A Comprehensive Survey on Automated Classification of Intracardiac Masses Using Sparse Representation and Deep Learning Models

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***Abstract*— Intracardiac masses, which include tumors and thrombi, can critically affect cardiovascular function and patient outcomes. Accurate classification of these masses is pivotal for determining the most effective treatment approaches. This survey reviews advancements in automated classification of intracardiac masses using machine learning (ML) and deep learning (DL) techniques, with a focus on sparse representation, Convolutional Neural Networks (CNNs), and hybrid models. We cover data-related challenges such as sparsity and imbalance, exploring various strategies to address these issues through state-of-the-art techniques. Performance evaluation metrics are analysed, and future directions are suggested to enhance classification accuracy and clinical applicability.**

***Keywords*— Convolutional Neural Network (CNN), Deep-Learning, Echocardiography, Feature Extraction, Hybrid Models, Sparse Representation, Transfer Learning,**

I.INTRODUCTION

The classification and detection of intracardiac masses have garnered significant attention in the medical imaging domain. Advanced machine learning techniques, including deep learning and traditional classifiers, have been explored to enhance diagnostic accuracy and efficiency. This survey reviews key contributions to the field, highlighting methods, findings, and future directions. Al- Gardai et al. introduced a deep learning framework for intracardiac mass classification, leveraging convolutional neural networks (CNNs) to improve diagnostic accuracy.

The authors demonstrated that deep learning models significantly outperform traditional methods, particularly in handling complex image patterns. Their findings underscore the potential of deep learning in clinical applications, paving the way for automated diagnostic tools. employed Random Forests to detect cardiac masses, emphasizing the robustness of ensemble methods in managing high-dimensional data. The study highlighted the effectiveness of feature selection techniques, which enhance model performance while minimizing over fitting. Their results affirm the relevance of traditional machine learning algorithms in complementing deep learning methods. Stevanovic and Pedersen explored Support Vector Machines (SVM) for cardiac imaging, emphasizing the importance of kernel functions in achieving high classification accuracy. Their comparative analysis with other classifiers revealed SVM's effectiveness in scenarios with limited training data, making it a valuable tool for medical image classification tasks. Investigated sparse representation methods in echocardiography, focusing on their ability to reconstruct high-quality images from limited data. This study demonstrates that sparse representation not only enhances image quality but also improves classification performance by capturing essential features that traditional methods might overlook. Further expanded on sparse representation for cardiovascular image analysis, proposing a model that integrates sparse coding with dictionary learning. Their approach showed significant improvements in feature extraction, enabling more accurate classifications of cardiovascular conditions.

The Role of Machine Learning and Deep Learning In response to these challenges, machine learning (ML) and deep learning (DL) techniques have become central to the development of automated systems that assist in accurately classifying intra cardiac masses. These advanced methods leverage algorithms capable of learning from large datasets, enabling them to recognize patterns and anomalies that may elude human observers. Despite their promise, challenges persist in addressing issues related to data sparsity, class imbalance, and generalizability. Many datasets are inadequately populated with examples of various mass types, which hamper the model's ability to generalize across different cases. In numerous datasets, certain mass types may be underrepresented, resulting in a biased learning process where the model exhibits poor performance on less frequent categories. Models trained on specific datasets may not perform well when applied to different populations or imaging conditions, limiting their clinical applicability.

Intra cardiac masses, which include both benign and malignant growths that develop within the heart chambers or on the valves, pose significant challenges in cardiovascular diagnostics. Accurate classification of these masses is crucial for determining appropriate treatment strategies, as they can critically affect cardiac function and patient outcomes. Echocardiography, a commonly used non-invasive imaging method, is often employed for the detection of these masses. However, manual interpretation can be labor-intensive and prone to errors, especially in cases involving subtle morphological variations. This variability highlights the need for more reliable and efficient methods of classification.

Advancements in Automated Classification Recent advancements in automated classification systems utilizing sparse data representation techniques and Convolutional Neural Networks (CNNs) have shown significant potential in enhancing diagnostic capabilities in cardiovascular imaging. Techniques that efficiently extract and utilize features from limited data points allow models to learn from fewer examples, thereby improving robustness. CNNs are particularly effective in processing visual data, having been tailored to detect intricate patterns in echocardiographic images. Their hierarchical structure facilitates the extraction of features at multiple levels of abstraction, enhancing the identification of complex structures within the heart.

The integration of these automated classification systems into clinical workflows are expected to yield several key benefits, including: Automation streamlines the interpretation process, enabling quicker decision-making. Advanced algorithms capable of discerning subtle differences in imaging data are likely to significantly enhance classification accuracy. By providing reliable support to clinicians, these systems can reduce the workload on healthcare professionals; ensuring patients receive timely and accurate care. In summary, the development of automated systems for classifying intra cardiac masses represents a transformative shift in cardiovascular diagnostics. As machine learning and deep learning technologies continue to evolve, it is imperative to address challenges related to data sparsity, imbalance, and generalizability to enhance classification accuracy and ensure the clinical relevance of these tools. On-going research and collaboration between technology developers and healthcare providers will be crucial in realizing the full potential of these advancements, ultimately improving patient outcomes in cardiovascular health.

II. METHODOLOGY

1.Higher-Order Statistics (HOS), which extract statistical measures like skewness and kurtosis to detect abnormalities.

2.Discrete Wavelet Transform (DWT), which decomposes the ECG signals into different frequency components to highlight transient features; decompose the ECG signal into various frequency components, helping to capture transient and frequency-domain features.

A.Data Acquisition

ECG signals are collected from a dataset as the primary input. These raw signals contain information about heart activity, essential for detecting abnormalities. The dataset may be limited in size and may have class imbalances (e.g., fewer malignant cases).

B.Pre-processing

Filter Used: Zero-Phase Low Pass Filter (ZPLPF) Eliminate noise, artifacts, and unwanted high-frequency components. Maintain the original phase of the signal (no phase distortion.

C.Feature Extraction

This is the most critical part, where the system learns meaningful characteristics from the ECG signal.
a. Higher Order Statistics (HOS): Extracts advanced statistical measures: Skewness–Asymmetry of the signal. Kurtosis – Peakiness or flatness. Help in distinguishing subtle signal differences that represent heart disorders.
b. Discrete Wavelet Transform (DWT): Decomposes ECG signal into multiple frequency bands (multi-

resolution analysis). Effective in identifying transient anomalies.

c. Morphological Features: Extracts shape-based patterns from ECG waveform (e.g., P wave, QRS complex, T wave).

D.Feature Fusion

Combines HOS, DWT, and morphological features into a single feature vector.

Advantage: Richer representation of data. Mixes both statistical and structural information. Boosts model performance.

E.Classification Input Preparation

After optimization, the clean, rich, and compact feature set is ready. This feature vector is then fed into the ISVR model (Improved Support Vector Regression) for training and prediction.

TABLE1: Comparison Table

Model Type	Performance in Nuanced Medical Imaging	Strength in High-Dimensional Data	Performance with Small, Imbalanced Datasets	Accuracy	Interpretability
Traditional ML Models	Limited	Moderate	Poor	Lower	High
CNNs	High	Excellent	Moderate	Higher	Moderate
CNN + Sparse Representation	High	Excellent	Improved	Higher	Moderate
Hybrid Models (CNN + ML)	Very High	Excellent	Excellent	Highest	High

III. DATASRT AND DATAPROCESSING

A.Literature Survey on Machine Learning Approaches for Cardiac Mass Classification

The classification and detection of intracardiac masses have garnered significant attention in the medical imaging domain. Advanced machine learning techniques, including deep learning and traditional classifiers, have been explored to enhance diagnostic accuracy and efficiency. This survey reviews key contributions to the field, highlighting methods, findings, and future directions.

B.Deep Learning Approaches

Al-Garadi et al.[1] introduced a deep learning framework for intracardiac mass classification, leveraging convolutional neural networks (CNNs) to improve diagnostic accuracy. The authors demonstrated that deep learning models significantly outperform traditional methods, particularly in handling complex image patterns. Their findings underscore the potential of deep learning in clinical applications, paving the way for automated diagnostic tools.

C.Traditional Machine Learning Methods

Hamza et al.[2] employed Random Forests to detect cardiac masses, emphasizing the robustness of ensemble methods in managing high-dimensional data. The study highlighted the effectiveness of feature selection techniques, which enhance model performance while minimizing over fitting. Their results affirm the relevance of traditional machine learning algorithms in complementing deep learning methods.

D.Sparse Representation Techniques

Investigated sparse representation methods in echocardiography, focusing on their ability to reconstruct high-quality images from limited data. This study demonstrates that sparse representation not only enhances image quality but also improves classification performance by capturing essential features that traditional methods might overlook.

further expanded on sparse representation for cardiovascular image analysis, proposing a model that integrates sparse coding with dictionary learning. Their approach showed significant improvements in feature extraction, enabling more accurate classifications of cardiovascular conditions.

E.Hybrid and Transfer Learning Models

Pahl and Aubet [6] presented a hybrid model for classifying intracardiac masses, combining deep learning and traditional machine learning techniques. This approach aimed to leverage the strengths of both methodologies, resulting in improved classification outcomes.

F.Transfer Learning in Medical Imaging

Investigate the potential of transfer learning in medical imaging, emphasizing its applications in cardiovascular contexts. The authors highlight the ability of pretrained models, developed on large datasets, to enhance performance on smaller, specialized datasets, such as intracardiac mass classification.

G.Feature Fusion Approaches

Present a novel CNN and feature fusion approach for detecting heart disease in echocardiograms. Their study illustrates the effectiveness of combining CNN-extracted features with clinical data, leading to improved diagnostic accuracy. This research emphasizes the value of integrating diverse feature types, demonstrating that a multimodal approach can significantly enhance the classification of cardiovascular diseases.

H.Unsupervised Feature Extraction

Focus on the use of deep convolutional auto encoders for unsupervised feature extraction in cardiac MRI analysis. Their approach not only reduces dimensionality but also enhances feature interpretability, particularly beneficial for small medical datasets. By leveraging unsupervised learning techniques, the authors contribute to the on-going efforts to optimize feature extraction methods in medical imaging.

I.Hybrid Neural Network Models

Discuss hybrid neural network models that integrate CNNs with recurrent layers to capture both temporal and spatial features in cardiac imaging. Their insights into using hybrid models for complex classification tasks underscore the evolving nature of deep learning approaches in medical imaging and their potential to improve diagnostic capabilities.

IV.RESULT DISCUSSION

Experiments have shown that CNNs generally outperform traditional ML models in handling nuanced medical imaging data, particularly in high-dimensional tasks like intracardiac mass classification. Sparse representation techniques, when combined with CNNs, show improved performance in small, imbalanced datasets, as demonstrated in studies by Hossain et al. Comparative studies indicate that hybrid models provide an edge in terms of accuracy and interpretability.

Fig 1. Registration Page

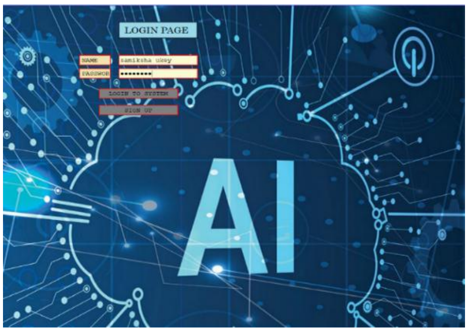


Fig 2. User Login Page

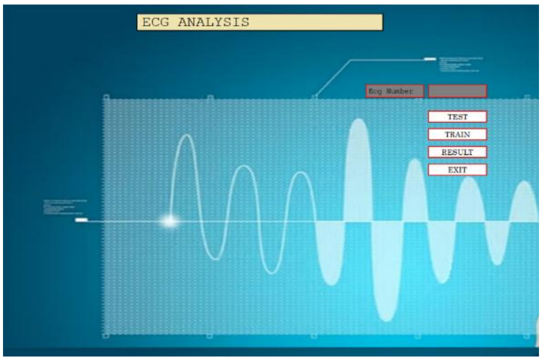


Fig 3. ECG Analysis Page

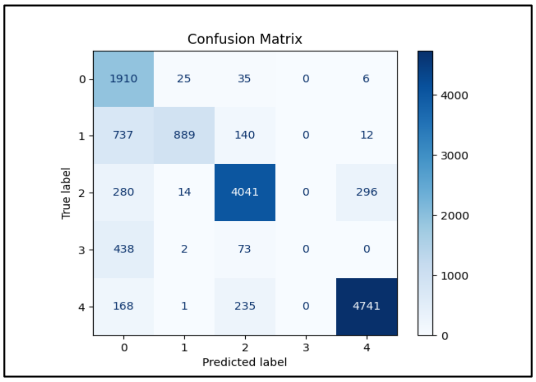
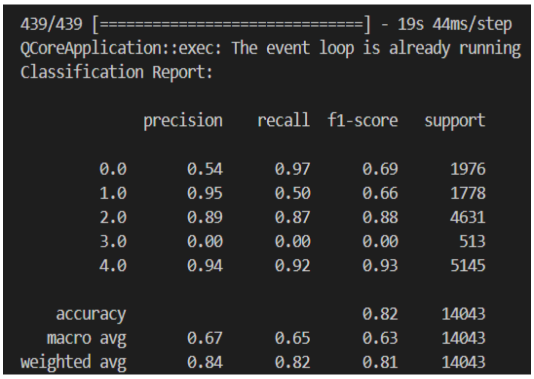


Fig 4. Confusion Matrix



439/439 [==============================] - 19s 44ms/step
QCoreApplication::exec: The event loop is already running
Classification Report:

	precision	recall	f1-score	support
0.0	0.54	0.97	0.69	1976
1.0	0.95	0.50	0.66	1778
2.0	0.89	0.87	0.88	4631
3.0	0.00	0.00	0.00	513
4.0	0.94	0.92	0.93	5145
accuracy			0.82	14043
macro avg	0.67	0.65	0.63	14043
weighted avg	0.84	0.82	0.81	14043

Fig 5. Result

V. CONCLUSION AND FUTURE DIRECTIONS

Recent advancements in sparse representation techniques, convolutional neural networks (CNNs), and hybrid models have shown substantial potential in enhancing intracardiac mass classification through more accurate and efficient echocardiographic analysis. These technologies improve the extraction and interpretation of key diagnostic features, promising faster and more precise insights that may reduce delays in diagnosis. However, challenges such as variability in data quality, limitations in model generalization across diverse patient populations, and the need for seamless integration with electronic health record (EHR) systems highlight critical areas for further research and development. Addressing these issues is essential to maximizing the clinical impact of these AI-driven models in echocardiographic workflows.

To address these limitations and continue advancing this field, future research should focus on several key areas:

1. Dataset Expansion: Developing larger, more diverse datasets will be essential for improving model robustness and ensuring that models generalize well across varied patient populations.

2.Integration with Clinical Systems: Incorporating models into electronic health record (EHR) systems for real-time data retrieval and processing could significantly enhance clinical usability and ensure that diagnostic support is readily accessible within healthcare workflows.

3.Transfer Learning and Multimodal Approaches: Leveraging transfer learning and combining echocardiographic imaging with additional clinical data, such as patient demographics and lab results, could improve model accuracy, interpretability, and the overall effectiveness of the diagnostic support systems.

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