The Heartbeat of Privacy: Exploring Federated Learning Based Cardiac Monitoring

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Abstract

Cardiac arrhythmias, or irregular heartbeats, often require large-scale data analysis for accurate detection and diagnosis, posing a significant patient privacy risk. Federated Learning (FL) offers a privacy-preserving solution by enabling collaborative model training across distributed devices without sharing raw medical data.

This project investigates the potential of Federated Learning (FL) to enhance the accuracy of cardiac arrhythmia classification models, particularly for embedded systems like the Raspberry Pi Pico W. Utilizing the MIT-BIH Arrhythmia Database [1], an initial model will be trained to detect specific arrhythmias.

Simulated FL updates, incorporating real-time ECG data acquired with an AD8232 module, will demonstrate how FL can refine models across diverse patient data while preserving privacy. This work explores the potential of FL for personalized, privacy-centric cardiac monitoring, paving the way for advancements in wearable health technologies.

Research objectives

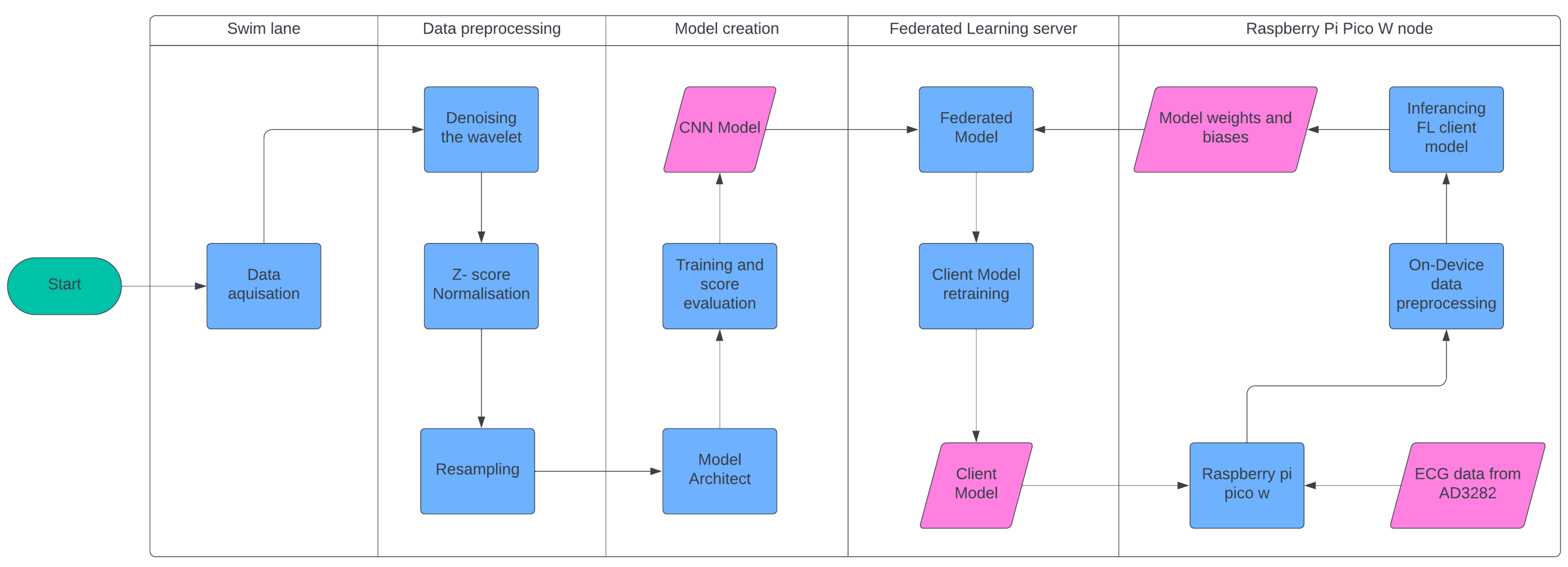
1. To explore the potential to unlock more accurate and adaptable cardiac monitoring solutions while safeguarding patient privacy, especially crucial for wearable and personalized healthcare using federated learning.
2. To explore the possibility of using low cost resource constrained raspberry pi pico w as a federated learning node to run light weight data processing before updating the federated learning model
3. to explore the possibility of using low cost AD3282 ECG modules in low power on-device heart monitoring for remote diagnosis

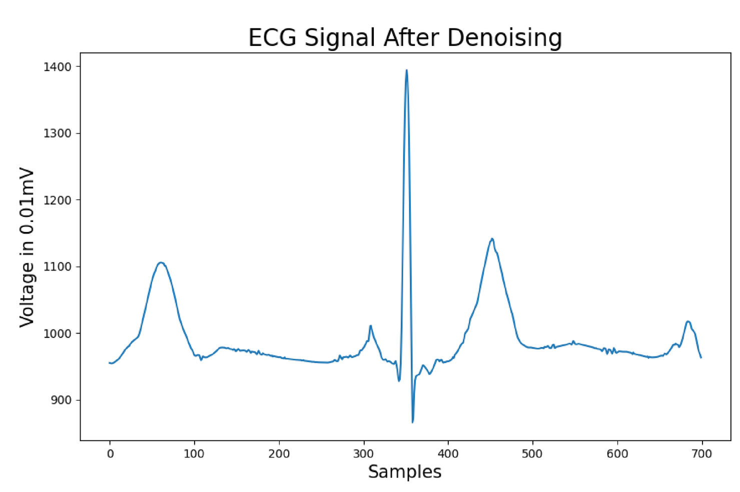
Introduction

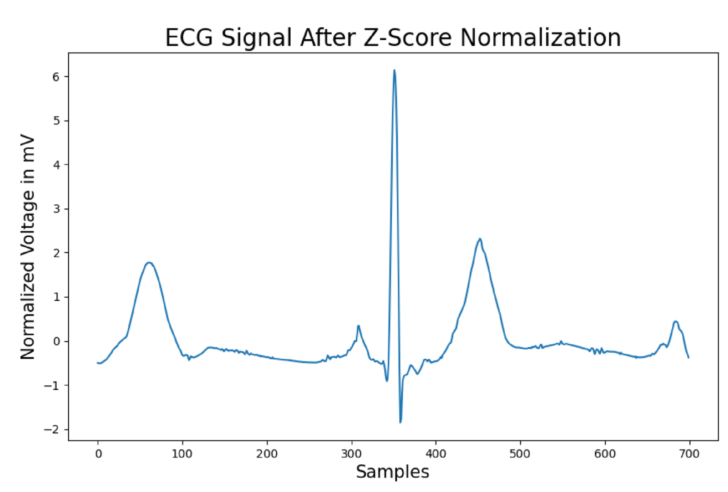
The use of egde computing in medical data analysis and artificial intelligence, healthcare practisioners may herald a new age of tailored patient care [2] however, this analysis of heart rhythm data to improve detection requires storing sensitive patient information in central locations. [3] introduces a novel hear disease diction system that requires age, sex, weight of athletes among other factors. This creates privacy risks, making people hesitant to share potentially life-saving data.

[4] introduces a novel method of using a lightweight model at the edge which abstracts the user personal data and a stronger central model which improves the accuracy of the machine learning model. Federated Learning (FL) offers a revolutionary solution. Imagine devices containing ECG data, like wearables or health monitors, each training a small model locally. Instead of sharing raw ECG recordings, only the model improvements are securely sent for updating a master model. This cycle repeats – the model continuously learns from diverse data without compromising individual privacy. FL has the potential to transform cardiac care, unlocking insights from large-scale ECG analysis while safeguarding patient data.

Methodology

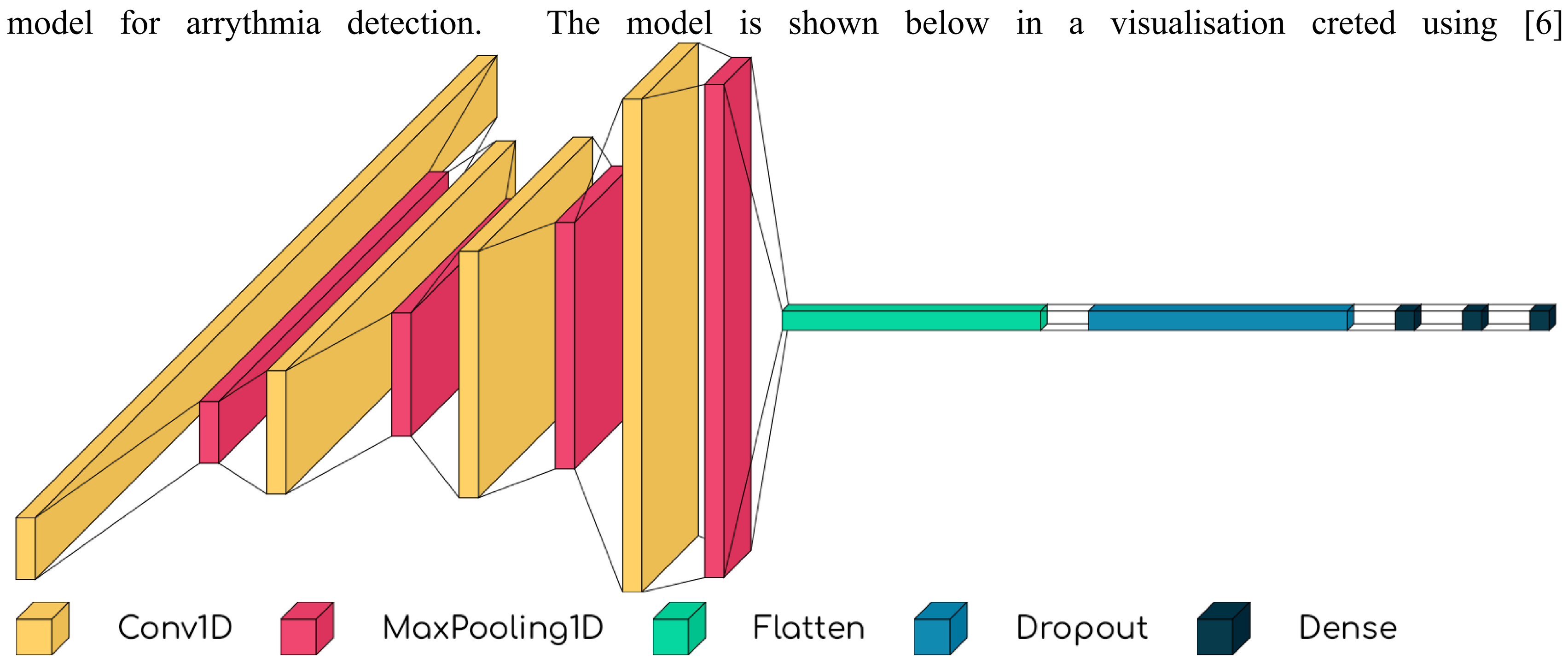






Model Architecture

The paper [5] explores the utilisation of a convolutional neural network (CNN) to detect QRS Complex and got over 97% accurate model. This forms basis for a guided look into the CNN model for arrythmia detection. The model is shown below in a visualisation creted using [6]

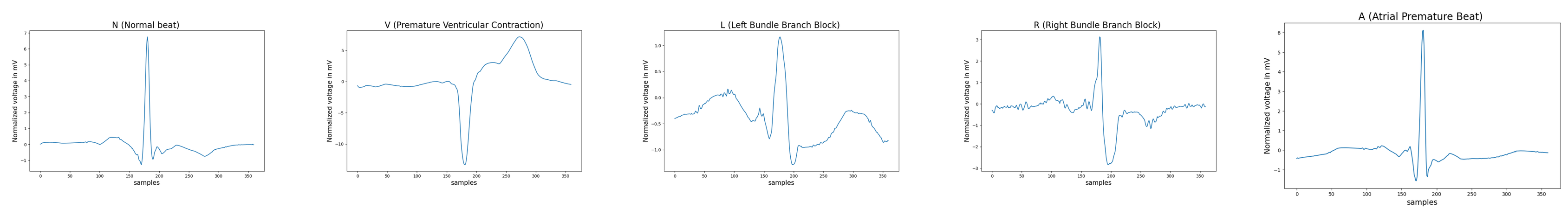


Plots

Training and Evaluation

The model was compiled with categorical cross-entropy and an optimizer Adam. The model was fitted on the data with a batch size of 30 for 20 epochs. The dataset was divided into training, validation, and testing sets with an $8:2$ split ratio. Model performance was assessed using the following metrics:

Classes of arrythmia



Main Equations

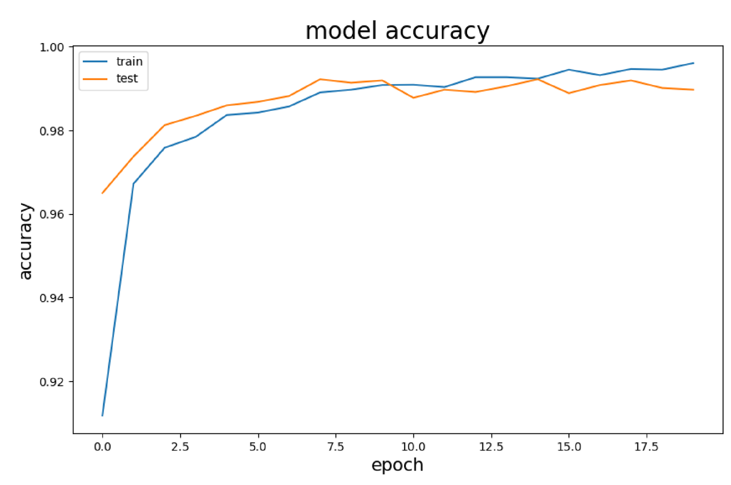
Convolution allows us to accumulate all interactions between the input vector and the kernel thus giving us features of the dataset in this case the shape of the dataset

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) g(t - \tau)\, d\tau \tag{1}$$

Max pooling after a Conv1D layer helps to reduce the spatial dimensionality of the feature maps while retaining the most significant features, aiding in translation invariance and computational efficiency for subsequent layers in the neural network.

$$\text{MaxPooling}(X, k, s)_{i,j} = \max_{m,n}(X_{i\times s+m, j\times s+n}), \quad 0 \le m, n < k \tag{2}$$

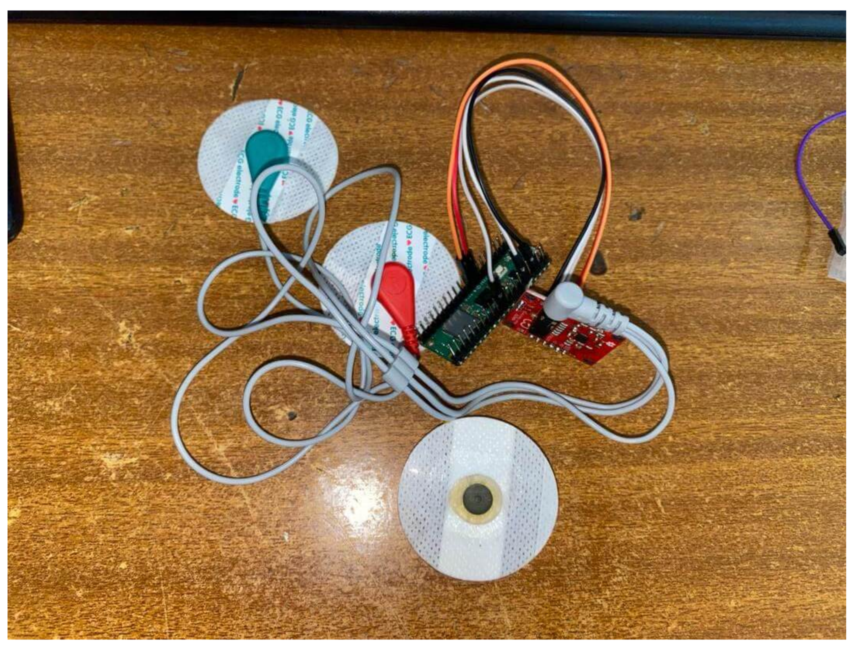
Key Results

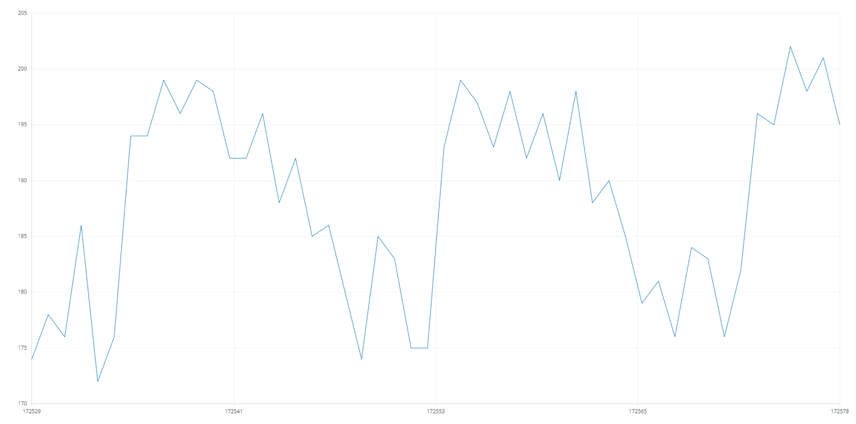


Class	Precision	Recall	F1-score	Support
N	0.9907	0.9831	0.9869	1947
L	0.9986	0.9972	0.9979	1423
R	0.9979	0.9986	0.9982	1407
A	0.9644	0.9911	0.9775	1010
V	0.9964	0.9880	0.9922	1413
Accuracy		0.9910		7200
Macro avg	0.9896	0.9916	0.9905	7200
Weighted avg	0.9911	0.9910	0.9910	7200

Table 1. Classification report

The hardware setup of a single federated learning client and data from the low cost ECG module is shown below





Conclusions

1. The low cost ECG module gave non accurate readings which could no be used in further training thus a need to explore a harwdare denoising alternative to the current hardware setup
2. To futher improve the accuracy of the low cost edge device, comparison with higher cost ECG machines is required to improve noise elimination and better match the expected cardiogram

Future Work

1. Try using an external ADC with its own voltage reference rather to eliminate noise
2. comparing the results with medical grade ECG machines to characterise and eliminate noise better in data preprocessing

References

[1] “MIT-BIH Database — kaggle.com.” https://www.kaggle.com/datasets/mondejar/mitbih-database. [Accessed 03-04-2024].

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