CS6611 – CREATIVE AND INNOVATIVE PROJECT

Team no: 30

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IoT-Enabled Non-Invasive Methods for Early Detection of Cardiotoxicity

Problem Statement:

The current state of cardiovascular health monitoring faces challenges in efficiently detecting cardio-toxicity. Accurate prediction of Cardiotoxicity remains a complex task, underlining the necessity for a portable device incorporating Deep Learning (DL) algorithms for improved diagnostics. This project proposes a non-invasive approach for cardiovascular health monitoring by implementing a real-time DL-based system that improves early detection, particularly in cases of cardio-toxicity, thereby enhancing overall patient health.

Objectives:

- To utilize deep learning algorithms to analyze and extract features such as Heart Rate Variability (HRV), Heart rate, Left Ventricular Ejection Fraction (LVEF) and other ECG wave morphologies.
- To detect Arrythmia from the abnormalities in ECG.
- To develop a non-invasive tool using IoT-based cardiac biosensors and Deep Learning (DL) algorithms to predict cTn levels.
- To enable real-time predictions of heart functions for timely interventions and improved healthcare outcomes.
- To integrate the trained model into an IoT wearable device for continuous monitoring and early detection of cardiovascular abnormalities.

Literature Survey:

In [1], a comparative analysis was conducted on the classification of heart failure using 13 features, employing various models including CNN, RNN, MLP, and LSTM, with CNN demonstrating superiority with an accuracy of 92.89%. The study incorporated IoT sensors for monitoring heart rate, blood pressure (BP), temperature, blood glucose, cholesterol, and ECG signals. Additionally, transfer learning approaches, VGC16 and AlexNet, were evaluated alongside their training times. The validation was performed using

10-fold cross-validation. Limitations include, dataset is highly imbalanced hence model is not trained well on minority classes.

In [2], this paper proposes methodology for classifying cardiac arrythmia into 17 classes, considering long duration ECG signal of 10s. It employs 1D CNN with 16 layer deep, achievingaccuracy of 91.33% and classification time of 0.015 s. It particularly focuses on reducing the computational complexity. Limitations include small no of ECG signal fragments are analysed, no possibility of classifying fragments of ECG signal containing more than one class.

In [3], the study employs a Modified Deep CNN for classification and integrates the Elephant Herd Optimization Algorithm (AEHO), while feature selection is done by Cuttlefish Optimization Algorithm. Simulation is achieved through the integration of microcontroller and LoRa communication hardware for data transmission to the cloud, incorporating the Omron HeartGuide smartwatch for blood pressure measurement and the AD8232 for ECG measurement. Limitations include actual data for serum cholestrol, chest pain and glucose level are not used, pseudo numbers are generated.

In [4], the study employs single-lead ECG to detect cardiotoxicity in cancer patients with minimal cardiovascular diseases following the first cycle of polychemotherapy, utilizing the CardioQvark mobile phone cover with an integrated ECG sensor for signal detection. Detection focuses on identifying left ventricular diastolic dysfunction, atrial fibrillation, and QTc prolongation. The limitations are sample did not include patients with intermediate and low LVEF.

In [5], the proposed wearable ECG monitoring system, IREALCARE, consists of an integrated ECG sensor where ECG data is collected, transmitted to the control unit, sampled at 250Hz, converted to digital signals using ADC, and wirelessly transmitted to a mobile device via Bluetooth. Preprocessing of the ECG involves enlarging by sliding window and denoising using Discrete Wavelet Transform (DWT). The system employs a confidence level-based training approach with ResNet as the training model, achieving an accuracy of 90.2%. Limitations include high reliability on the optimal selection of the confidence level, which may vary based on the dataset and label quality.

In [6], the approach utilized in the study is LSTM-DBN, achieving an accuracy of 88.42%. This approach combines LSTM for learning long-term dependencies with DBN for feature selection. Stochastic Gradient Descent (SGD) is employed for optimizing the loss function. From four datasets, twelve main features are extracted, including Heart Rate Variability (HRV) from ECG signals, used for classifying cardiovascular diseases. Comparative analysis is conducted with four other deep learning approaches (CNN, RNN, GRU, Ensemble) and four machine learning approaches (MLP, LR, SVM, RF). Limitations include high computational efficiency and memory is required for DBN as compared to other algorithms.

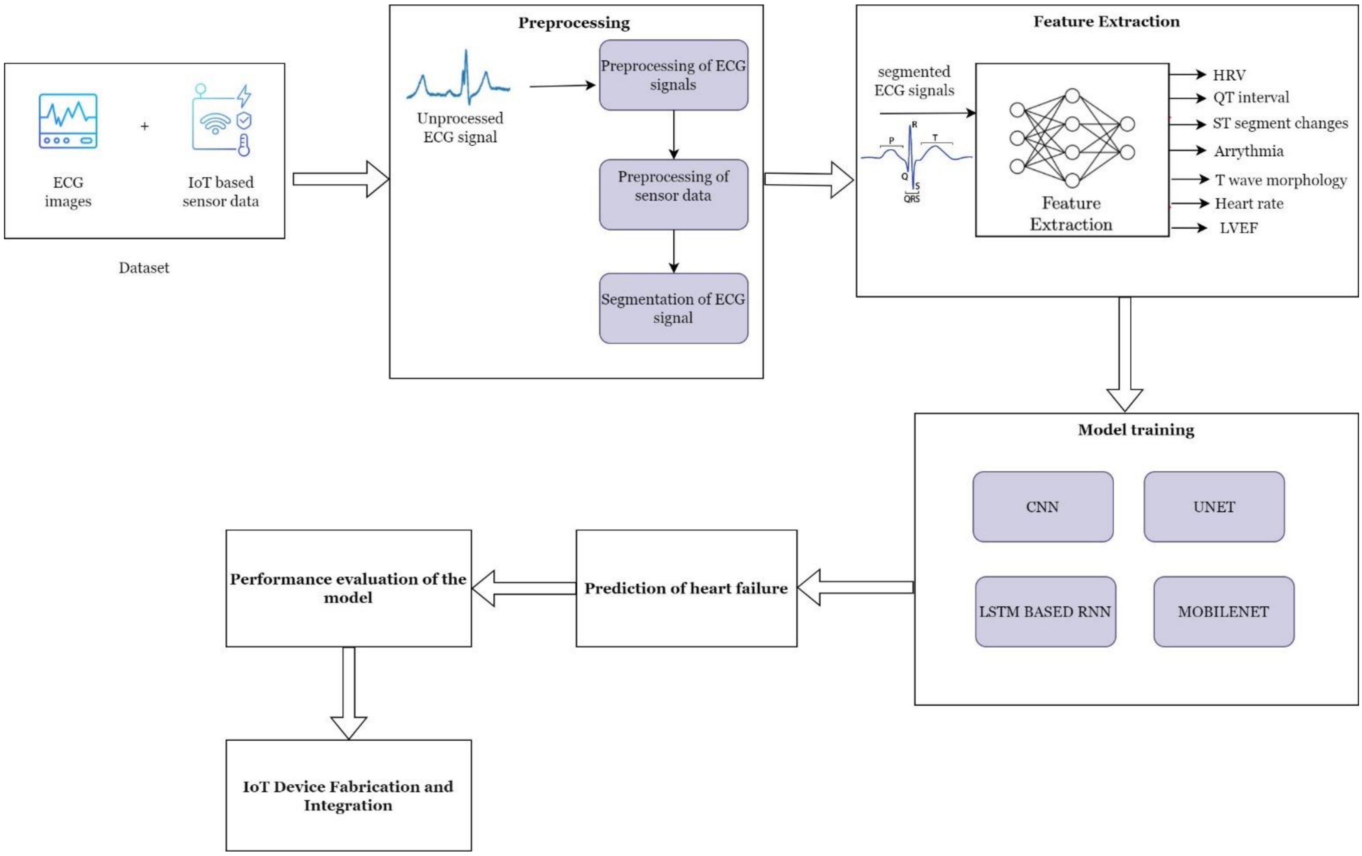
In [7], the study focuses on remote monitoring of cardiac signals through the integration of IoT and machine learning techniques, with detction of various arrhythmia including ventricular, supraventricular, and fusion beats. The components include the Polar H10 ECG sensor for signal acquisition, a CRUD REST API for data management, a Monitoring GUI for visualization, an Arrhythmia Detection Component for automated analysis, all facilitated by the MQTT protocol for communication. The chosen algorithm for arrhythmia classification is k-nearest neighbors with accuracy of 97%. Limitations include lack of discussion on robustness to noise and variability in ECG signals.

In [8], the system enables real-time monitoring of ECG signals by filtering and localizing R-peaks using the Pan Tompkin’s algorithm. Feature extraction is performed using a combination of Fast Fourier Transform (FFT) and discrete wavelet transform (DWT). Classification of extracted features is achieved through twin support vector machines (TSVM) tuned by Particle Swarm Optimization (PSO). The prototype is implemented on a microcontroller platform equipped with a Wi-Fi module for data transmission and connectivity. Limitations include more specific selection of features based on R-wave morphology, lacks the discussion about power consumption of the platform.

In [9], the approach utilized is ECG-GAN for data augmentation and the ResNet BiLSTM-Attention for classification achieving accuracy of 99.4%. ResNet is used for local feature extraction and BiLSTM for global feature extraction. DWT is used for denoising and QRS waveform detected using Pan Tompkin’s algorithm. Limitations include, integrating ResNet and BiLSTM models introduces complexity to the classification process, optimization of hyperparameters is not performed.

In [10], this paper presents a lightweight Convolutional Neural Network (CNN) model for predicting four major cardiac abnormalities using a public dataset of ECG images. The study investigates transfer learning using low-scale pretrained deep neural networks (SqueezeNet and AlexNet) and proposes a new CNN architecture for cardiac abnormality prediction achieving 99.79% accuracy. The pretrained models and the proposed CNN model are used as feature extraction tools for traditional machine learning algorithms. Limitations include, training and testing time for SquuezeNet based algorithm is longer, optimization algorithms are not used to determine the value of hyperparameters.

System Model:



Contributions:

- **Integration of Multiple Data Sources:** The project integrates data from diverse sources, including 12-channel ECG signals, wearable IoT devices, and cTn biosensors. By combining information from these sources, the platform offers a comprehensive assessment of cardiovascular health, enabling early identification of cardiac abnormalities and prediction of HF.

- **Model Selection:** The project evaluates four different classification models CNN, UNet, LSTM based RNN, MobileNet to determine the most suitable one for predicting heart failure based on the integrated data. Each model is assessed based on its accuracy, sensitivity, specificity, and computational efficiency.

- **Early Detection of Cardiotoxicity:** By monitoring cTn levels, the platform enables early detection of cardiac damage, allowing for timely intervention and potentially preventing serious complications. This is particularly important for cancer patients undergoing treatment that may impact cardiovascular health.

- **Non-Invasive Monitoring:** The platform offers a non-invasive method for measuring HF, reducing the need for invasive procedures and improving patient comfort and compliance. This makes it suitable for long-term monitoring and management of cardiac health.

- **Potential for Scalability and Accessibility:** The proposed platform has the potential for scalability and accessibility, making it suitable for widespread deployment in diverse healthcare environment.

Modules:

1. Preprocessing and feature extraction
2. Model training using CNN
3. Model training using U-net
4. Model training using LSTM based RNN
5. Model training using MobileNet
6. Prediction of heart failure
7. Performance evaluation of the models
8. IoT device fabrication and integration

Module 1: Preprocessing and Feature extraction

Preprocessing of ECG signals:

- Convert ECG image to grayscale
- Resizing, cropping, grid removal of images to focus on the Region of Interest(ROI)
- Binarization converts the enhanced ECG image to binary by setting pixels above a threshold to white and others to black.
- Generative Adversial Network(GAN) is employed for data augmentation to increase the number of images in the ECG dataset to avoid imbalance in dataset.
- FCN based Denoising Autoencoder (DAE) approach used for removal of noise in ECG signals.

Preprocessing of sensor data:

- Replacing of missing attributes
- Removal of outliers
- Normalization

Segmentation of ECG signals:

The Pan-Tompkins Algorithm is used to detect R waves from the QRS complex present in the ECG signals to determine the Heart Rate of an individual. The algorithm works by analysing the slope, amplitude and width of the QRS complexes present in the filtered ECG signal.

I. Filtering the ECG signal

Bandpass Filter: Bandpass filter is used to attenuate the noise in the input signal. The input signal is first passed through a low pass filter and then through a high pass filter

Derivative Filter: The derivative of the input signal is taken to obtain the information of the slope of the signal.

Squaring: The squaring process is used to intensify the slope of the frequency response curve obtained in the derivative step. This step helps in restricting false positives which may be caused by T waves in the input signal.

Moving Window Integration: The moving window integration process is done to obtain information about both the slope and width of the QRS complex.

II. Peak Detection

Fiducial Mark: Initial QRS complex location is approximated by detecting the rising edge of the integration waveform. Changes in slope indicate fiducial marks.

Threshold Adjustment: Two threshold sets are used: higher for initial peak detection and lower for a searchback process.

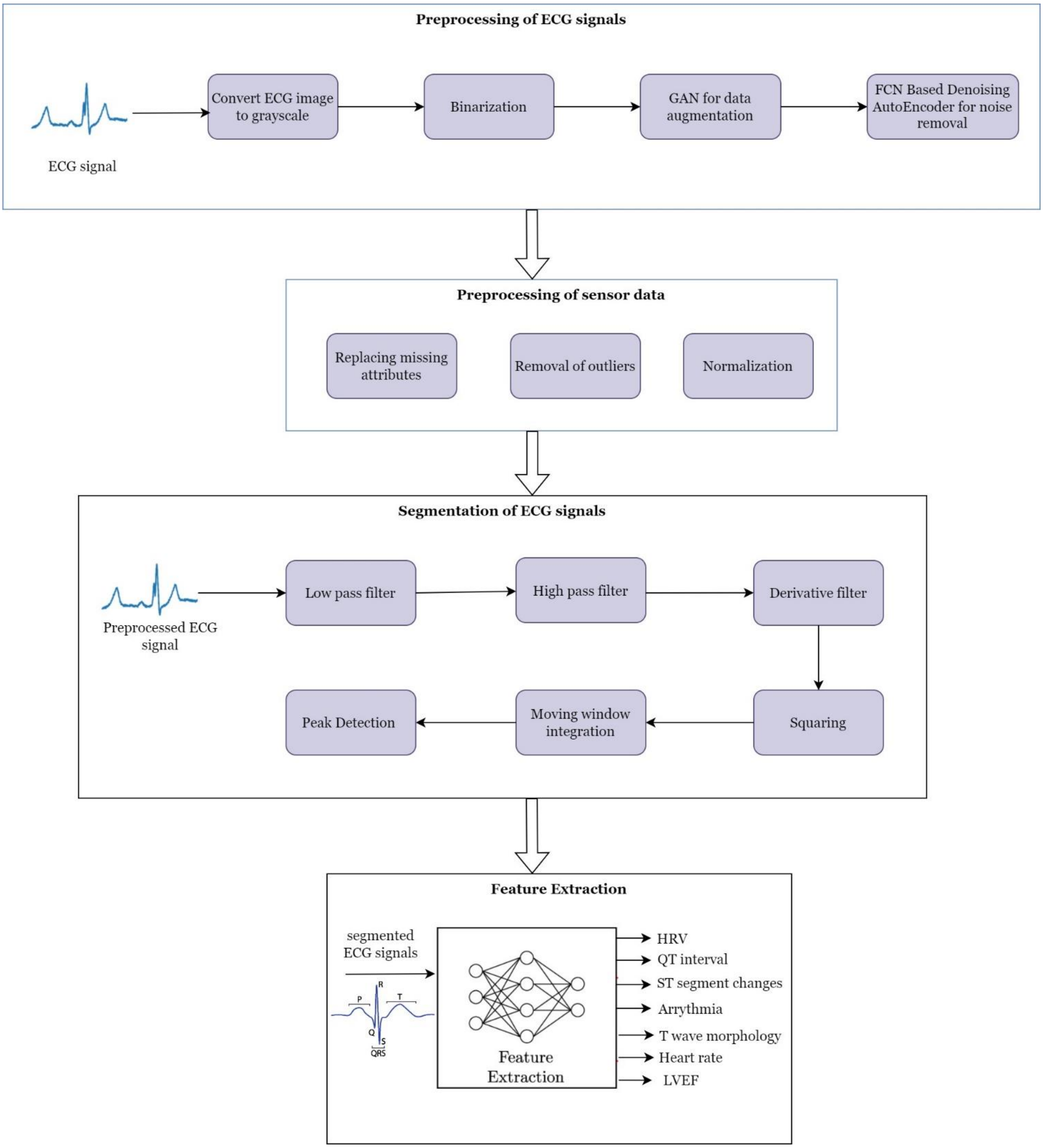
RR Interval Adjustment: Two RR intervals are tracked, updating rate limits. If a QRS complex isn't found within limits, a searchback process starts.

T Wave Identification: If RR interval is less than sample frequency, the waveform's maximal slope is calculated. If it's less than half the previous QRS complex slope, it's considered a T wave.

Feature Extraction:

The following features will be extracted from the ECG for cardiotoxicity detection,

1. Heart Rate Variability(HRV)
2. QT Interval
3. ST Segment changes
4. Presence or absence of arrhythmia
5. T wave morphology
6. Heart rate
7. Left Ventricular Ejection Fraction(LVEF)



Evaluation Metrics:

1. Accuracy
2. Precision
3. Recall
4. Specificity

5. F1-score
6. AUROC curve
7. Confusion matrix

Accuracy=TP+TN/TP+TN+FP+FN

Precision=TP/TP+FP

Recall=TP/TP+FN

Specificity=TN/TN+FP

F1-score=2×Precision×Recall / Precision+Recall

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