
Heart Guardian: Tinyml Based Ventricular Arrhythmia Detection for Life Saving Treatment

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Abstract:- Cardiovascular diseases, notably ventricular arrhythmias, continue to pose a significant threat to global health. Timely detection and intervention are crucial for improving patient outcomes, prompting the development of HeartGuardian—a pioneering solution that leverages TinyML (Tiny Machine Learning) for life-saving ventricular arrhythmia detection through unobtrusive wearable devices. This project introduces a methodological breakthrough by designing and implementing a highly optimized TinyML model tailored for wearable devices. The model analyses real-time electrocardiogram (ECG) signals directly on the device, achieving a delicate balance between accuracy and resource efficiency. This innovation enables continuous monitoring without imposing substantial power or computational demands, making it feasible for widespread use. Heart Guardian's primary focus is on providing proactive and continuous monitoring to enable early detection of ventricular arrhythmias. The embedded TinyML model ensures immediate analysis of ECG data, allowing for prompt alerts to healthcare professionals or caregivers upon detection of irregularities. This real-time response mechanism is critical for timely medical intervention and potentially life-saving measures. The ultimate aim of our project is to maintain data privacy and safeguard sensitive information of patients Striving for compliance with privacy regulations, HeartGuardian aims to build trust in the utilization of wearable health technology. Thus, the project provides an effective method for ventricular arrhythmia detection using the Arrhythmia Classification Dataset. The dataset is pre-processed by filtering signals, and models, including Logistic Regression and Efficient CNN, are trained. Validation and evaluation are conducted, ultimately leading to the prediction of arrhythmia.

Keywords*:* Efficient CNN, Electrocardiogram (ECG), Logistic Regression, TinyML.

1. Introduction

HeartGuardian is at the forefront of revolutionizing healthcare with its pioneering application of TinyML (Tiny Machine Learning) technology for life-saving ventricular arrhythmia detection. Ventricular Arrhythmia are abnormal heartbeat which results in Cardiogenic Shock and Sudden cardiac arrest and it will occur in lower chambers of heart where it pumps the blood throughout the body if the Arrhythmia is not treated and left it will cause even to patients' death. With Heart Guardian's innovative approach, these dangerous arrhythmias can be identified swiftly and accurately, enabling timely interventions to save lives.

TinyML refers to the deployment of machine learning models on low-power, resource-constrained devices, such as wearable sensors or implantable medical devices. By leveraging the power of TinyML, HeartGuardian has developed compact algorithms that can run efficiently on devices with limited computational capabilities, making it possible to continuously monitor heart rhythms in real-time without draining battery life or requiring constant connectivity to external systems.

This breakthrough technology represents a paradigm shift in the field of cardiac monitoring, as it allows for the integration of advanced machine learning algorithms directly into wearable devices, pacemakers, and defibrillators. By bringing intelligence to the edge of healthcare devices, HeartGuardian enables proactive detection of ventricular arrhythmias, providing patients with early warnings and healthcare providers with actionable insights to deliver timely interventions.

With Heart Guardian's TinyML-powered solution, patients at risk of ventricular arrhythmias can enjoy greater peace of mind knowing that their heart health is being monitored continuously, while healthcare providers benefit from enhanced diagnostic capabilities and improved patient outcomes. As the world embraces the era of connected healthcare and personalized medicine, HeartGuardian stands at the forefront, driving innovation to safeguard cardiac health and save lives. The objectives of the project are to Develop an TinyML for Life-Saving Ventricular Arrhythmia Detection. And ensure minimal latency in processing cardiac signals to enable timely intervention and potentially life-saving treatment and for Training models, including Logistic Regression and Efficient CNN, to achieve high accuracy in ventricular arrhythmia detection.

The ultimate aim is to make TinyML algorithms analyses cardiac signals in real-time, allowing healthcare providers to remotely assess patients' cardiac health and intervene promptly if ventricular arrhythmias are detected. TinyML facilitates the development of portable monitoring systems that can analyses cardiac data on-the-go, providing a comprehensive assessment of heart health in various scenarios. Mobile apps equipped with TinyML can offer personalized insights into cardiac health, alerting users to potential arrhythmias and encouraging them to seek medical advice promptly.

2. Literature Survey

The TinyML Design Contest (TDC) which was held at 41st International Conference on Computer-Aided Design (ICCAD) it actually focuses on the innovation of Artificial Intelligence (AI) and Machine Learning (ML) on various wearable devices for real world solution for medical problems. The main challenge is to develop a AI/ML detection algorithm for Heart diseases through low based microcontroller which is based on implantable cardioverter-defibrillators (ICD) The dataset has 38000 5-s intracardiac electrograms (IEGMs) segments divided into eight different types of rhythm this is used for monitoring patients health care of patients and it achieves high accuracy because of more trained extensive dataset it may also lead to disadvantages like biased or insufficient data[1]For the life threatening Ventricular Arrhythmia are the main cause of sudden cardiac attack in US which is a significant cause of natural death where this implantable cardioverter defibrillator(ICD) it delivers shock based on irregular rhythms in patient heartbeat and detect Ventricular Arrhythmia based on criteria parameters to avoid challenges we developed a computing framework for deep learning to detect based on medical IOT systems this will improve detection accuracy and cooperative inference based on CNN personalization for each patient this method reduce inappropriate shock and improved accuracy and the failure is complexity of personalized deep learning model for medical IOT systems[13]The most common heart disease/ cardiac arrhythmia occurs in Atrial and ventricular defibrillation so in this paper they have designed a detector system using R-R interval of Electrocardiogram(ECG) signals when R-R Interval of ECG is detected irregularly are taken into Physio Net as samples and tested under Normal Sinus Rhythm(NSR) with amplitude of 5V where rising edge indicated R peaks show that system can classify correctly and they enable automatic response based on the detection of certain events and they require sophisticated signal processing for designing circuit which is a disadvantage[10].

3. Existing System

TinyML is a new advancement in Machine Learning, By learning deep learning we can able to discover more IOT devices and microcontrollers even though TinyML is challenging due to hardware constraints and TinyML doesn't hold more deep learning model for cloud and mobile platforms therefore we need to design an algorithm for system stack to use TinyML in this paper they discussed about the challenges , scope and the application of TinyML and they started with MCU and how to achieve ImageNet-scale AI applications on IoT devices with design and the largest model today we are using can be very tiny model after decades tiny ML needs to evolve and adapt the changes over time. MCUNet enables edge computing whereas it is not supported in high complex devices

3.1 Disadvantages

- **Privacy Risks:** Storing patient data on cloud servers or medical IoT systems increases the risk of privacy breaches, threatening patient confidentiality and trust in healthcare services.
- **Implementation Complexity:** Developing and maintaining personalized deep learning models or complex algorithms requires specialized expertise and resources, adding to the overall complexity of arrhythmia detection systems.
- **Generalizability Challenges:** While certain methods may excel in detecting specific arrhythmia types, their effectiveness across diverse datasets and patient populations may be limited, necessitating further validation and refinement.
- **Limited Algorithmic Diversity:** The focus on low-power microcontrollers may limit the diversity of machine learning algorithms explored for ventricular arrhythmia detection.
- **Resource Constraints:** Complex algorithms or models that require extensive processing power may be challenging to implement, potentially compromising the accuracy of arrhythmia detection.
- **Scalability Issues:** The exclusive focus on low-power microcontrollers may raise concerns about the scalability of the proposed solution.
- **Infrastructure Dependency:** Relying on cloud computing can lead to accessibility issues and potential downtime, impacting the effectiveness of arrhythmia detection systems.

4. Proposed System

The proposed system introduces a groundbreaking TinyML contest focused on ventricular arrhythmia detection, utilizing advanced algorithms optimized for low-power microcontrollers. To enrich the training data, it employs the Arrhythmia Classification Dataset, ensuring diversity and comprehensiveness in cardiac rhythm samples. Pre-processing steps, including signal filtering, refine the dataset for improved accuracy. Models like Logistic Regression and Efficient Convolutional Neural Networks (CNNs) are then trained on this enhanced dataset. These models offer a robust approach to arrhythmia detection, capable of accurately identifying abnormalities while minimizing computational resources. By integrating cutting-edge algorithms with curated datasets and optimized pre-processing techniques, the proposed system aims to revolutionize cardiac health monitoring. The TinyML contest further drives innovation in the field, encouraging the development of compact yet powerful solutions for early arrhythmia detection, ultimately leading to improved patient outcomes and potentially saving lives.

4.1 Working

Heart Guardian’s pioneering venture in ventricular arrhythmia detection through TinyML technology involves meticulous steps designed for precision and efficiency in life-saving interventions. Initially, diverse cardiac rhythm data is meticulously collected and curated to form a robust training dataset. Following this, a rigorous pre-processing phase employs advanced signal filtering and normalization techniques to enhance data quality.

The Arrhythmia Classification Dataset further enriches the training data, exposing models to a wide range of cardiac rhythm patterns. Subsequently, machine learning models are trained using optimized algorithms like Logistic Regression and Efficient Convolutional Neural Networks (CNNs). These models are fine-tuned for efficiency and accuracy, crucial for operation on low-power microcontrollers.

Validation using separate datasets ensures the models' reliability in real-world scenarios. Upon successful validation, the trained models are deployed onto low-power microcontrollers, seamlessly integrating into wearable and implantable medical devices. This deployment empowers healthcare providers with timely warnings, facilitating proactive interventions to save lives. Through innovation and dedication, HeartGuardian pioneers the convergence of TinyML and cardiac health monitoring, driving advancements to improve patient outcomes and ensure cardiac well-being.

4.2 Advantages

- **Algorithmic Diversity:** The proposed system fosters algorithmic diversity, exploring various machine learning approaches to enhance the robustness of ventricular arrhythmia detection.
- **Optimized Resource Utilization:** The proposed system seeks to optimize resource utilization, ensuring efficient and effective arrhythmia detection.
- **Comprehensive Dataset and Model Training:** Utilizing the Arrhythmia Classification Dataset and training models like Logistic Regression and Efficient CNN contribute to a more comprehensive and accurate system for predicting ventricular arrhythmias.

5. System Architecture

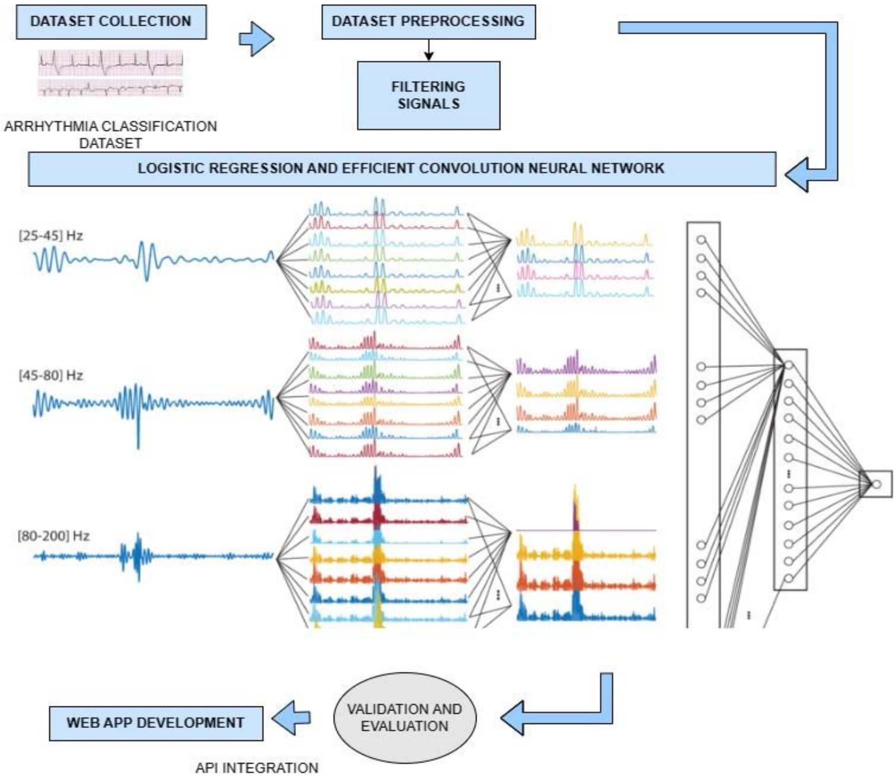

Figure 1 System Architecture

6. System Analysis

The modules used in the project are:

A. Dataset Collection: The dataset is collected from Kaggle.com where it will be fed for training the machine learning algorithms it will increase the accuracy by the number of datasets and we can perform the prediction more accurate for real world medical challenges By using the dataset we can perform classification, regression and ranking and we can train and test the data based on the conditions

Three methods of collecting datasets:

- Gather diverse ECG data from sources like hospitals and wearables.
- Collaborate with healthcare professionals to accurately label ventricular arrhythmias.
- Clean and format the data for TinyML, ensuring its noise-free and standardized.

- Arrhythmia Classification Dataset is collected from kaggle.com for this proposed system.

B. Data Pre-processing: it is a preparation of raw data used in Machine Learning In the Project a commonly used type of Dataset pre-processing technique is Filtering Signals

- Apply bandpass filtering to ECG signals, focusing on the frequency range relevant to arrhythmias.
- Employ noise reduction techniques, such as adaptive filtering, to enhance signal clarity.
- Utilize signal segmentation to isolate specific intervals, like QRS complexes, for precise analysis in TinyML-based ventricular arrhythmia detection by HeartGuardian.

C. Training with Logistic Regression and Efficient Convolutional Neural Network

- **Logistic Regression:** This foundational method is employed for baseline model training, offering simplicity and effectiveness in identifying linear relationships within the data. Logistic Regression provides valuable insights into the fundamental patterns of cardiac rhythms.

- **Efficient CNN:** Utilizing Efficient Convolutional Neural Networks (CNN), the framework extracts complex features crucial for detecting ventricular arrhythmias in TinyML. CNNs excel in capturing intricate patterns within the data, enabling precise identification of abnormalities.

By combining insights from both Logistic Regression and Efficient CNN, the framework achieves a comprehensive understanding of the data. This synergy enhances the overall accuracy and reliability of the TinyML model, facilitating precise and timely detection of ventricular arrhythmias. This integrated approach strengthens cardiac health monitoring systems, ultimately leading to improved patient outcomes and potentially life-saving interventions.

D. Validation and Evaluation

After training with machine learning algorithms, it will validate and evaluate the datasets. Validation in machine learning is like an authorization or authentication of the prediction done by a trained model. While on the other hand, evaluation in machine learning or deep learning refers to assessment or test of the entire machine learning or deep learning model and its performance in various circumstances. It involves assessment of machine learning or deep learning model training process and how accurate are the predictions given in different situations.

E. API Integration

Flask is a popular web framework in Python that is commonly used for API development and integration.

F. Web App Integration

Web app Development involves combining the functionalities and data to work together seamlessly. This Development can enhance user experiences, improve efficiency, and streamline processes. In this Project, ReactJS is used for Web app Development.

7. Conclusion And Future Work

The project has been successfully implemented to detect life-threatening ventricular arrhythmias with Machine Learning. The Heart Guardian project pioneers TinyML for ventricular arrhythmia detection, showcasing its potential in cardiac care. Demonstrating feasibility on portable devices, it offers real-time monitoring, enhancing remote healthcare. Rigorous testing confirms its accuracy, paving the path for clinical application. Leveraging edge computing ensures reliability in remote settings. In the coming future, we will be implementing more algorithms in the next phase. Future work will focus on Algorithm refinement, wearable integration, long-term monitoring, UI optimization, and clinical validation are pivotal for Heart Guardian's advancement in TinyML for ventricular arrhythmia detection. These efforts enhance accuracy, user experience, and clinical efficacy, reinforcing our commitment to saving lives through early intervention. In this field there are more chances to develop or convert this project in many ways.

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8. Outputs Obtained

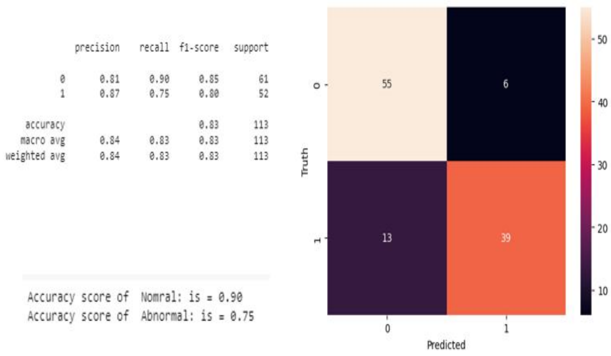

Figure 2 Logistics Metrices

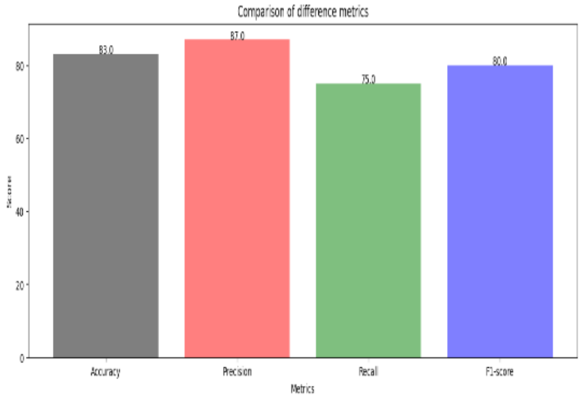

Figure 3 Comparison Metrics of Logistic Regression

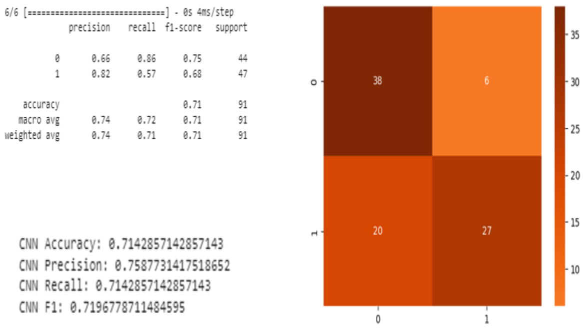

Figure 4 Efficient Convolutional Neural Network Metrices

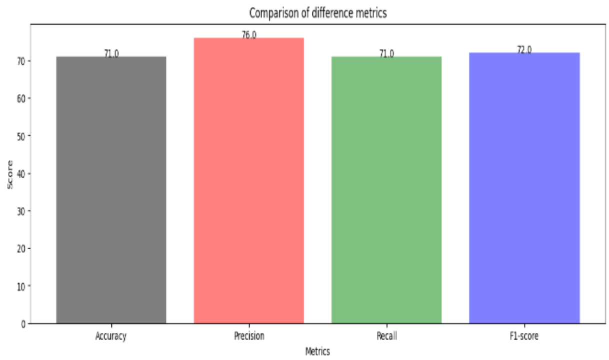

Figure 5 Comparison Metrics of CNN

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