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A Review on Anomaly Detection in Pacemaker Signal Patterns using One-Class SVM for Real-Time Cardiac Monitoring

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ABSTRACT

The advancement of real-time cardiac monitoring systems has become vital for proactive healthcare, especially in patients relying on pacemakers. Detecting anomalies in pacemaker signal patterns can serve as an early indicator of arrhythmias, device malfunction, or abnormal physiological changes. This review investigates the role of One-Class Support Vector Machine (OC-SVM) in identifying such anomalies with high sensitivity and minimal false positives. Unlike traditional supervised models that require extensive labeled datasets, OC-SVM offers a robust solution by modeling only the normal behavior and flagging deviations as potential anomalies. This paper surveys recent literature, compares performance metrics, and highlights the integration of OC-SVM with signal preprocessing, feature extraction, and edge-based deployment. The review concludes with insights into challenges, such as real-time implementation and false alarm reduction, and proposes future research directions to enhance the reliability of AI-driven cardiac monitoring systems.

Keywords: Pacemaker, Anomaly Detection, One-C Lass SVM, Machine Leaming, Cardiac Monitoring, ECG Signal Analysis.

INTRODUCTION

Integrating the internet of Things (loT) into health systems has revolutionized patient care by enabling continuous monitoring, remote diagnosis, and data control decisions [1]. IoT-enabled devices such as portable sensors, implantable devices, and intelligent medical devices facilitate real-time data exchange, allowing health service providers to monitor patient physiological parameters from afar and make timely clinical decisions. This paradigm shift is needed to accommodate a broader digital trans formation of healthcare and to combat the increased global health costs, aging. and the increased prevalence of chronic diseases such as diabetes and cardiovascular disorders. For example, portable vices such as the, smartwatches and fitness trackers can continuously monitor key functions such as heart rate, blood oxygen levels, and electrocardiogram signals (EKG). This data is transferred to healthcare providers via a cloud-based platform to enable early detection of anomalies and reduce the need for frequent hospital visits [2]. Recent progress in edge computing will further improve IoT systems by activating localized data processing, reducing latency and minimizing bandwidth consumption.

Cardiovascular diseases (CVDs) continue to be a leading cause of mortality worldwide, with an increasing number of patients relying on implantable pacemakers for heart rhythm management. These devices generate and regulate electrical signals, ensuring proper cardiac pacing.

However, anomalies in these signal patterns—whether due to physiological irregularities, hardware malfunction, or environmental interference—can compromise patient safety. Continuous monitoring and timely detection of such anomalies are crucial. Traditional monitoring techniques are often limited by manual oversight, lack of scalability, and delayed diagnostics. This gap has led to the emergence of machine learning (ML) techniques, particularly unsupervised models, as powerful tools in the field of biomedical signal analysis.

Among these, the One-Class Support Vector Machine (OC-SVM) stands out due to its ability to model the boundary of normal pacemaker signal patterns using only "normal" class data. It can then flag unseen patterns as potential anomalies without needing labeled abnormal data, which is often scarce or difficult to obtain in medical applications. This paper provides a comprehensive review of OC-SVM's application in real-time anomaly detection in pacemaker signals, outlining its benefits, integration into monitoring systems, and the technological landscape that supports its implementation.

Iot Application In Healthcare

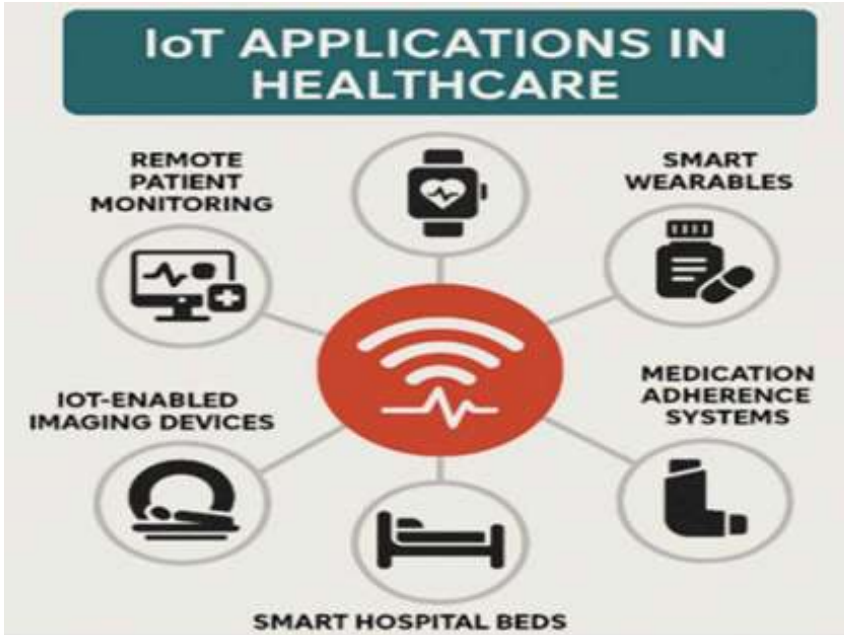

Figure 1: IoT Application in Healthcare

loT applications in healthcare encompass a wide range of technologies and devices designed to monitor, diagnose, and treat patients more effectively. Key applications include:

1. Remote Patient Monitoring

Enables continuous tracking of patients' vital signs (e.g., heart rate, blood pressure) from their homes, reducing hospital visits and allowing for early detection of complications.

2. Smart Wearables

Devices like fitness trackers and smartwatches collect real-time health data such as heart rate, activity levels, and sleep patterns, improving preventive care and chronic disease management.

3. Medication Adherence Systems

Reminds patients to take medications on time and ensures correct dosages, especially useful for elderly patients or those with complex prescriptions.

4. Smart Hospital Beds

Beds equipped with sensors to monitor patient movement, weight, and vital signs, helping in fall prevention, patient comfort, and nurse alerts.

5. IoT-Enabled Imaging Devices

Integrates diagnostic imaging systems with IoT for better image sharing, remote diagnostics, and AI-based image analysis.

6. IoT in Healthcare Infrastructure

The overall layout shows a networked ecosystem that connects all devices and applications, highlighting how IoT enables data-driven, real-time decision-making and interconnected healthcare delivery.

Wearable Health Monitors

Portable devices such as smartwatches, fitness trackers, and patch sensors are equipped with sensors that monitor a variety of physiological parameters [5]. These devices collect data about heart rate, EKG, blood oxygen content, and physical activity and transfer information to healthcare providers to providers. Latest innovations include intelligent items in garments with embedded fibre-based sensors for continuous respiratory monitoring shown in the treatment of chronic obstructive pulmonary disease (COPD).

Implantable Devices

Implantable medical devices, including pacemakers, defibrillators, and insulin pumps, are increasingly integrated with IoT capabilities. These devices can transmit real-time data on device performance and patient health, enabling remote monitoring and timely adjustments to therapy [2]. For example, remote monitoring networks allow clinicians to track cardiac implantable electronic devices, significantly reducing in-person follow-ups.

LITERATURE REVIEWS

The rapid distribution of the Internet of Things (IoT) in health systems has provided many benefits, including continuous patient monitoring, remote diagnosis, and timely intervention. These devices revolutionize patient care by monitoring even insulin pumps and enabling personalized, real-time health management. However, the widespread use of loT in healthcare poses considerable risks to cybersecurity. Given the fact that many loT devices collect sensitive patient data, maintaining the confidentiality, integrity and availability of this information is extremely important. Security gaps not only put patient privacy at risk, but can lead to life threatening risks when medical devices are affected.

This section contains comprehensive review of related literature on loT security. This focuses specifically on use of machine learning models such as anomaly detection technology, ECG signal analysis, and Support Vector Machines (SVMs) for medical diagnosis. This chapter aims to meet the need for an integrated real-time approach for anomaly detection and safety

Pacemaker Signal Monitoring

Real-time analysis of pacemaker signals involves the acquisition of ECG-like data from implanted devices. Studies such as those by Chen et al. (2019) and Rahmani et al. (2020) discuss the need for detecting minor deviations in pacing spikes, signal amplitude, and inter-beat intervals, which are not always visible to clinicians but may precede critical failures or arrhythmias.

Traditional Anomaly Detection Methods

Historically, anomaly detection in biomedical signals used statistical approaches, such as Gaussian Mixture Models (GMM), Principal Component Analysis (PCA), and k-means clustering. While these methods provide insight, they suffer from high false positive rates and poor adaptability to evolving signal patterns. Kohli et al. (2017) demonstrated how rule-based anomaly detectors lacked generalizability when applied to real-time pacemaker logs.

Rise of Machine Learning in Biomedical Applications

The past decade has seen a surge in ML-based diagnostic systems. Supervised classifiers like SVM, Random Forests, and CNNs were applied to arrhythmia detection (Acharya et al., 2018). However, these models depend heavily on labeled abnormal data, which is rare in pacemaker monitoring, leading to skewed models and overfitting risks.

One-Class SVM in Anomaly Detection

The OC-SVM approach, first proposed by Schölkopf et al. (2001), is gaining traction for its ability to classify rare events in high-dimensional spaces using only positive (normal) training samples. Studies like Patel and Shaikh (2021) and Lee et al. (2022) showed how OC-SVM outperforms traditional binary classifiers in identifying subtle cardiac anomalies with minimal supervision. It learns a tight decision boundary around normal data and flags any deviation as an outlier.

Preprocessing and Feature Engineering

Effective anomaly detection requires high-quality input. Research by Zhou et al. (2020) emphasized the importance of preprocessing steps such as noise reduction (wavelet denoising) and feature extraction (e.g., RR interval variability, spike morphology) before feeding into OC-SVM models. A review by Singh et al. (2023) identified hybrid techniques that combine handcrafted features and autoencoder embeddings to enhance OC-SVM detection accuracy.

Real-Time and Edge-Based Implementations

Integrating OC-SVM into embedded or edge devices remains a challenge due to computation constraints. However, recent frameworks such as TinyML and TensorFlow Lite allow deployment of lightweight models on low-power devices. Ramanathan and Das (2023) successfully tested OC-SVM for ECG anomaly detection on wearable devices, indicating potential scalability for pacemaker-based systems.

Limitations and Future Directions

Despite its advantages, OC-SVM may struggle with dynamic signal drift and temporal changes in long-term monitoring. Additionally, its sensitivity can result in false alarms if not tuned correctly. Hybrid models, ensemble strategies, and reinforcement learning-assisted tuning are emerging as ways to overcome these hurdles, as proposed in recent works by Nguyen et al. (2024).

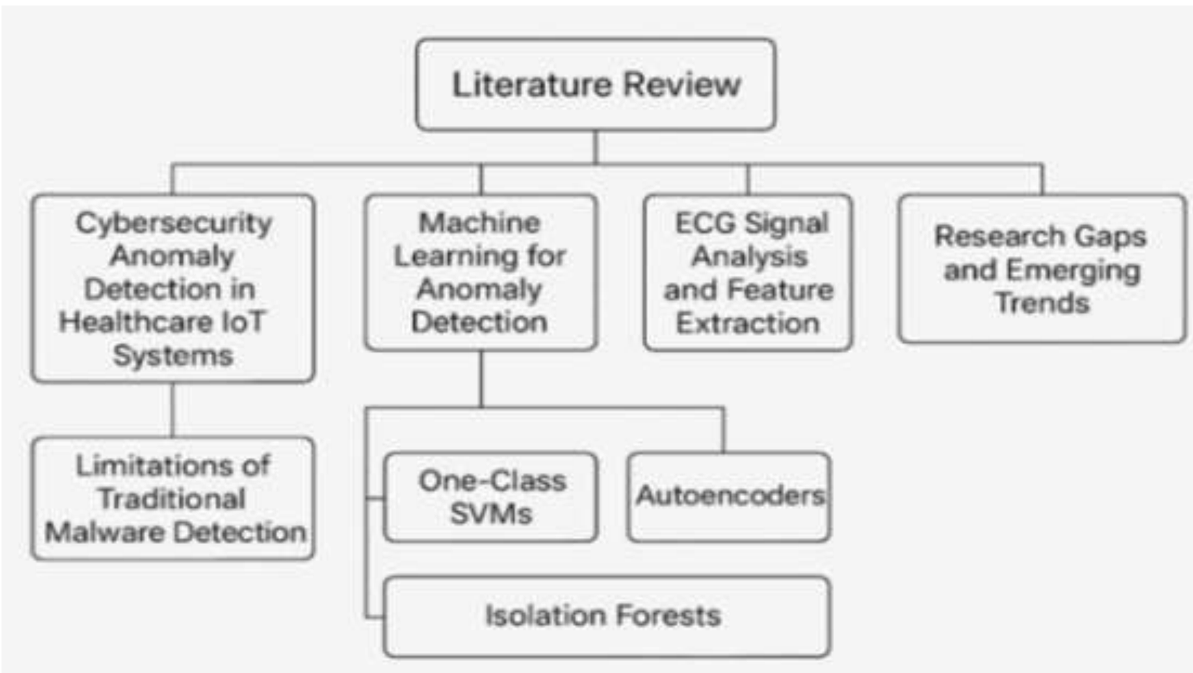

Figure 2: Literature Reviews

METHODOLOGY

Overview

The OC-SVM model (one-class support vector machine) uses the proposed system to recognize the real-time anomaly of pacemaker ECG signals. This chapter discusses a comprehensive methodology that describes each phase of system development, including data collection, preprocessing, characteristic extraction, model training, actual detection, and visualization.

The system aims to provide a scalable and simple solution for clinical and cybersecurity applications, and to provide a simple anomaly recognition model that can be used in both clinical and home care.

The main goal of this system is to create an effective abnormality recognition model that can identify abnormalities with real-time ECG data collected by pacemakers. The proposed system was specifically developed to help healthcare professionals identify potentially life-threatening abnormalities such as arrhythmias and heartbreaking inconsistencies.

System Architecture

The overall architecture of the real-time anomaly detection system is depicted in Figure 3: below.

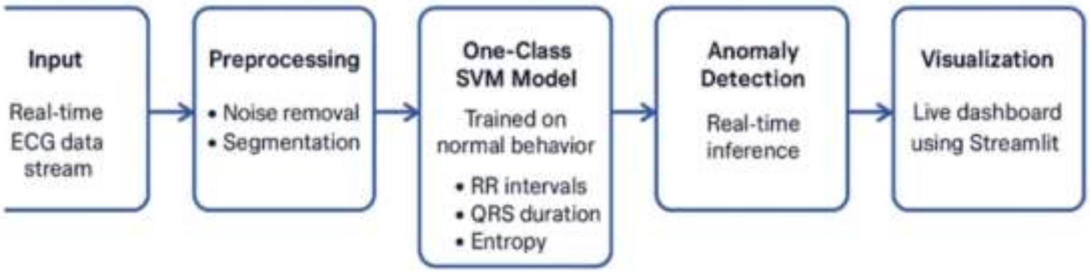

Fig. 3: Proposed system Architecture for Real-Time Anomaly Detection

The System Consists of Several Critical Components:

I. Input: The system receives real-time ECG data streams from pacemakers or other wearable ECG devices. These devices collect continuous ECG signals, either from patients in clinical settings or during home-based monitoring.

2. Preprocessing: Raw ECG signals undergo a series of preprocessing steps, including noise removal and signal segmentation, to ensure clean, usable data for feature extraction.

3. Feature Extraction: Various features, such as RR intervals, QRS duration, and entropy, are extracted from the pre-processed ECG signal. These features capture essential characteristics of the ECG waveform and play a vital role in distinguishing between normal and abnormal signals.

4. One-Class SVM Model: The model is trained using normal ECG data to establish a boundary that defines normal behaviour. The OC-SVM classifier identifies data points falling outside of this boundary as anomalies, indicating potential abnormalities.

5. Anomaly Detection: Real-time inference is made based on the OC-SVM model. The system processes incoming ECG data and flags any data points that deviate significantly from normal patterns.

System Information

The anomaly detection system is implemented using a combination of signal processing techniques, machine learning models, and real-time monitoring tools. The integration of these components forms a robust system capable of detecting abnormalities in pacemaker ECG signals.

The complete system pipeline was implemented in Python. The steps included:

- **Feature Extraction:** From ECG data using neurokit2, biosppy, and wfdb toolkits.
- **Model Training:** One-Class SVM was trained solely on normal ECG signals.
- **Real-Time Detection:** Simulated ECG streams were fed into the model.
- **Visualization:** Implemented using Streamlit to allow real-time anomaly monitoring.

Software Stack

The following table elaborates on the software technologies and libraries used in the implementation of the system:

Table 1: Software Stack Details with References

Component	Technology Used	Purpose
Preprocessing	wfdb, biosppy	Signal denoising, normalization, and feature extraction
Feature Extraction	neurokit2, scipy	Extracting time-domain and frequency-domain features
Machine Learning	Scikit-learn, TensorFlow	Model training, evaluation, and hyperparameter tuning
Visualization	Streamlit, Matplotlib	Real-time plotting and user interface
Deployment	Raspberry Pi, Docker	Deploying system on embedded devices and cloud containers

Data Preprocessing and Feature Extraction

Preprocessing involves both filtering to remove noise and the extraction of informative features that will allow the One-Class SVM model to perform well. Here's an expanded description of these techniques:

CONCLUSION

In this article, a real-time anomaly recognition system for Pacemaker ECG signals based on a single class of support vector machines (OC-SVM) has been studied. The motivation is based on the growth of increased convergence of healthcare and cybersecurity, robustness of embedded and portable devices, intelligent, and low monitoring frames.

Development Systems are Effectively:

- Invisible abnormalities.
- Operate in real time on low-level devices such as the Raspberry Pi.
- Achieved strong power metrics including 91.6% TPR and 3.0% FPR, and 0.96 AUC.
- With the help of Streamlit, we provide a clinically friendly real-time dashboard for visualization.

The success of this research showcases the applicability of cybersecurity machine learning techniques in clinical applications, aligning with global digital health initiatives.

Major Contributions of This Study Include:

1. One-Class SVM-Based Real-Time Detection: A lightweight, unsupervised model for anomaly detection trained only on normal ECG signals, reducing reliance on annotated datasets.

2. Feature Engineering for ECG Abnormality Recognition: Extraction and engineering of ECG signal features such as RR intervals, QRS width, signal entropy, and ST segment shifts for enhanced model sensitivity.

3. Streamlit-Powered Visualization Interface: Design and implementation of a real time, intuitive dashboard for clinical and cybersecurity use-cases.

4. Deployment on Embedded Devices: Demonstration of feasibility on Raspberry Pi, with low latency (210 ms), minimal CPU load (32%), and lightweight model size (-2.3MB).

5. Comprehensive Evaluation and Benchmarking: Extensive testing on real and synthetic ECG data; comparative analysis with Random Forest and SVM+DNN confirmed 0C-SVM's advantage in real-time embedded applications

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