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Anomaly Detection in Patient Vital Signs for Early Warning of Critical Health Events

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1 Problem Definition

Anomaly detection (AD) refers to the process of identifying patterns that deviate from expected or normal behavior in the data [PSCH21]. The importance of this data analysis lies in the fact that these deviations, known as anomalies [1], may lead to critical actionable information [LTZ08]. For instance, AD plays a crucial role in the healthcare domain, as they can, when properly processed, indicate potential diseases or critical health events in patients. More specifically, cardiovascular diseases (CVDs) are the leading cause of mortality worldwide, accounting approximately one third of global deaths [LDD+22, Org21]. Apart from the impact on health, CVDs also have economic consequences as, in the United States, for example, the total cost of CVDs was estimated at 616 billion dollars in 2015 and is projected to reach 1.2 trillion dollars by 2035, factoring in caregiver costs, healthcare services, medication, and lost productivity due to mortality [DKB+18].

2 Objectives

2.1 Main objective

The main objective of the Bachelor's Degree Final Project is to develop an AI-based system for anomaly detection in healthcare time-series data, with a focus on electrocardiogram (ECG) signals, to enhance the early identification of critical health events, specifically cardiovascular diseases. Additionally, as an experimental objective, multi-class classification will also be explored to distinguish between various types of cardiac anomalies, rather than limiting the scope to binary (normal/anomalous) classification.

ECG signals are widely utilized in medical diagnosis as they provide critical information about cardiac electrophysiology in a non-invasive manner [AG11]. This time-series signal captures the electrical activity of the heart, reflecting how electrical impulses propagate through cardiac tissues and can be detected via electrodes placed on the skin [AN04].

This work focuses on ECG signals, as their analysis is one of the most widely utilized methods for early detection of CVDs, providing valuable insights into cardiac electrophysiology.
This work focuses on ECG signals, as their analysis is one of the most used methods for early detection of CVDs, providing information about cardiac electrophysiology. This time-series signal is widely used in medical diagnosis because of its non-invasive and effective advantages in cardiologist tools [AG11].

Specifically, the ECG measures the electrical activity of the heart, following the principle that these electrical impulses propagate through the body and can be detected on the skin [AN04]. Its graphical representation, shown in Figure 9, consists of 12 leads (channels), each providing a unique

[1] Data patterns that have different data characteristics from normal instances

electrical perspective of the heart. Anomalies in ECG signals can reveal various cardiac conditions such as coronary artery disease (CAD), heart failure (HF), arrhythmia (ARR), and other cardiac diseases. Given the important role of early warning in healthcare, anomaly detection approaches have been applied within ECG data, helping with the identification of anomalous patterns.

2.2 Specific objectives

- Understanding anomaly detection role in healthcare
- Review and analyze the main anomaly detection techniques for time-series data, with emphasis on binary classification. Additionally, explore the potential application of multi-class classification as a secondary, experimental objective.
- Procurement of healthcare time-series data: in particular, collecting and pre-processing ECG signals data
- Implement and train AI models to detect anomalies in ECG time-series data. Multi-class classification will be explored as a supplementary experiment.
- Evaluate the performance of the trained models using suitable metrics for time-series data
- Develop a visualization tool to display detected anomalies in a clear way for healthcare professionals

3 Methodology

Literature Review and Analysis of Anomaly Detection Approaches:

- Literature Review on Anomaly Detection Techniques: Perform a search given reliable and quality academic papers using academic search engines such as Google Scholar and Scopus to understand the task at hand and the necessity of anomaly detection in time series data. More specifically, physiological data such as ECG will be the main focus to relate it within anomaly detection state-of-the-art (SoA) approaches applied to time series data in healthcare.
- Challenges in Anomaly Detection for Healthcare Time-Series Data: Analyze the main challenges in anomaly detection when using physiological data to overcome them during the length of the work, e.g. imbalanced data, unlabeled data, noisy data, etc.
- Comparative Analysis of Anomaly Detection Techniques in the Healthcare domain: Analyze and compare different actual anomaly detection techniques given literature and open source code to determine the feasibility of the task at hand. The goal is to obtain those studies that show the most promising approaches to deal with physiological data and the challenges that it comprises.

Procurement of Healthcare Dataset

- Identification and Selection of time-series datasets: A review of existing datasets mainly used in approaches that deal with this task or similars will be performed, including both open-access and restricted databases for this study using repositories such as *Physionet*[2]. The criteria of selecting the most promising dataset will consider dataset quality, availability, realism, and ideally, the linkage within patient metadata such as demographic information or other electronic health records.
- Data Collection, Exploratory Data Analysis (EDA), and Preprocessing:
  - Collect data from various repositories to compare them regarding the above mentioned criteria
  - Use of programming languages such as *Python* and libraries such as *wfdb*[3] to load and visualize the time series data
  - Perform exploratory data analysis (EDA) using Python visualization tools such as *matplotlib* and *wfdb* to understand the complexity of this typology of data.
  - Implement ECG pre-processing techniques such as noise removal, normalization and pattern extraction to multivariate time-series.

[2] https://physionet.org
[3] https://physionet.org/content/wfdb-python/4.1.0/

Implementation of AI Models

- Model Selection and Training: Utilize machine learning frameworks such as *PyTorch* and *TensorFlow* to implement selected models for anomaly detection. Additionally, a monitoring process through frameworks such as *Weights and Biases*[4] will be used for real-time tracking of model performance.

- Hyperparameter Optimization: Hyperparameter tuning will be used to ideally encounter the perfect parameters such as learning rate, batch size or architecture design to be used within the task at hand.

Development of a Visualization Dashboard (Streamlit or Flask)

- Storyboard and Proof of Concept (PoC) Development: A conceptual end-user design will be provided to make an initial overview of the final application. This PoC will be used so that the user interface aligns with the project objectives.

- User-Centric Interface for Medical Professionals: Develop a front-end using *Streamlit*[5] or *Flask*[6], to provide a valuable experience for clinicians to:
  - Upload data via the user dashboard.
  - Visualize detected anomalies in those files that contain an ECG waveform format for explainability reasons.
  - Provide a report of possible risks given the identified anomaly.

4 Planning

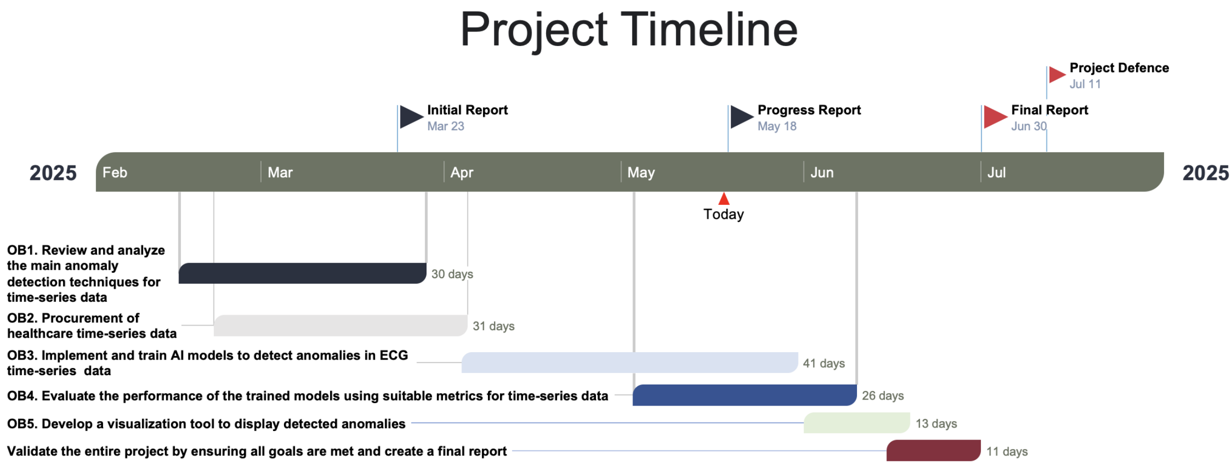

Figure 1: Provisional Timeline for the TFG

As shown in Figure 1, the planning of this project follows a waterfall-like methodology, where each stage progresses sequentially. While the methodology proposes a clear and structured order, it maintains some flexibility, allowing for phase adjustments if there are challenges encountered along the project timeline.

The process begins with a literature review to conduct a feasibility study of the project, once the background is established, the focus changes into a practical direction, where data exploration and model implementation is performed. Following this, after training, the models are evaluated using appropriate metrics. Finally, a user-friendly UI is developed to enable healthcare professionals to visualize the anomalies detected in the data.

However, during the training phase, issues with the selected datasets delayed the entire process, as the models were unable to learn the intended patterns. Consequently, additional time was allocated to revising dataset selection and refining preprocessing techniques to address these challenges.

Despite this setback, adjustments to the dataset and training schedule were implemented to address these unexpected challenges.

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[4] https://wandb.ai/site/
[5] https://streamlit.io
[6] https://flask.palletsprojects.com

5 Related Work

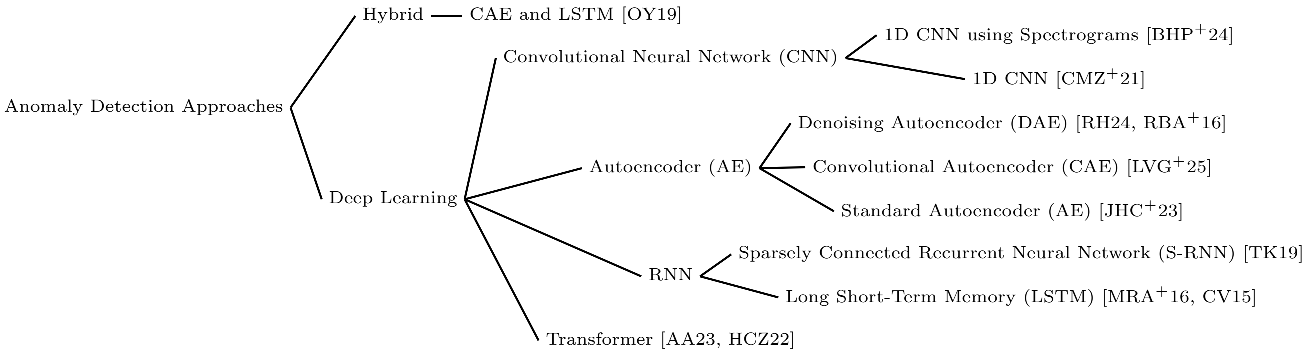

Figure 2: Anomaly Detection Approaches in ECGs

The field of anomaly detection in healthcare has evolved over time. First approaches relied heavily on rule-based systems and small-scale medical documentation, which were limited when handling the overall complexity of multivariate time-series data such as ECG or EEG signals. Nowadays, recent methods use machine learning techniques to deal with complex data in healthcare originating from the abundant electronic health records (EHRs). We can categorize all approaches in four major categories as below:

5.1 Deep Learning Approaches

Transformer Models: Transformer-based methods have been used for anomaly detection to address the lack of labeled data in the medical domain, more specifically, in the detection of anomalies in ECG. Besides, the high-capacity when dealing with long time intervals of data is also a challenge where transformers have been demonstrated to perform well [AA23, HCZ22].
Recurrent Neural Networks (RNN): Long Short-Term Memory (LSTM) networks have been used in this typology of tasks because of their long-term temporal dependencies capabilities [MRA+16, CV15]. As well as that, other RNN-based approaches such as Sparsely Connected Recurrent Neural Networks (S-RNN) have been used [TK19].

5.2 Autoencoder-based Methods

Autoencoders (AE): Autoencoders are neural networks that learn to reconstruct the input data, capturing the important features of normal patterns. In the context of ECG anomaly detection, normal patters are defined as consistent P-QRS-T[7] wave morphology, a stabilized heart rate and proper intervals of these waves [Her22]. So, autoencoders are effective when dealing with imbalanced datasets, where normal ECG recording are more common than anomalous ones. During the testing phase, AEs can identify anomalies without having to be trained with anomalous data [JHC+23].
Convolutional Autoencoders (CAE): Convolutional autoencoders apply the concept of convolutional layers to autoencoders so that it is more effective for feature extraction. This method is strong for creating spatial relationships in the signal [LVG+25].
Denoising Autoencoders (DAE): Denoising autoencoders increase the robustness of the model by adding noise to input signals, so it can be resilient to noise in cases where signals are prominently noisy. E.g. an ECG can contain noise because of the machine that is recording the signal. [RH24, RBA+16].

5.3 Convolutional Neural Networks (CNN)

1D CNN: A 1D convolutional neural network can be applied in the detection of arrythmia processing ECG waveforms as time-series data, where each signal is represented as a one-dimensional vector[CMZ+21]. In this approach, convolutional filters are applied to capture both spatial and temporal features.
1D CNN with Spectrograms: A similar version of the above mentioned method, a 1D CNN

[7] The basic pattern of electrical activity across the heart[AN04]

that uses frequency-based representations instead of ingesting time-series ECG signal as input. [BHP+24].

5.4 Hybrid Approaches

CAE and LSTM Combination: Hybrid models are also interesting approaches. For instance, a combination of a convolutional autoencoder with Long Short Term Memory (LSTM) can outperform other single-technique approaches [OY19].

6 Method

6.1 Problem Formulation for Anomaly Detection in 12-Lead ECGs

A multivariate time series is a sequence of data points along m dimensions. In the context of ECG signals, each dimension corresponds to one of the 12 leads, resulting in $m = 12$. Therefore, a 12-lead ECG can be represented as a multivariate time series:

$$T = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_T\}, \quad \mathbf{x}_t \in R^m \quad \text{[AMG}^+\text{20]} \tag{1}$$

where each observation $\mathbf{x}_t \in R^{12}$ is a 12-dimensional vector representing the simultaneous channel recordings from the 12 leads at time t.

In this unsupervised learning setting, the objective is to identify anomalous ECG samples based on a training dataset T that is assumed to contain only normal ECG samples. Given an unseen test sample $\hat{\mathbf{x}}_t$, the task is to determine whether it deviates from the learned normal patterns in the training set T.

To measure this difference, an anomaly score S_t is defined, which is compared against an automatic threshold τ_t to assign a binary anomaly label y_t:

$$y_t = \begin{cases} 1 & \text{if } S_t > \tau_t \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

6.2 Preprocessing Pipeline

To enhance the model's generalization capability, multiple 12-lead ECG datasets–comprising both publicly available and restricted–were merged to achieve data augmentation using real signals. The combined dataset was then preprocessed through filtering and normalization.

6.2.1 Dataset Preprocessing and Merging

As shown in Table 1, a combined dataset was created by merging three different 12-lead ECG datasets. Each dataset provides 12-lead recordings and supports a 500 Hz sampling rate, ensuring uniformity in sampling frequency and lead configuration, which simplifies preprocessing and merging. The labels from each dataset were also mapped consistently to differentiate between normal and abnormal samples. However, this choice remains under consideration, as the selection of datasets and preprocessing parameters is treated as a hyperparameter to potentially enhance model performance.

Dataset	Number of ECGs	Number of Patients	Availability
PTB-XL[1]	21,799	18,869	Public
MIMIC-IV ECG[2]	800,000+	160,000+	Restricted
CPSC 2018[3]	6,877	477	Public

Table 1: Datasets used in the study. All datasets include 12-lead ECGs and support extraction at a 500 Hz sampling rate.

As illustrated in Figure 3, the merged dataset contains significantly more abnormal samples than normal ones. This imbalance highlights the importance of aggregating data from multiple sources to ensure a diverse and comprehensive representation of ECG patterns. Combining datasets allows the model to better generalize across various abnormalities and reduces bias towards the majority class.

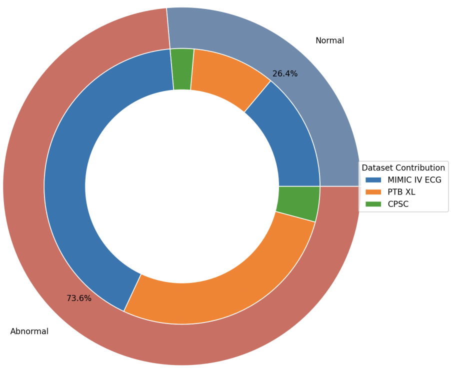

Figure 3: Distribution of Normal vs Abnormal ECG samples with Dataset Contribution

6.2.2 Window Segmentation

Window segmentation is considered as a possible training input in some of the experiments performed. This approach is used to observe its ability to capture localized patterns within the ECG signals.
If this windowing approach is used, the training dataset is conformed by overlapping windows W, where each window represents a fixed-length segment of the ECG signal:

$$W = \{\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_n\}, \quad \mathbf{w}_i \in R^{L \times m} \tag{3}$$

where:

- L = Number of samples per window,
- m = Number of leads (12 in the case of ECG signals),
- n = Total number of windows.

6.2.3 Filtering and Normalization

After reviewing the literature and experimenting with different filtering and normalization configurations, the following techniques were chosen as optimal:

1. ECG signals are cleaned using a combination of bandpass and notch filters[KSH+23, LRLA21, EKEB13]. Specifically, a 3rd-order Butterworth bandpass filter with cutoff frequencies of 0.5 Hz and 50 Hz is applied to remove baseline wander. Then, a notch filter centered at 50 Hz removes powerline interference. These filters are applied independently to each ECG lead to preserve signal quality.

2. After filtering, the signals are normalized to the range [0, 1] on a per-lead basis to ensure consistent amplitude scaling across the dataset, which facilitates effective training of machine learning models.

$$x_{t,i}^{\text{normalized}} = \frac{x_{t,i} - \min x_i}{\max x_i - \min x_i + \epsilon'} \tag{4}$$

The constant vector ϵ' is introduced to the denominator to prevent division by zero when a feature has zero range. By normalizing the data using these values, each feature is scaled approximately to the interval $[0, 1)$, which improves numerical stability and aids model training [TCJ22].

As observed in Figure 4, the effects of filtering and normalization (in blue) are clearly noticeable compared to the raw signals (in red). This preprocessing step effectively reduces baseline drift and powerline interference, thereby improving the clarity of the ECG signals and enabling more robust anomaly detection.

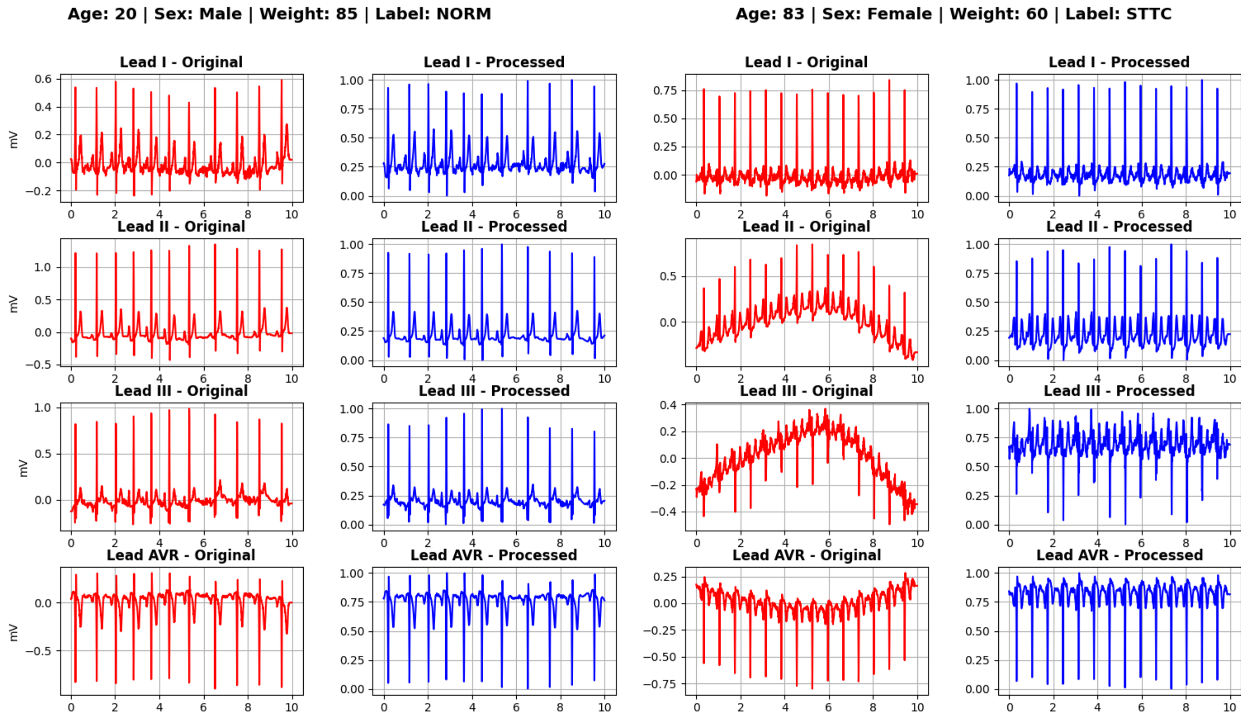

Figure 4: Comparison of non-processed and pre-processed ECG signals

6.3 Models Used

6.3.1 Autoencoder

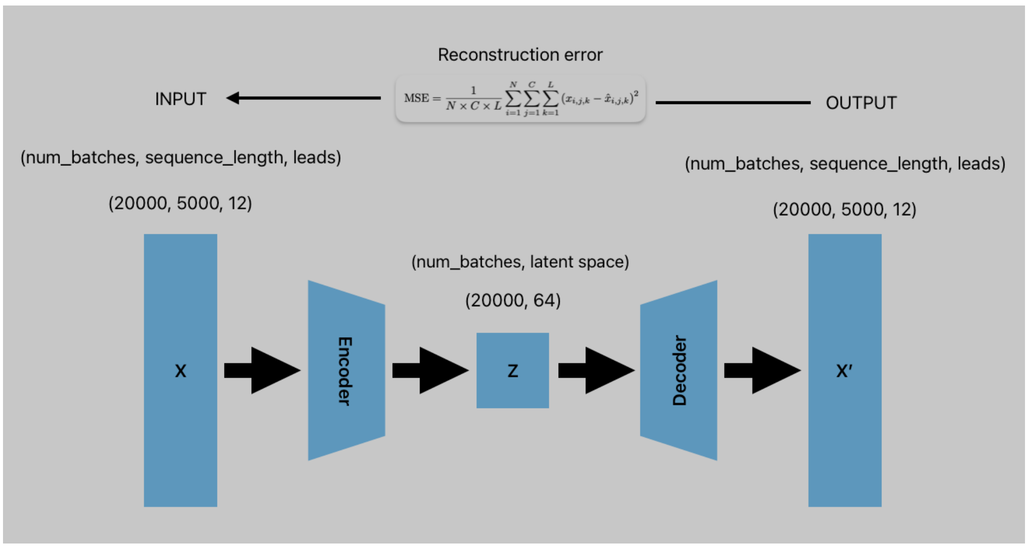

Figure 5: Autoencoder architecture

An autoencoder is a type of unsupervised artificial neural network that consists of two main components: an encoder and a decoder[RHW86]. The encoder maps the input data $\mathbf{X} \in R^m$ to a lower-dimensional latent representation $\mathbf{Z} \in R^d$, where $d < m$. The decoder then reconstructs the input from the latent space by mapping $\mathbf{Z}$ back to the input space, resulting in a reconstruction $\mathbf{R} \in R^m$.

$$\mathbf{Z} = f_{enc}(\mathbf{X}) \in R^d \tag{5}$$

$$\mathbf{R} = f_{dec}(\mathbf{Z}) \in R^m \tag{6}$$

Where:

- $\mathbf{X} \in R^m$: Input data, where m is the dimensionality of the original data (e.g., the number of features or time steps in an ECG window).
- $\mathbf{Z} \in R^d$: Latent representation, where d is the dimensionality of the encoded (compressed) data. Typically, $d < m$.
- $\mathbf{R} \in R^m$: Reconstructed data, ideally approximating the original input $\mathbf{X}$.
- f_{enc}: The encoding function that maps the input data to the latent space.
- f_{dec}: The decoding function that reconstructs the input data from the latent space.

The objective of the autoencoder is to minimize the reconstruction error[8], particularly in this case, when comparing normal and abnormal ECG samples, as anomalies are expected to produce higher reconstruction errors.

6.3.2 Variational Autoencoder (VAE)

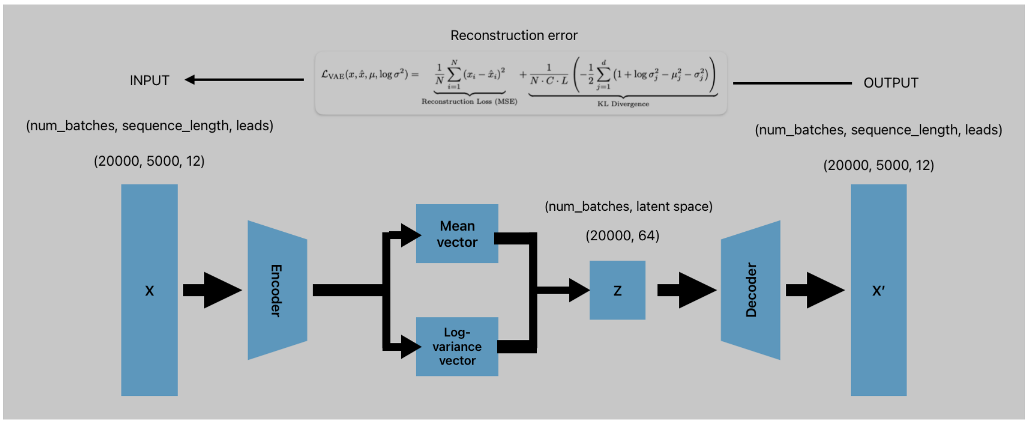

Figure 6: Variational Autoencoder architecture

The Variational Autoencoder (VAE) extends the vanilla autoencoder by incorporating a probabilistic approach. Instead of mapping input data $\mathbf{X}$ to a deterministic latent space $\mathbf{Z}$, the VAE learns to encode data as a probability distribution, allowing for more robust representations.

The objective of the VAE is to maximize the Evidence Lower Bound (ELBO)[9].

The ELBO consists of two main components:

- Reconstruction Log-Likelihood: Measures how well the VAE reconstructs the input data from the sampled latent space by maximizing $\log p_\theta(\mathbf{X}|\mathbf{Z})$.
- Kullback-Leibler Divergence (KL Divergence): Quantifies the divergence between the learned posterior distribution $q_\phi(\mathbf{Z}|\mathbf{X})$ and the prior distribution $p_\theta(\mathbf{Z})$. This term acts as a regularizer to prevent overfitting.

7 Experiments

7.1 Datasets

During experimentation, three ECG datasets were utilized to train and evaluate the used anomaly detection models: **PTB-XL**, **MIMIC-IV ECG**, and the **CPSC**. The data is divided into training and testing sets as follows:

- **Training Set:** The training set consists of normal ECG samples from the PTB-XL, MIMIC-IV ECG and CPSC datasets. This strategy ensures that the model learns to reconstruct only normal patterns.

[8]The reconstruction error is the difference between the original input data X and the reconstructed output R generated by the autoencoder.

[9]The ELBO is a variational approximation of the log-likelihood of the data, serving as a trade-off between accurate reconstruction and regularization of the latent space.

- **Testing Set:** The testing set is composed of a combination of normal and abnormal samples derived from PTB-XL dataset. This allows for the evaluation of the model's capability to detect anomalies.

7.2 Evaluation Metrics

To evaluate the performance of the proposed anomaly detection model, we employ a set of standard metrics commonly used in anomaly detection literature, including precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC-ROC). These metrics provide a comprehensive assessment of the model's ability to accurately detect anomalies in ECG data.

Precision, Recall, and F1 Score: The primary evaluation metrics are precision (P), recall (R), and F1 score (F_1), which are defined as follows:

$$P = \frac{TP}{TP + FP}, \quad R = \frac{TP}{TP + FN}, \quad F_1 = 2 \cdot \frac{P \cdot R}{P + R} \tag{7}$$

where:

- TP: True Positives (correctly detected anomalies)
- FP: False Positives (normal samples incorrectly labeled as anomalies)
- FN: False Negatives (anomalies missed by the model)

AUC-ROC: The Area Under the Receiver Operating Characteristic curve (AUC-ROC) measures the trade-off between the true positive rate and the false positive rate across various decision thresholds. AUC-ROC provides an overall assessment of the model's discriminative power in distinguishing between normal and anomalous samples.

7.3 Results

Based on the performance metrics presented in Table 2, it can be observed that the experiment using the VAE architecture with partitioned windows, filtered, and normalized data achieved the highest scores in terms of F1 and AUC. Furthermore, its reconstruction error during training on normal patterns remained below 0.001, indicating a high capacity to reconstruct normal ECG signals, indicating a strong capacity to accurately reconstruct normal ECG signals while effectively distinguishing anomalies.

However, the autoencoder architecture demonstrated limitations in precision when anomalous patterns are close to the normal distribution. This suggests that the latent space learned by the AE model is less discriminative than the VAE latent space.

Table 2: Model Performance Comparison with Adam Optimizer and Early Stopping in all experiments

Model	**F1 Score**	**AUC**
Autoencoder (lr = 1e-3, batch size = 32, epochs = 50, latent dim = 64)	0.67	0.7
Variational Autoencoder (lr = 1e-3, batch size = 32, epochs = 50, latent dim = 64)	0.775	0.82
Variational Autoencoder with 39 windows per lead partition	**0.78**	**0.83**
ResNet1d [10]	0.66	0.69

As shown in Figure 7, a sample of a lead from a normal ECG is presented to illustrate the reconstruction capabilities of the VAE model. The reconstructed sample (orange) closely aligns with the original sample (blue), demonstrating the model's ability to accurately capture the underlying structure of normal patterns.

[1] `https://physionet.org/content/ptb-xl/1.0.3/`
[2] `https://physionet.org/content/mimic-iv-ecg/1.0/`
[3] `http://2018.icbeb.org/Challenge.html`

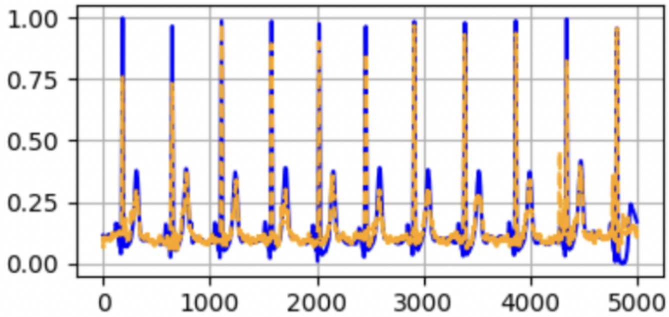

Figure 7: VAE Reconstructed ECG sample

8 Storyboard

As observed in Figure 8, the storyboard provides an overview of how the user interface (UI) will function for the end-user.

- **Document Upload:** Users can upload patient-related files, including ECG recordings (e.g., .hea and .dat files) and demographic details.
- **ECG Visualization:** The interface displays two ECG images:
  - The original, unaltered ECG graph.
  - An annotated version highlighting potential anomalies.
- **Annotation and Editing:** Users can interact with the annotated ECG:
  - Amplify specific channels for better visualization.
  - Adjust AI-generated annotations and add new markers.
  - Zoom into sections and modify display settings.
- **Export and Save:** The final annotated ECG can be exported as a report or stored for future reference.

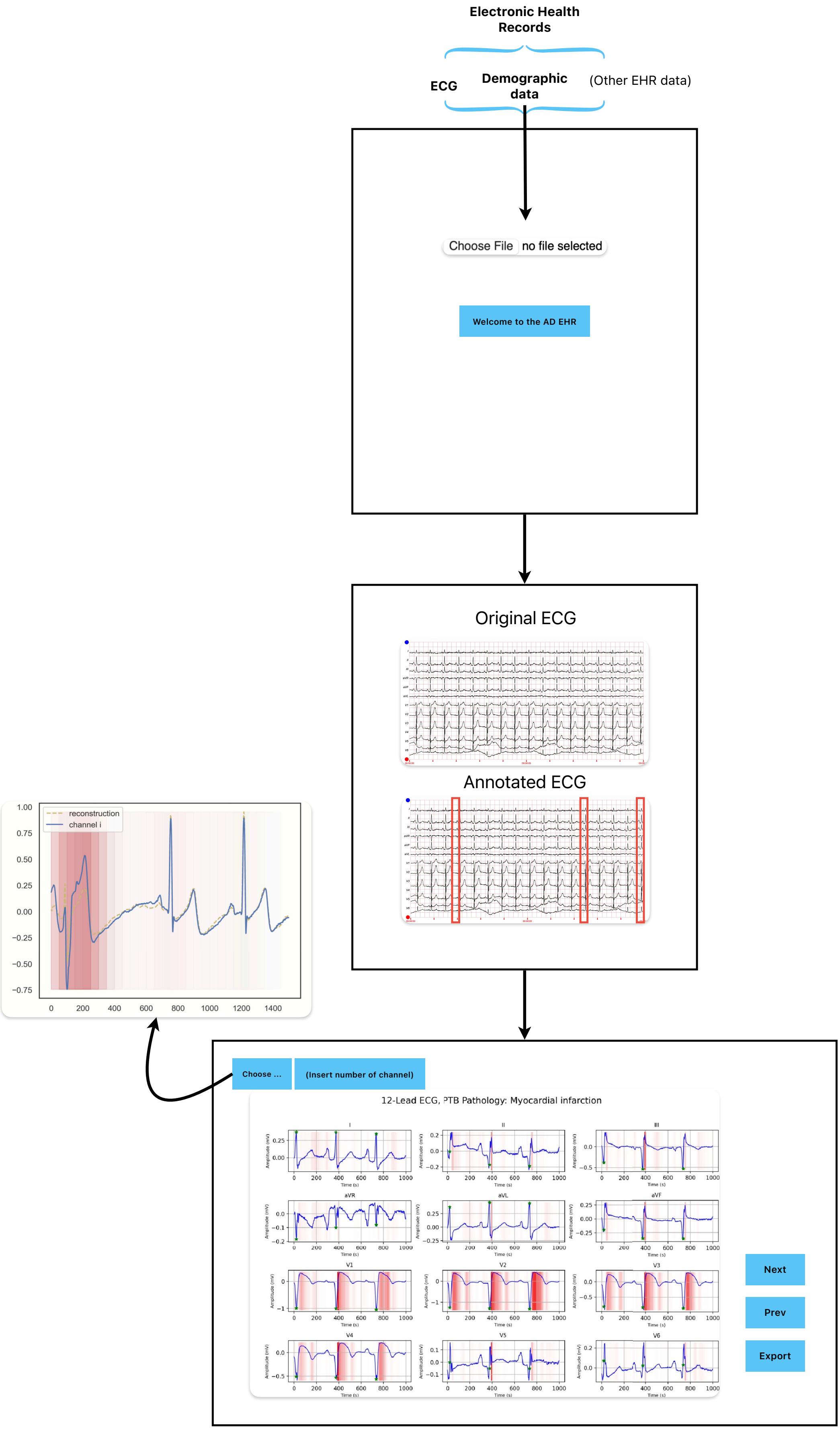

Figure 8: Provisional Storyboard for the UI

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A Annex A: Additional Tables

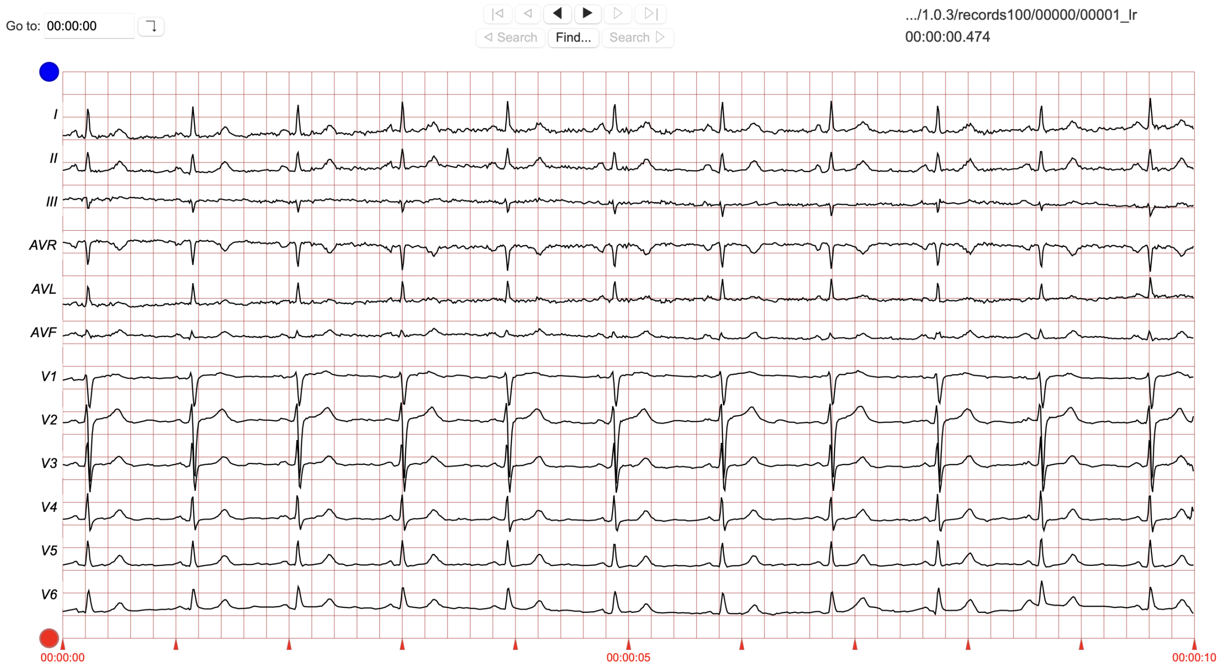

Figure 9: ECG sample