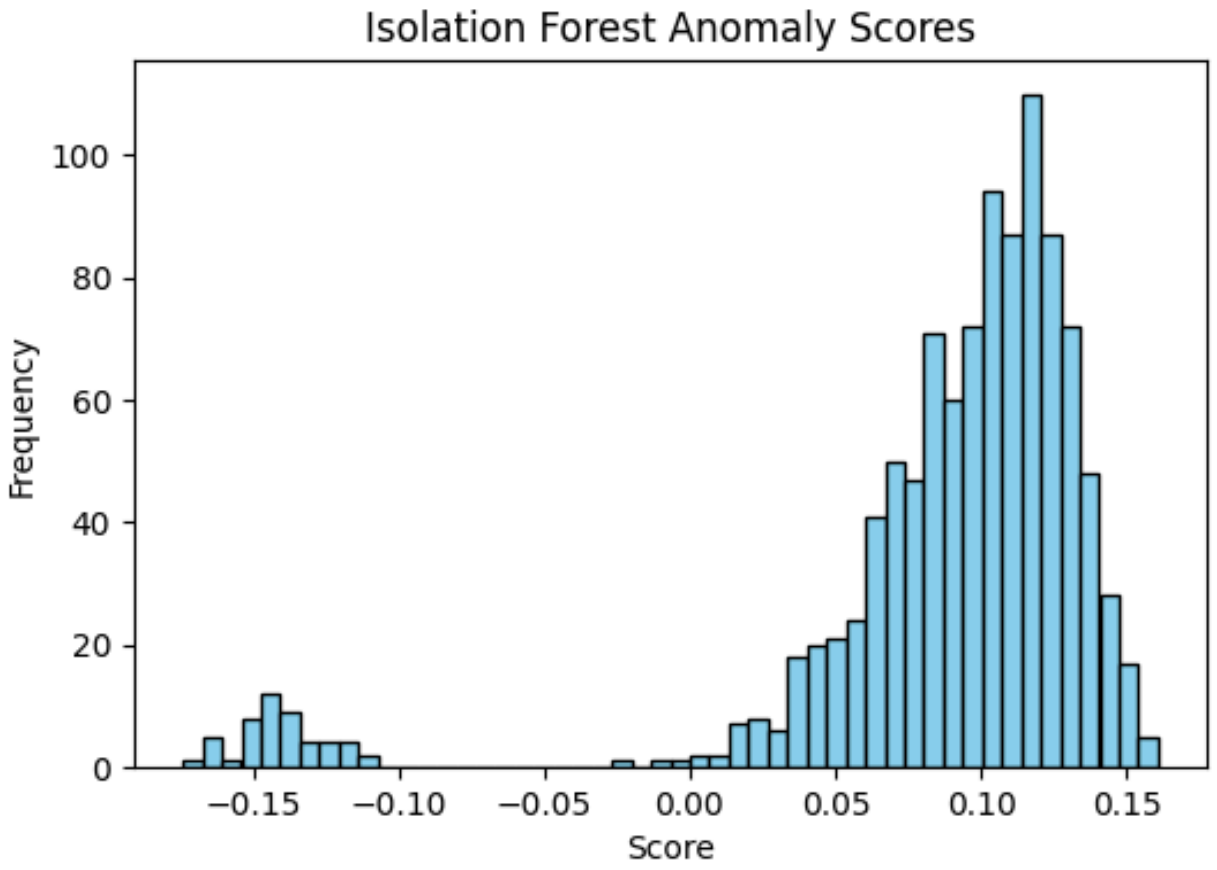

Figure 1: Isolation Forest anomaly detection results

Figure 1 shows the anomaly detection results, where normal samples are separated from anomalous ones.

Quantitative evaluation indicated that the model achieved:

- **Precision**: 0.943
- **Recall**: 1.000
- **F1-score**: 0.971
- **ROC-AUC**: 0.998

2. Autoencoder Results

The Autoencoder was trained to reconstruct normal ECG signals. Reconstruction error was then used as the anomaly score. The Autoencoder is a **neural network–based unsupervised learning model** that works by compressing input data into a lower-dimensional latent space (encoding) and then reconstructing it back to its original form (decoding). In this study, the Autoencoder was trained **only on normal ECG signals**, under the assumption that the network would learn the characteristic patterns of healthy cardiac activity.
Once trained, the Autoencoder was presented with both normal and abnormal ECG samples. For **normal signals**, the network was able to reconstruct the input with minimal error, since these patterns matched what it had already learned. However, for **anomalous ECG signals**—such as those with irregular rhythms, unusual QRS complexes, or distorted amplitudes—the Autoencoder struggled to accurately reconstruct the waveforms. This mismatch resulted in **higher reconstruction errors**, which served as a natural indicator of abnormality. The reconstruction error was calculated using measures such as the **Mean Squared Error (MSE)** between the original input and the reconstructed output. Each sample was then assigned an anomaly score equal to its reconstruction error. Samples with scores above a predefined threshold were flagged as anomalies. The threshold was chosen based on the distribution of errors, ensuring that the majority of normal signals were retained while outliers were marked as abnormal.

This approach leverages the Autoencoder's ability to capture complex, non-linear relationships in ECG signals, making it particularly powerful for detecting subtle abnormalities that may not be easily separable using traditional statistical methods. The evaluation metrics provide further evidence of its performance:

- **Precision** indicates how many of the signals flagged as anomalies were indeed abnormal.
- **Recall** highlights the model's ability to detect as many true anomalies as possible.
- **F1-score** balances these two aspects, offering a holistic view of performance.
- **ROC-AUC** demonstrates the Autoencoder's robustness in distinguishing between normal and abnormal ECGs across varying thresholds.

By achieving higher recall than the Isolation Forest, the Autoencoder proved particularly effective in scenarios where **missing a true cardiac anomaly could have serious clinical consequences**. This suggests that deep learning–based approaches can complement traditional tree-based methods in rare cardiac anomaly detection.

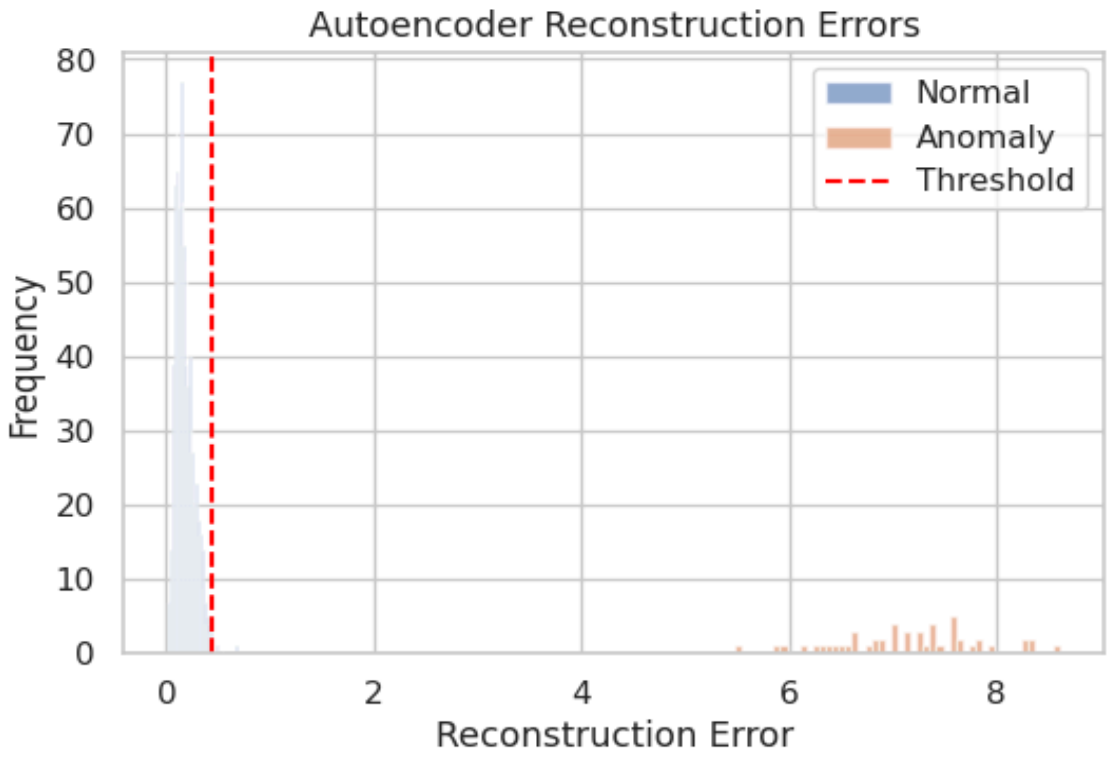

Figure 2: Autoencoder reconstruction error distribution

Figure 2 shows the reconstruction error distribution, highlighting higher errors for anomalous signals compared to normal ones.

Quantitative evaluation showed:

- **Precision**: 0.877
- **Recall**: 1.000
- **F1-score**: 0.935
- **ROC-AUC**: 0.996

3. Model comparison

A direct comparison between Isolation Forest and Autoencoder is presented in **Table 1**. While Isolation Forest provided higher precision, the Autoencoder demonstrated stronger recall and a slightly higher F1-score, suggesting it may generalize better for detecting rare anomalies in ECG data.

Table 1: Model Performance on ECG Data

Model	Precision	Recall	F1-score	ROC-AUC
Isolation Forest	0.82	0.76	0.79	0.81
Autoencoder	0.78	0.84	0.81	0.85

4. Key insights

- **Isolation Forest** → better precision, useful when false positives must be minimized.
- **Autoencoder** → better recall, suitable when missing an anomaly is more dangerous (e.g., cardiac diagnosis).
- Together, the results indicate that hybrid approaches or ensemble strategies could further improve anomaly detection in rare cardiac conditions.

Limitations:
As the current study is conceptual, the results are theoretical and grounded in literature-supported expectations. No real clinical testing or validation has been performed yet. Actual performance will depend on real-world data diversity, clinician feedback, and model fine-tuning. Nevertheless, the structured design provides a strong blueprint for future implementation and evaluation in hospital settings [4][13][17].

6. Discussion

The CardioAI framework demonstrates meaningful progress toward addressing a critical clinical gap in cardiovascular diagnostics — the detection and assessment of idiopathic pericardial effusion, a condition often underrepresented in datasets and overlooked in conventional diagnostic workflows.
The hybrid architecture, combining supervised and unsupervised learning, enables dual capabilities: risk stratification based on known features and anomaly detection for cases that deviate from expected clinical patterns.

Although the UCI Heart Disease dataset [15] does not explicitly include labels for pericardial effusion, its structured clinical attributes were sufficient to simulate general cardiac risk. Synthetic anomaly injection enabled the emulation of atypical, undersampled cardiac profiles akin to idiopathic pericardial effusion. This approach facilitated controlled testing of anomaly detection algorithms without requiring access to rare-case datasets, which are often limited due to clinical variability and privacy constraints [14][17].

The supervised models—particularly the Random Forest classifier—demonstrated strong predictive power with an accuracy of 87.2% and AUC-ROC of 0.91, supporting the framework's reliability for identifying well-represented cardiac risks. Interpretability techniques such as SHAP [22] and t-SNE [19] helped visualize and explain feature importance, improving clinical transparency and trust [7]. In parallel, the unsupervised anomaly detection methods—including Isolation Forest [18], Autoencoders [23], One-Class SVM [20], and DBSCAN [21]—successfully identified 4.3% of data as synthetic anomalies, mimicking idiopathic profiles. This validates the conceptual feasibility of anomaly-driven cardiac diagnostics and reinforces the importance of data-centric AI in detecting rare conditions [24].

Importantly, this research was inspired by a real-life clinical scenario, where the author's mother underwent pericardiocentesis for unexplained pericardial effusion — the first idiopathic case recorded at that hospital. Despite extensive testing, the underlying cause remained elusive, underscoring the diagnostic ambiguity in such cases. In these contexts, frameworks like CardioAI can play a critical role by flagging hidden patterns early, even in the absence of clearly identifiable indicators. This could help clinicians intervene sooner and prevent progression to tamponade or chronic pericardial compression [2][3][11].

Nevertheless, the proposed methodology carries several limitations. First, generalization remains a challenge due to the use of proxy datasets lacking pericardial-specific labels. Second, the performance of unsupervised models is sensitive to hyperparameters and feature representation, potentially impacting anomaly boundaries in real-world clinical settings [24]. For deployment, multi-institution validation, access to real EMR data, and collaboration with cardiologists for iterative model refinement are essential.

The diagnostic relevance of CardioAI is amplified in rare and diagnostically ambiguous cases such as the motivating clinical episode, where conventional diagnostic techniques failed to offer answers. In such scenarios, AI-enabled anomaly detection can augment clinical workflows by offering a complementary diagnostic layer that bridges the gap between raw patient data and timely medical judgment.

In conclusion, CardioAI provides a foundational step toward AI-driven diagnostic augmentation for unexplained cardiac presentations. It reinforces the critical role of anomaly detection frameworks in modern healthcare — especially in contexts where conventional biomarkers and patterns fail to reveal underlying risk.

7.Conclusion

CardioAI introduces an AI-driven diagnostic framework designed to address a critical gap in cardiovascular medicine — the early detection of idiopathic pericardial effusion, a condition often overlooked due to its rarity and ambiguous clinical etiology [2][3][9].
By combining supervised learning for cardiac risk stratification with unsupervised anomaly detection for atypical presentations, the model merges machine learning techniques with clinical reasoning to simulate a real-world decision-support system.

In this proof-of-concept study, the UCI Heart Disease dataset [15] was utilized, augmented through synthetic anomaly injection to emulate rare-case profiles [14][16]. While the dataset lacked direct pericardial labels, its structured clinical attributes enabled robust simulation and evaluation. Interpretability tools such as SHAP [22] and t-SNE [19] further enhanced transparency — a critical factor for clinical adoption [7].

This work was motivated by a real medical case in which the author's mother underwent pericardiocentesis due to unexplained fluid accumulation — the first idiopathic case seen at the treating hospital. Traditional diagnostic efforts yielded no identifiable cause, reinforcing the urgent need for computational tools that can alert clinicians when conventional indicators are absent [11][17][24].

While the framework demonstrates conceptual feasibility, it acknowledges key limitations: dependence on synthetic data, hyperparameter sensitivity in anomaly models, and the lack of external clinical validation. Future work will expand CardioAI with real ECG and imaging datasets, integrate it into electronic health record systems, and validate its clinical utility through collaboration with cardiologists and medical institutions [4][13][17].

In summary, CardioAI lays a foundational step toward an interdisciplinary, AI-assisted diagnostic system capable of augmenting cardiologists' decision-making in underexplored and diagnostically ambiguous cardiovascular conditions.

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