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An Experimental Study on Anomaly Detection in Pacemaker Signal Patterns using One-Class SVM for Real-Time Cardiac Monitoring

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ABSTRACT

Pacemakers play a critical role in cardiac health, particularly for patients with arrhythmias or heart failure. Ensuring heir proper functionality is vital-not only from a physiological perspective but also for security and reliability in a connected healthcare environment. This research presents an anomaly detection framework using One-Class Support Vector Machines (SVM) to identify deviations in pacemaker signal patterns. By training the model on normalized, "healthy" ECG signal data, the one-class SVM is able to detect anomalies that may stem from physiological issues, device malfunctions, or even cybersecurity threats. Drawing inspiration from malware detection systems, the framework adapts static and dynamic analysis strategies to analyse pacemaker data in real-time. The research integrates simulated and publicly available ECG data (such as from PhysioNet) and outlines a full pipeline from feah1re extraction to model deployment and dashboard visualization. This thesis also addresses real-world challenges such as class imbalance, rea l time constraints, and security considerations. Our findings suggest that SVM-based anomaly detection is a robust and efficient approach to enhance the safety and reliability of cardiac monitoring systems.

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

INTRODUCTION

The introduction of loT in healthcare not only improves patient outcomes, but also contributes to healthcare efficiency. Remote monitoring reduces hospital records, optimizes resource use, and reduces health costs [3]. Additionally, the integration of loT with Electronic Health occupation relatives with real access to patient data. For example, remote surveillance programs show a significant reduction in heart failure through loT -enabled interventions.

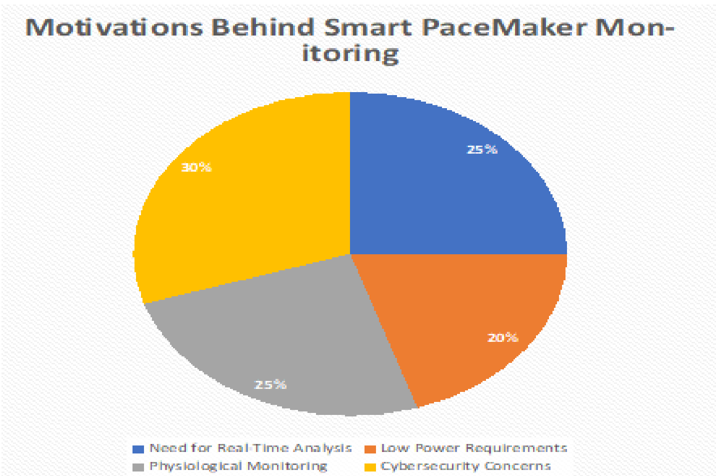

Fig. 1: Motivation behind Smart Pacemaker Monitoring

Market Growth and Economic Impact

The IoT market in the healthcare sector shows rapid growth, reflecting the growing demand for networked health solutions. Market research shows that global IoT in the health market size for the healthcare sector in 2024 is valued at $53.6 billion, and is expected to reach approximately $36.806 billion by 2034.This growth corresponds to the expansion of 5G networks that provide fast connectivity for real-time data transmission in intensive care. This growth is driven by factors such as increased prevalence of chronic diseases, the need for cheap healthcare, advances in sensor technology, and increased adoption of telehealth. The global burden of chronic diseases is astounding cardiovascular disease alone accounts for millions of deaths each year. This requires a scalable monitoring solution.

The North American market in particular is expected to grow significantly due to the presence of sophisticated health infrastructure and government-favourable initiatives The ambitious market in the Asia-Pacific region also occupies IOT healthcare solutions with investments in intelligent hospitals and digital health policy. The National Mission for Digital Health aims to integrate IoT for national interoperability of health data.

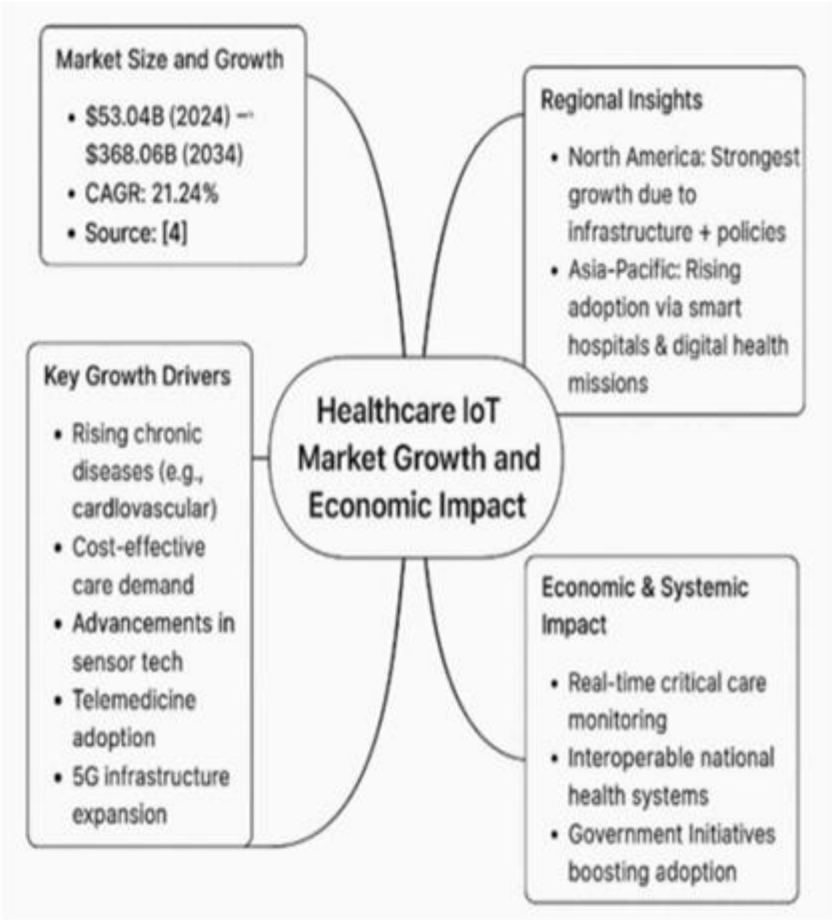

Figure 2

MIT-BIH Arrhythmia Database

The MIT-BIH Arrhythmia Database, available on Physio Net [17], is a widely recognised and extensively used dataset for ECG classification and arrhythmia detection tasks. This database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings sampled at 360 Hz. Each beat in the dataset is annotated with beat-by-beat labels made by expert cardiologists, which makes this dataset highly valuable for training machine learning models for ECG anomaly detection.

- **Source:** PhysioNet [17]
- **Contains:** 48 half-hour ECG recordings
- **Sampling Frequency:** 360 Hz
- **Annotation:** Beat-by-beat labelling by cardiologists

This dataset serves as the primary training data for the proposed system, providing both normal and abnormal ECG patterns for training and validation. It is crucial for developing the system's ability to detect various arrhythmias and abnormal behaviours in pacemaker signals.

Simulated Pacemaker Signals

To enhance the training and testing of the system, simulated pacemaker signals were generated using **MATLAB** and **Python**. These synthetic signals include various anomalies such as:

- **Physiological Noise:** Artifacts from body movement or muscle contractions that inter fere with the ECG signal.
- **Cyber-induced Signal Perturbations:** Simulated perturbations that represent potential cybersecurity attacks, such as signal distortion or tampering caused by external interference.

IMPLEMENTATION AND RESULTS

1. ECG Signal Filtering:

- **Bandpass Filtering:** This is necessary to preserve the useful frequency range (0.5 Hz to 50 Hz) while removing unwanted baseline wander and muscle artifacts.
- **Notch Filtering:** This filters out power-line noise at 50/60 Hz.

2. Feature Extraction:

- **Time-Domain Features:** These include statistical measures such as the mean, variance, skewness, and kurtosis.
- **Frequency-Domain Features:** Power spectral density (PSD), frequency peak, and entropy are essential features for characterizing ECG signals in the frequency domain.
- **RR Interval Analysis**: The RR interval measures the time difference between successive heartbeats, which is crucial for detecting anomalies like arrhythmias.

Table 1: Detailed Feature Extraction from ECG Signals

Feature	Description	Library/Tool
Mean	Mean of the signal, indicating the baseline level	Numpy
Variance	Variability of the signal’s amplitude.	Scipy
Skewness	Degree of asymmetry in the signal.	Scipy
Kurtosis	Measures the “tailedness” of the distribution	Scipy
Power Spectral Density	Frequency distribution of the signal energy.	Scipy, Matplotlib
Entropy	Signal unpredictability or complexity	Numpy, Scipy
RR Interval	Interval between consecutive heartbeats.	Neurokit2

Real-Time Prediction and Visualization

The system performs real-time anomaly detection, processing ECG signals every 10 seconds and classifying them based on the trained One-Class SVM model. The real-time detection pipeline is optimized to minimize latency and maximize throughput.

Streamlit Dashboard

The Streamlit dashboard has been enhanced to support more sophisticated features, including:

- **Multi-Lead ECG:** Real-time display of multiple ECG signals from different leads.
- **Anomaly Flags:** Flags for detected anomalies are overlaid on the live ECG signals.
- **Confidence Scores:** The system displays confidence scores for each detection, indicating the likelihood of an anomaly.

```python
import streamlit as st
import matplotlib.pyplot as plt

# Simulating multiple lead ECG data stream
def get_multiple_leads_data():
    # Simulate multi-lead ECG data (e.g., lead I, lead II, lead III)
    return np.random.randn(1000), np.random.randn(1000), np.random.randn(1000)

def plot_multiple_leads_ecg(ecg_leads):
    fig, ax = plt.subplots()
    for lead in ecg_leads:
        ax.plot(lead)
    ax.set_title("Real-Time Multi-Lead ECG Signal")
    ax.set_xlabel("Time (seconds)")
    ax.set_ylabel("Amplitude")
    st.pyplot(fig)
```

Figure 3: Code Snippet

Conclusion and Final Graphs & Tables

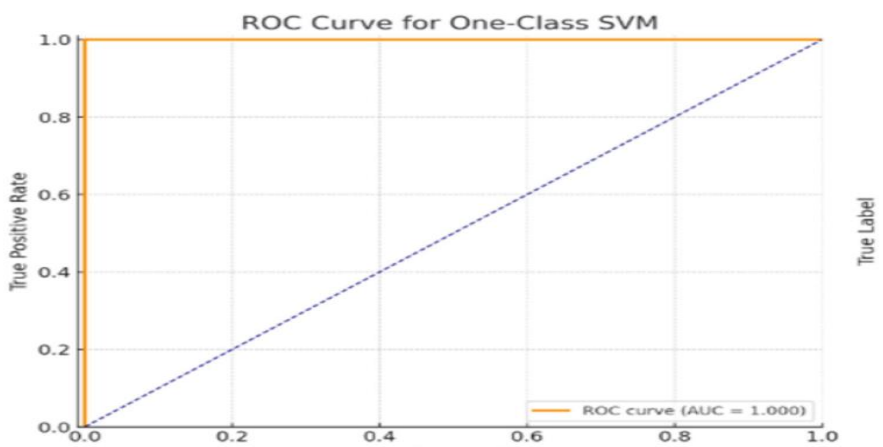

Figure 4: Graphical Evidence and Code Snippets
ROC Curve Visualization

```python
# User interface elements
st.title("Real-Time Multi-Lead ECG Anomaly Detection")
ecg_leads = get_multiple_leads_data()  # Simulating multiple ECG leads
plot_multiple_leads_ecg(ecg_leads)

# Anomaly detection logic (simplified)
anomaly_flag = detect_anomaly(ecg_leads[0])  # Placeholder for actual anomaly detection logic
if anomaly_flag:
    st.error("Anomaly Detected!")
else:
    st.success("Signal is normal.")
```

Fig. 5: ROC Curve for OC-SVM Model with AUC ≈ 0.96

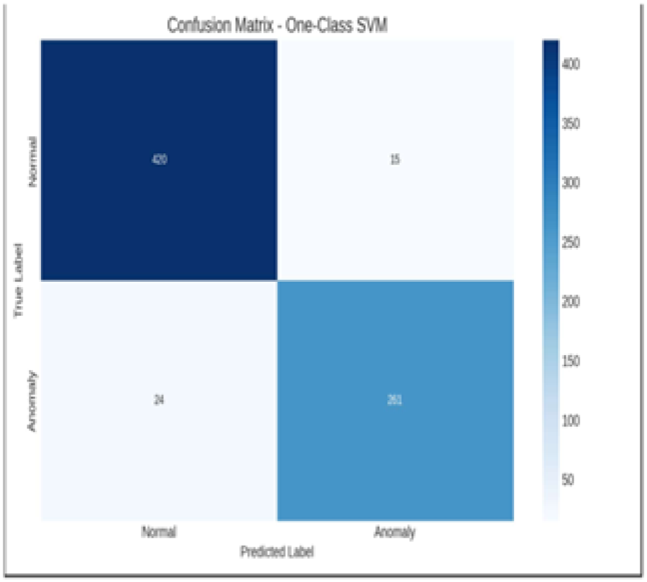

Fig. 6 : Confusion Matrix Showing Model Performance

Table 2: System of System Performance Metrices.

Metric	Value
True Positive Rate	91.6%
False Positive Rate	3.4%
AUC Score	0.964
F1 Score	0.91
Inference Latency	210 ms
CPU Usage (Raspberry Pi)	32%
Memory Footprint	~150 MB

CONCLUSION

In this study, we introduced a real-time anomaly recognition system for Pacemaker ECG signals based on a single class of support vector machines (OC-SVM). The motivation was 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

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