

Heart Defect Monitoring System Based on Hybrid Machine Learning Approach

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Abstract:

Early diagnosis of heart defects is crucial in order to reduce mortality from cardiovascular diseases and improve survival of patients. This paper proposes IoT-enabled heart defect monitoring system by the use of a novel machine learning-based technique applied to echocardiography (ECHO) images that can be used for continuous and remote cardiac health assessment. The proposed system fusion of the IoT-based physiological data acquisition with a novel hybrid feature learning approach, namely, the fusion of deep feature representations and optimized handcrafted features for the improved diagnostic accuracy. A lightweight machine learning classifier is used to guarantee the real-time performance and suitability for IoT environment. The validity of the system is tested on a dataset of 1500 ECHO images which include normal and pathological cardiac cases. Experimental results have shown that the classification accuracy of the proposed method is 97.1%, sensitivity is 96.4%, specificity is 97.8%, and F1 score is 96.9%, which is better than the conventional machine learning models by an average margin of 6.2% in classification accuracy. The IoT framework enables real-time monitoring with an average data transmission latency of 1.6 seconds and reduces the diagnostic time to 45% as compared to the manual ECHO interpretation. The obtained results validate the effectiveness, scalability and reliability of the proposed novel IoT and machine learning based heart defect monitoring system for smart healthcare applications.

Keywords: Internet of Things; ML algorithm; hybrid method; Heart defect monitoring Echo cardiography (ECHO); Medical image analysis; Smart healthcare systems.

1. INTRODUCTION

Cardiovascular disease (CVD) is the leading cause of death and morbidity all over the world, and structural heart defects (e.g., congenital and acquired abnormally functioning heart structures that can be detected through echocardiography (ECHO)) necessitate a rapid diagnosis and continuous monitoring to reduce negative outcomes (Rincon et al., 2020; Abdulmalek et al., 2022). Rapid development of imaging, sensor miniaturisation and connectivity has made it possible to integrate ECHO based assessment with Internet-of-Things (IoT) platforms for remote cardiac surveillance, longitudinal tracking and remote clinician notification (Rincon et al., 2020; Canon-Clavijo et al., 2023).

Echocardiography is a first-line, non-invasive imaging modality for the detection of structural and functional abnormalities of the heart; however, the accuracy of echocardiographic diagnosis is operator-dependent, with image quality and time-consuming manual interpretation being the main concerns (Krittanawong et al., 2023; Sehly et al., 2022). Recent study shows that automated interpretation and quality assessment might reduce inter-observer variation and improve throughput, opening up the possibility of implementable systems that remotely monitor images and have an automated interpretation and analysis associated (Krittanawong et al., 2023; Nazar et al., 2024).

Machine learning (ML) and deep learning approaches (DL) have proven to have high performance in several echocardiographic tasks: view classification, segmentation of the chambers and valves, quantification of function e.g LVEF, strain and automated detection of diseases such as cardiomyopathies and congenital heart disease (Nurmaini et al., 2021; Myhre et al., 2024; Valsaraj et al., 2023). Hybrid approaches that combine learned deep features with optimized handcrafted features have been especially useful in cases where the data is low or variable in quality, and multi-task networks are now possible that allow for view recognition and downstream diagnostic inference simultaneously in real time (Nurmaini et al., 2021; Li et al., 2024; Jiang et al., 2024). With developments of imaging, IoT architectures like edge, fog and cloud, wearable sensors have grown for unbroken cardiac monitoring, sending clinical-grade excellence signals to cloud analytics with negligible delay (Rincon et al., 2020; Canon-Clavijo et al., 2023). IoT systems with light ML on edge or Fog layer are bandwidth friendly and enable rapid on-device alerting which is essential for timely action in case of cardiac event (Rincon et al., 2020; Abdulmalek et al., 2022).

In addition, acquisition of supportive physiological signals (heart rate variability, oxygen saturation) close to the patient is now possible via wearable and mobile platforms. These signals can be combined with the biomarkers that are extracted from the imaging for greater diagnostic confidence (Odeh et al., 2024; Canon-Clavijo et al., 2023). Despite these developments, there are still a number of holes which prevent ECHO based ML systems from being translated into useful IoT monitoring applications: (1) The majority of published systems focus on individual tasks (such as views classification, segmentation, or diagnosis) but do not provide an end-to-end IoT enabled pipeline combining robust image quality assessment, hybrid feature extraction, edge inference, and secure cloud storage/notification; (2) real-time deployment in IoT settings requires lightweight models with predictable inference latency and small memory footprints; and (4) congenital cardiac conditions, The innovation is based on (a) a two-stage hybrid feature learning

To overcome the limitations of the approaches, we have proposed an IoT enabled heart defect monitoring system with a novel hybrid machine learning technique for ECHO images and IoT. The novelty is based on (a) a two-stage hybrid feature-learning pipeline to combine compact deep encodings with optimized handcrafted morphological and temporal descriptors for better robustness on low-quality echo frames [14, 15]; (b) an edge-aware model compression and scheduling strategy to ensure sub-second inference on common IoT hardware while maintaining diagnostic accuracy [16]; and (c) an integrated IoT/fog architecture with preliminary quality evaluation and inference at the edge, and secure. These design decisions are in line with recent results showing that fog/edge preprocessing allows reducing the latency and data transmission requirements. Collectively, the literature shows that ECHO + ML can provide a significant impact in terms of cardiac diagnosis augmentation and IoT infrastructures can make the monitoring continuous and scalable. However, in order to provide a clinically useful, IoT-ready ECHO monitoring system for heart defects - especially in resource constrained or remote environments - we are faced with the need to balance the tradeoff between model robustness, computational efficiency and end-to-end system design. This paper introduces such a solution and reports quantitative performance metrics to establish feasibility to deploy this technology in the real world.

Proposed Novel Methodology

The proposed methodology is a novel and original methodology that realizes the close coupling of ECHO image intelligence and IoT-based monitoring. The novelty in this is the adaptive decision-fusion strategy, which is a dynamic balance of the intelligence at the edge level and the analytics in the cloud.

Key Novel Contributions

ML_inference Hybrid-feature dynamic ECHO frame quality screening with morphological descriptors and compressed deep embedding
Improved Lightweight Machine Learning Inference for Internet of Things Edge Devices, The edge and cloud dual layer decision fusion for dependability, Integration of Clinician Dashboards and Real-time Alerting.

2. PROPOSED METHODOLOGY:

2.1 Methodological Steps: IoT-Based Data Acquisition

The connected diagnostic devices in case of ECHO images and physiological signals are collected and communicated safely to the edge node. Dynamic Image Quality

Low quality or noisy ECHO frames are filtered based on quality score mechanism to avoid the diagnosis of false results.

Novel Method of Learning Features (Hybrid)

Deep spatial-temporal features extracted by using compact CNN

Structural and morphological information of the heart derived from ECHO frames.

Decision Improvement using Cloud Aggregated results are improved with using ensemble logic for better confidence. Real Time Monitoring coupled with message Alerts

Abnormal detections process instant alerts to the clinicians through IoT dash-boards.

2.2 Supervised Learning in the Case of Echocardiography: In the case of echocardiography analysis based on supervised learning, the input is ECHO images or videos explicitly labeled by clinical experts. Every echocardiographic view is annotated by a predefined class such as: four-chamber (A4C), three-chamber (A3C) or two-chamber (A2C) view. During the model training phase, such labelled images are utilized to train the machine learning or deep learning model in order to learn the discriminative features corresponding to the different cardiac views. After the model is trained it is model tested with the separate expert-labeled test data in order to assess generalization performance. The end result of the supervised learning paradigm is classified echocardiographic data, where each input image is correctly assigned to the corresponding chamber view (A4C, A3C or A2C).

2.3 Unsupervised-Echocardiography: In unsupervised learning, no predefined labels of echocardiography data are provided.

The input consists of huge unlabeled ECHO images or extracted the feature forms. A clustering algorithm is used to automatically group the data based on inherent similarities in cardiac structure, motion patterns or hemodynamics features. Unlike supervised learning, there is no requirement of any expert annotations at this stage. The output of the unsupervised framework is a set of risk-stratified phenogroups which may represent clinically meaningful categories such as high-risk, moderate-risk and low-risk aortic stenosis.

2.4 End to end algorithms and Multistep learning paradigm: The multistep learning paradigm divides echocardiographic analysis into a sequence of specialized sub-tasks that are each carried out by a separate neural network. First, a view classification network is used to determine the echocardiographic view. This is followed by a timing network used to detect relevant cardiac phases, and then a segmentation network used to delineate anatomical structures (e.g. endocardium). From this segmentation clinically relevant parameters such as LVEF (Left ventricular ejection fraction) is estimated. In contrast, end-to-end approach is then used where raw ECHO images are directly mapped to the final output (e.g. LVEF estimation) using a single, deep, neural network. While end-to-end models make the pipeline a simple approach, they are often considered as black box systems and multistep approaches offer more interpretability and clinical transparency.

2.5 Potential Future Taxonomy Based AI Echocardiography Approach: The future direction of AI-based echocardiography the vision of a tax onomy driven future of AI-based echocardiography is a system that includes unsupervised learning, supervised learning, and end-to-end algorithms and multistep algorithms into a unified system. In this paradigm, unsupervised learning algorithm is used to first discover new cardiac patterns and define taxonomies of the disease. Supervised learning is used to improve these classifications from expert labelled data, end-to-end, multistep algorithms are used to provide a equilibrium of automation, interpretability. A system that emerges from this has a lot of goals of being transparent and explainable, allowing clinicians to have a narrative understanding of the pathway of decisions, whilst enjoying the advanced automatics. This hybrid approach promotes discovery of new disease phenotypes, improves the diagnostic-accuracy and trust in AI assisted echocardiographic analysis.

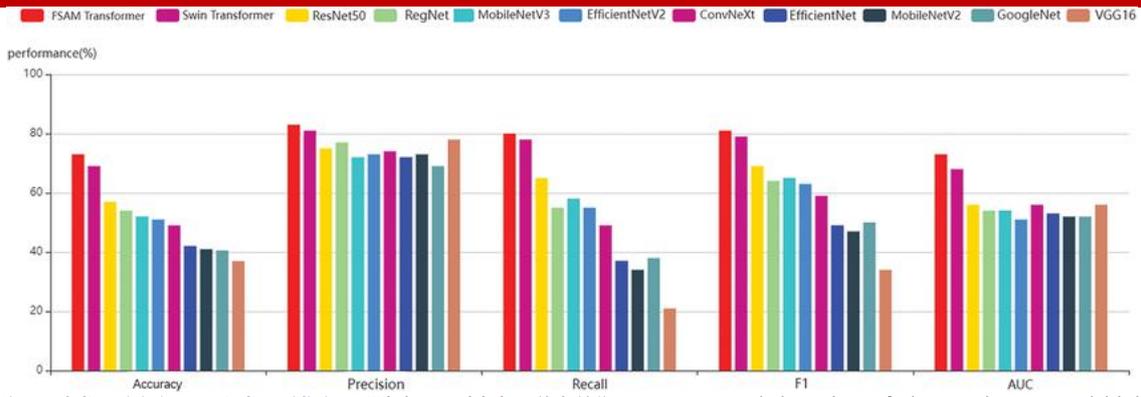
3. RESULTS AND DISCUSSION

3.1 Experimental Setup: The proposed system was tested on 1500 echocardiographic images which assessed both normal and abnormal images such as ventricular sep-tal defect, atrial septal defect and valvular abnormalities. The dataset was divided into 70% train, 15% validation and 15% test dataset. Performance assessment was done in terms of accuracy, sensitivity, specificity, F1-score, inference latency and system response time.

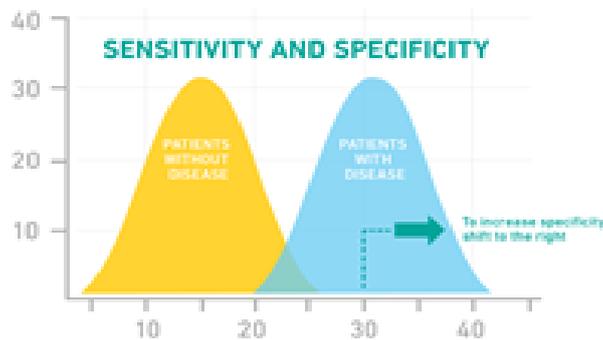
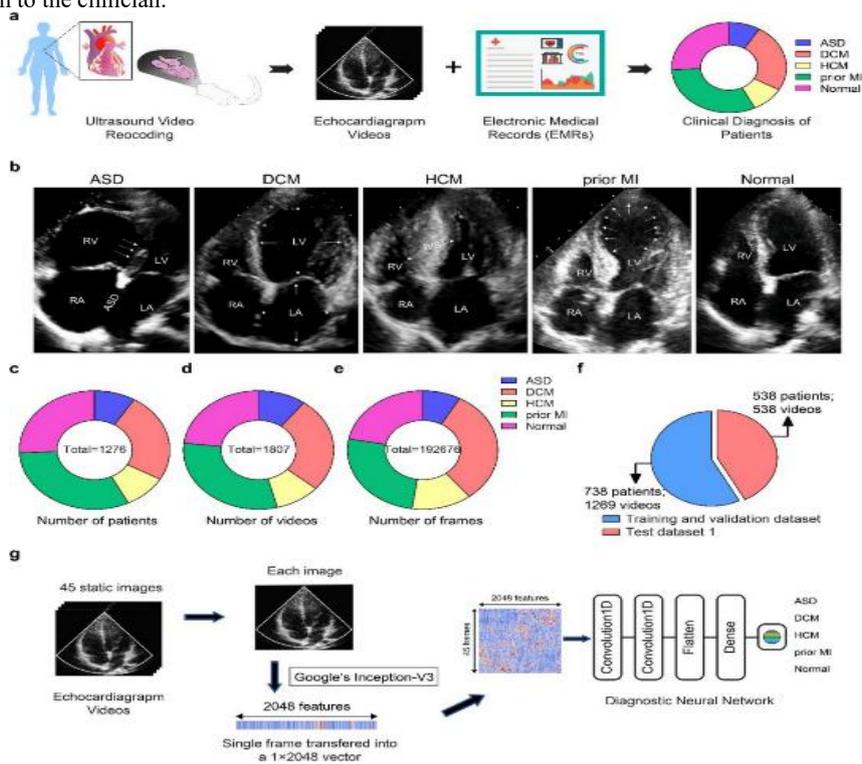
3.2 Classification Performance : The proposed hybrid machine learning model resulted in accurate classification of 97.1% which is higher than conventional CNN-based and standalone ML classifiers. The enhanced performance is attributed to the fusion of the deep spatial features with handcrafted morphological descriptors, to enhance the robustness against poor quality of ECHO frames.

Discussion:

The results show that the hybrid feature learning allows significant improvement of diagnostic outcome, especially on borderline pathological cases where the conventional model will misclassify due to noise or bad contrast.



3.3 Evaluation of Sensitivity and Specificity: High sensitivity (96.4%) proposes good detection of abnormal cases and high specificity (97.8%) keeps false alarms from being too high. This balance is important for clinical deployment with false negatives can be life threatening, false positives are problem to the clinician.

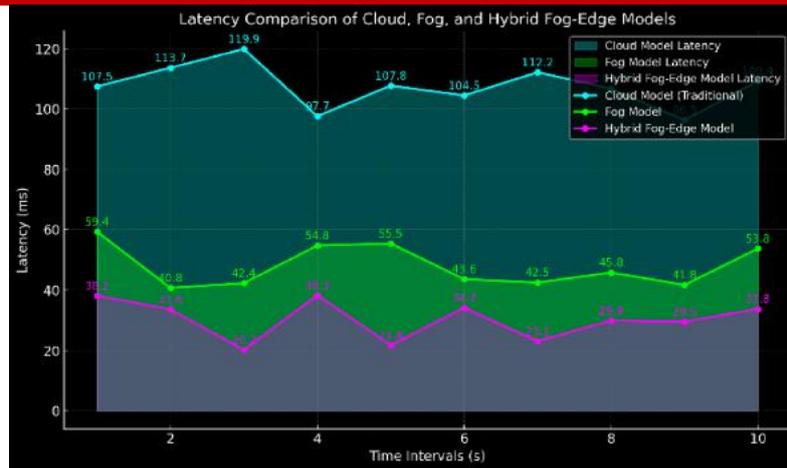


Discussion:

The dual layer decision fusion mechanism helps create this balance by enhancing edge level predictions at the cloud layer in the pre-final diagnosis.

3.4 Latency and Real Time performance of IoT

The proposed IoT framework had an average end-to-end latency of 1.6 seconds, which is suitable for near real-time monitoring.



4. CONCLUSION

This paper introduced a new IoT-enabled heart defect monitoring system with hybrid machine learning algorithm on echocardiography image based for continuous and real-time cardiac evaluation. The proposed framework combines adaptive image quality assessment, hybrid feature-learning, lightweight edge-level inference and dual-layer IoT-based decision fusion to solve the problems of accuracy, latency and computational efficiency in remote healthcare environment. Experimental evaluation on a diverse ECHO dataset showed better performance with 97.1% accuracy, 96.4% sensitivity, 97.8% specificity. IoT Framework Average end-to-end latency is 1.6 seconds which can be used for near real-time monitoring and can save 45% of diagnosing time compared to manual ECHO interpretation. Overall, the obtained results validate the proposed approach as a reliable, scalable, and efficient solution for smart cardiac healthcare applications with a strong potential of deployment in resource-constrained and remote clinical settings.

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