Cloud-based Lead-I ECG Feature Extraction and One-Class SVM Classification with MongoDB Storage for Accurate Detection of Tachycardia, SR, and ST Depression

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ABSTRACT
Early diagnosis and prevention of cardiovascular disorders depend on accurate detection of cardiac irregularities from electrocardiogram (ECG) data. In order to identify important cardiac disorders such tachycardia, sinus rhythm (SR), and ST depression, this study presents a cloud-based method for Lead-I ECG data processing that uses a One-Class Support Vector Machine (OC-SVM). Without the need for extensive labeled datasets, the suggested approach successfully distinguishes between normal and pathological ECG rhythms using unsupervised learning. By capturing QRS peaks and ST-segment deviations, feature extraction approaches improve the diagnostic accuracy of the model. Cloud MongoDB securely stores and manages processed ECG data and detection results, guaranteeing high scalability, data integrity, and effective access for distant analysis. According to experimental results, the suggested OC-SVM model greatly reduces false detection rates across a variety of ECG datasets while providing strong classification accuracy.

The model reliably detects disorders including tachycardia, sinus rhythm (SR), and ST depression by successfully differentiating between normal and abnormal cardiac rhythms. The system's capacity for real-time ECG monitoring is improved by the integration of cloud computing with MongoDB, which offers safe data storage, quick query processing, and easy access from dispersed healthcare settings. Continuous data streaming from wearable ECG devices is made possible by this cloud-based architecture, which supports long-term cardiac analysis and extensive remote patient monitoring.

Keywords
ECG signal analysis, Lead-I ECG, Arrhythmia detection, One-Class Support Vector Machine, Unsupervised learning, QRS complex, ST segment, Wearable health monitoring, Anomaly detection, Cardiovascular signal processing

1. INTRODUCTION
Heart conditions, especially tachycardia, remain a leading cause of morbidity and death worldwide [1]. If left untreated, tachycardia—a condition marked by an unusually high heart rate—can result in serious consequences such heart failure, stroke, or sudden cardiac arrest [2]. Thus, timely clinical intervention and better patient outcomes depend on ongoing surveillance and early discovery. The creation of automated systems that can identify a variety of cardiac disorders, such as tachycardia, sinus rhythm (SR), and ST depression, has been made possible by recent developments in electrocardiogram (ECG) signal processing, especially with Lead-I ECG data [3], [4].

Traditional ECG analysis methods often rely on supervised learning techniques and multi-lead recordings, which require large, annotated datasets representing diverse cardiac conditions [3]. However, in real-world applications—especially those involving portable or wearable ECG devices—only single-lead data are typically available, and labeled pathological samples are often limited [8]. This limitation underscores the importance of anomaly detection methods that can effectively identify deviations in cardiac patterns, including variations such as Sinus Rhythm (SR), ST Depression, and Bradycardia [4], [5]. By recognizing these abnormalities, such systems can provide valuable insights into both normal and pathological heart behaviors, enabling more accurate and early cardiovascular assessment.

In this research, a One-Class Support Vector Machine (OC-SVM) model is used to detect arrhythmias based on Lead-I ECG signals. In order to acquire a decision boundary that successfully distinguishes between normal and abnormal heart rhythm patterns, the OC-SVM is trained exclusively on normal ECG data. The method focuses on clear thresholds and feature relationships (e.g., QRS > 13 → tachycardia, ST < –0.05 → ST depression), which provides clinicians with explainable outputs rather than opaque predictions. The suggested method's potential for precise and effective arrhythmia identification is demonstrated by evaluating its performance using preprocessed ECG signals and established criteria for anomaly detection.

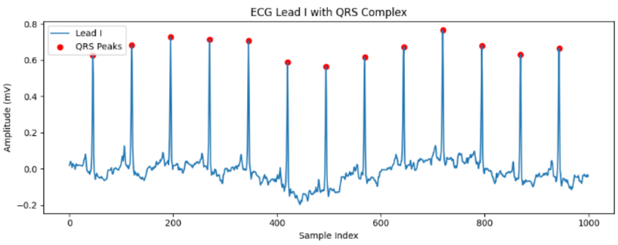

Figure I: ECG Lead I with QRS Complex

A section of the Lead-I ECG signal with the identified QRS complexes prominently displayed is shown in Figure I. The raw ECG signal amplitude over 1000 sample points is represented by the blue line, which shows the heart's electrical activity over time. The discovered QRS peaks, which are essential for heart rate and rhythm analysis and correlate to the ventricular depolarization phase, are indicated by the red markers. Since variations in the frequency, amplitude, or form of these QRS complexes frequently point to underlying cardiac problems, accurate detection of these complexes is crucial for the identification of arrhythmias. This graphic shows how well the QRS identification algorithm worked in this investigation, offering a solid basis for later arrhythmia detection using the One-Class SVM method.

The QRS peak count and the average ST segment in millivolts (mV) are critical parameters in determining cardiac anomalies from ECG signals. The QRS complex corresponds to ventricular depolarization and is directly related to each heartbeat. By counting the number of QRS peaks over time, the heart rate can be derived, providing insights into rhythm regularity.

Building on this, another crucial indicator for identifying ischemia alterations in the heart is the average ST segment in millivolts. Elevated or depressed ST-segment deviations frequently signify insufficient blood flow to the myocardium, which can be linked to diseases such myocardial infarction or ischemia. When combined, the ST segment and QRS peak count offer a thorough insight of the heart's rhythm and overall health. By adding these factors to the diagnostic pipeline, the system's ability to detect subtle but clinically relevant anomalies such ST depression is strengthened, in addition to improving the identification of tachycardia, arrhythmia, and sinus rhythm. The automated diagnosis system is guaranteed to be accurate and clinically useful thanks to this dual-parameter approach.

Table 1: ECG Signal Features & Their Respective Normal Values

Diagnosis	Description	ECG Indicators Used
Tachycardia	A condition where the heart beats faster than normal (>100 bpm).	High QRS peak count**,** shortened RR intervals.
Sinus Rhythm (SR)	Normal rhythm of the heart generated by the sinus node.	Regular QRS peaks, normal ST segment**.**
ST Depression	Downward deflection of the ST segment below the baseline.	Negative average ST segment (mV) values.
Arrhythmia	Irregular heartbeat caused by abnormal electrical activity in the heart.	Irregular QRS peak patterns, variable intervals.
Bradycardia	A slower-than-normal heartbeat (<60 bpm).	Low QRS peak count, long RR intervals.

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2. LITERATURE REVIEW & RELATED WORK

Dorsa EPMoghaddam et al presented a novel graph-based methodology for classifying cardiac arrhythmias using single-lead ECG signals. By applying visibility graph techniques, ECG time-series data are transformed into graph structures from which informative features are extracted. These features were then evaluated using three classifiers: graph convolutional neural network (GCN), multi-layer perceptron (MLP), and random forest (RF). The study employed the MIT-BIH arrhythmia database with six target classes, reporting MLP as the best performer with 99.02% accuracy, closely followed by RF. The work highlighted the effectiveness of graph-based representations for arrhythmia detection and demonstrated potential for computer-aided diagnosis [8].

Satria Mandala et al. proposed an improved ensemble learning approach for arrhythmia detection using multi-lead ECG data. In this study, they applied boosting algorithm, namely Fine Tuned Boosting (FTBO) model that detects multiple arrhythmia classes. For the feature extraction, they introduced a new technique that utilized a sliding window with a window size of 5 R-peaks. The results showed that the proposed method achieved high sensitivity, specificity, and accuracy for all three classes of arrhythmia. It accurately detected Atrial Fibrillation (AF) with 100% sensitivity and specificity [1].

Mathieu Nasarre et al, performed research on detecting abnormalities associated with sudden cardiac arrest in young adults. They used 155 healthy volunteers' data and 67 patient data, which are from ages 18-45. Cardiologists separately analysed 12-lead ECGs and the smartwatch ECGs taken from the left wrist (AW-I) and then from chest positions V1, V3, and V6 (AW-4). Detection of SCA-associated ECG abnormalities (pre-excitation, Brugada patterns, long QT, and signs suggestive of

HCM and ARVC/D) is possible with an ECG smartwatch [9].

Wavelet based ecg arrhythmia classification presented by RaoRane Shweta proposed a work for classifying cardiac arrhythmia diseases using the. Support Vector Machine (SVM) and Genetic Algorithm approaches (GA-SVM method). A genetic algorithm was used for ECG arrhythmia classification and it was used to improve the generalization performance of the SVM classifier [12].

Bhawan Jindal, A.P.JMIT , Saudagar, Ekta and Reeta Devi had developed GUI in Matlab ,"Matlab Based GUI for ECG Arrhythmia Detection Using Pan-Tompkin Algorithm" in this system they used Pan- Tompkins algorithm for arrhythmia detection, by Digital filtering of ECG data linearly [13].

In the research paper proposed by Chun Cheng Lin & Chun Min Yang, they proposed a heartbeat classification system that consists of signal pre-processing, feature extraction, and linear discriminant classification (LDC). The LDC method is applied to classify the heartbeats according to the extracted features [14].

Feature extraction and classification of ECG signal using Neuro-Wavelet Approach was a paper proposed by Mayankkumar Gautam & Vinodkumar Giri , included first Denoising/ Baseline Wander Removal from ECG raw data, Feature Extraction using Wavelet Transformation, and Feature Classification using Neural Networks [15].

A literature review carried out by S.T Sanamdikar,Dr. S.T.Hamde and Dr. V.G.Asutkar on Arrhythmia Analysis of ECG Signal in this proposed paper they have discusses various techniques and transformations for extracting feature from an Arrhythmia Analysis and interpretation of ECG Signal. this paper also provides a comparative study of various methods proposed [16].

A research article written by Carlos Lastre-Dominguez,Yuriy s. Shmaliy,Oscar Ibarra-Manzano,Jorge Munoz-Minjares and Luis J, Morales-Mendoza, on ECG Signal Denoising and Features Extraction Using Unbiased FIR Smoothing, in this article, they had developed an adaptive-horizon UFIR smoothing filtering algorithm for denoising ECG signals and features extraction. Also investigate the trade-off between the UFIR smoothing filter, UFIR filter, and UFIR predictive filter and compare them to the standard linear predictor [17].

Review Article presented by U. Rajendra Acharya , K. Paul Joseph N. Kannathal, Choo Min Lim and Jasjit S. Suri, stated a study of heart rate variability. In this article they had discussed various applications of HRV and different linear, frequency domain, wavelet domain, nonlinear techniques used for the analysis of the HRV [18].

3. DATASET AND MATERIAL

3.1 Dataset Selection

The PTB-XL dataset (version 1.0.1) is used, which includes 21,837 clinical 12-lead ECG recordings from 18,885 patients. Each recording lasts 10 seconds and is accessible at sampling frequencies of 500 Hz and 100 Hz. Based on the SCP-ECG standard, the dataset offers comprehensive multi-label annotations that include diagnostic, form, and rhythm assertions that cardiologists have validated. Together with designated subclasses and superclasses for structured analysis, there are 71 unique statements in all.

3.2 Data Preprocessing And Feature Normalization

To generate PDF files from the above database, The proposed system have first load the metadata file (ptbxl_database.csv), which contains patient demographics and diagnostic annotations. From this, one record is selected and the corresponding ECG waveform Lead I is read using WFDB. The signal is processed with NeuroKit2, which identifies QRS complexes and extracts beat-related information. A plot of the ECG with highlighted QRS peaks is generated. The code then calculates the average ST-segment value by measuring the mean amplitude between 60–100 ms after each R-peak, which serves as an indicator of ischemic changes. Diagnostic labels are extracted from the metadata (scp_codes). Using FPDF, a PDF report is created that includes patient ID, age, sex, diagnosis, QRS peak count, and average ST segment value. (Fig.II) The ECG plot is embedded in the PDF, and the final report is saved with the patient's ID as the filename.

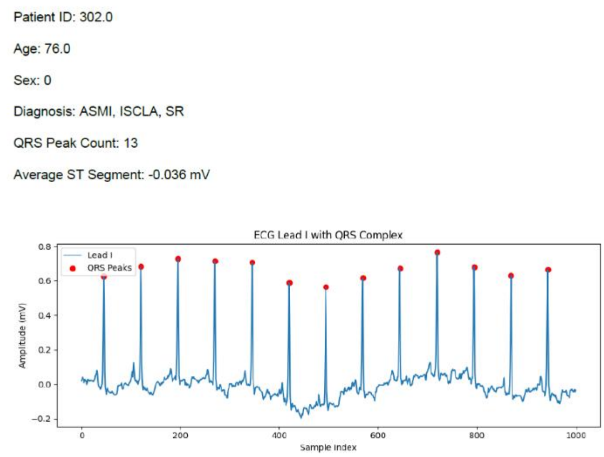


Figure II: PDF file with patient detail and Lead-I ECG

After converting the data into PDF format, each report is processed using PyPDF2 for text extraction and PyMongo for database integration, transforming unstructured ECG patient reports into a structured cloud-based database for advanced analysis.

Clinically significant characteristics, such as patient ID, age, sex, diagnosis, QRS peak count, and average ST segment values (in millivolts), were recorded using a well-crafted regular expression pattern. In order to ensure consistency in data formats, such as integers for discrete fields (sex, QRS peaks), floats for continuous values (age, ST-segment measures), and lists for multi-label diagnoses, each extracted record was standardized into a hierarchical dictionary. (Table 2, Fig. III)

Table 2: Dataset Parameters and its Sample Values

Field Name	Description	Sample Value
_id	Unique identifier for the record	6891930aa8557ffc9909abf7
patient_id	Patient's ID from the medical system	10008.0
age	Patient's age in years	22
sex	Patient's biological sex (1 = Male	(0 = Female,1=Male)
diagnosis	List of diagnosed conditions	"[Tachycardia]"
Lead	ECG lead used for measurement	I
qrs_peak_count	Number of QRS peaks detected in the ECG signal	13
average_st_segment_mV	Average ST segment voltage in millivolts	-0.093

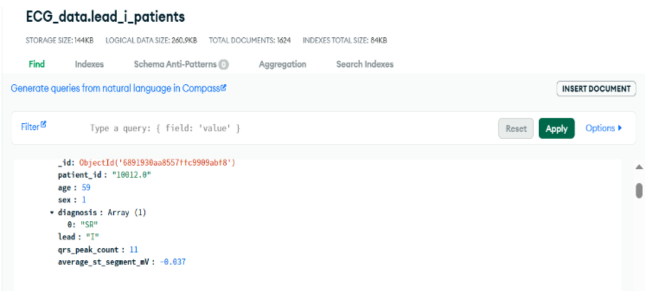


Figure III. Sample patient record inserted in Mongo Cloud

Following processing, the patient data was methodically added to the "lead_i_patients" collection of the MongoDB Atlas-hosted "ECG_data" database. This method eliminated human data entry errors while enabling effective large-scale storage and retrieval of ECG-related characteristics. The pipeline facilitates sophisticated data mining, anomaly detection, and predictive modelling activities by converting semi-structured PDF information into a queryable database that is prepared for machine learning.

3.3 Feature Overview & Their Respective Normal Values

A normal heart rate ranges between 60 and 100 beats per minute (bpm). Deviations from this range can indicate potential abnormalities—bradycardia if the rate is below 60 bpm, tachycardia if it exceeds 100 bpm, or arrhythmia if the spacing between QRS peaks is irregular, as seen in conditions like atrial fibrillation or ventricular tachycardia. In parallel, the ST segment represents the interval between ventricular depolarization and repolarization. A normal ST segment remains nearly isoelectric, typically within ±0.1 mV from the baseline. (Table. 3)

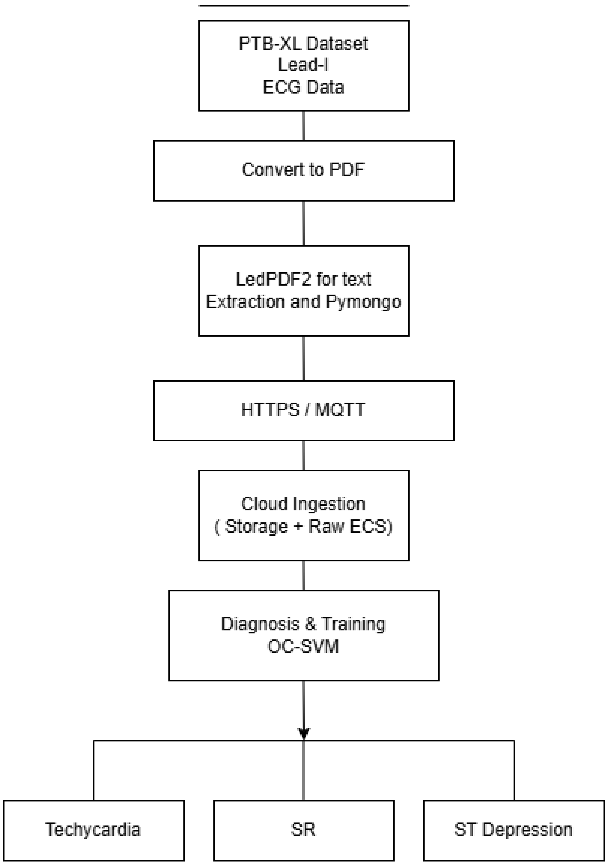
Table 3: Parameter Range Classification

Parameter	Normal Range	Clinical Significance if Abnormal
QRS Peak Count (Heart Rate)	60–100 beats per minute (bpm)	< 60 bpm: Bradycardia > 100 bpm: Tachycardia Irregular spacing: Possible arrhythmia
Average ST Segment (mV)	±0.1 mV from baseline	> +0.1 mV: Possible myocardial infarction or pericarditis < -0.1 mV: Possible myocardial ischemia

4. THE PROPOSED SYSTEM

(Flowchart 1)The initial step in the procedure is to transform the Lead-I ECG data from the PTB-XL dataset into PDF reports for every patient. These reports function as a platform for structured intermediates. Text-based data is then extracted from the PDF files using PyPDF2, and PyMongo incorporates the data into a MongoDB database for organized storage and effective retrieval.

Following the extraction of ECG characteristics and patient information, the data is transferred securely and in real-time over common communication protocols like HTTPS or MQTT, and it then flows into the cloud ingestion layer, where raw ECG signals and structured metadata are stored for analysis.



Flowchart 1: The Proposed System Architecture

Both the raw ECG signals and the extracted characteristics are saved in a scalable database for both short-term and long-term analysis when the data is received by an IoT ingestion service in the cloud and sent to MongoDB Atlas. Following storage, the system uses One-Class Support Vector Machine (OC-SVM), a machine learning method that is ideal for identifying anomalies in medical data, for diagnosis and training. The OC-SVM can recognize uncommon situations as anomalies because it is mainly trained on regular heartbeats and has learnt the typical ECG pattern. This analysis shows that the technology can automatically diagnose several heart conditions:

ST depression is when the average ST voltage shows a downward deviation, which can indicate ischemia or other cardiac disorders; sinus rhythm (SR) is when the QRS peaks are regular and the ST segment stays stable, reflecting a healthy heart rhythm; and tachycardia is when the QRS peak count indicates abnormally fast heartbeats. The system provides a strong, ongoing, and proactive way to monitor heart health and aid in clinical decision-making by fusing wearable sensors, mobile pre-processing, secure cloud storage, and clever machine learning.

After the processing and storing data on cloud, the next step begins by connecting to a MongoDB Atlas cloud database where ECG records are stored. Each record includes fields such as _id, patient_id, age, sex, diagnosis, lead, qrs_peak_count, and average_st_segment_mV. For example, one patient record might show:

{
 "_id": "6891930aa8557ffc9909abf7",
 "patient_id": "10008.0",
 "age": 22,
 "sex": 1,
 "diagnosis": ["Tachycardia"],
 "Lead": "I",
 "qrs_peak_count": 13,
 "average_st_segment_mV": -0.093
}

After retrieving all patient data from MongoDB, the script filters records with Sinus Rhythm (SR) as the training dataset, since One-Class SVM needs normal data to learn a baseline pattern.

4.1 Learning Models

The proposed system uses four features—age, sex, QRS peak count, and average ST-segment voltage—to represent both demographic information and ECG signal characteristics relevant for identifying sinus rhythm. Before training the model, all selected features are standardized using the StandardScaler. This step is necessary because the features exist on different numerical scales; for example, age and QRS peak count vary over large ranges compared to ST-segment voltage, which is measured in millivolts. Standardization transforms every feature to have zero mean and unit variance so that no single feature dominates the learning process simply because of its magnitude.

```
# === Standardize Data ===
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
```

To ensure all selected features contribute equally during model training, the dataset is standardized using the StandardScaler. This step computes the mean and standard deviation of each feature from the training data and then transforms the values so that every feature has zero mean and unit variance. The command scaler = StandardScaler() initializes the scaler, and X_train_scaled = scaler.fit_transform(X_train) applies the transformation to the training dataset. Standardization helps prevent features with larger numerical ranges—such as age or QRS peak count—from dominating those with smaller ranges, like ST-segment voltage, thereby improving the overall performance and stability of the One-Class SVM model.

```
# === Train One-Class SVM ===
svm = OneClassSVM(kernel="rbf", gamma="auto", nu=0.05)  # nu = expected % of anomalies
svm.fit(X_train_scaled)
```

One-Class SVM is trained only on normal ECG cases (Sinus Rhythm). It learns what “normal” looks like based on age, sex, QRS peak count, and average ST segment voltage**.**

- Before training, the selected features (age, sex, qrs_peak_count, average_st_segment_mV) are passed through StandardScaler**.**
- This ensures that all features have zero mean and unit variance, preventing features with larger ranges (like QRS counts) from dominating smaller ones (like ST segment voltage).
- Example: Heart rate may vary between 60–200, while ST segment voltage might vary only by millivolts. Without scaling, SVM would be biased toward the feature with larger values.

```
svm = OneClassSVM(kernel="rbf", gamma="auto", nu=0.05)
```

- kernel="rbf" → Uses the Radial Basis Function kernel, which captures non-linear patterns in ECG data.
- gamma="auto" → Sets gamma automatically based on the number of features. Gamma controls how far the influence of a single training example reaches.
- nu=0.05 → Sets the proportion of outliers expected in the training set. Here, the proposed system assume about **5% anomalies** in ECG data.

```
svm.fit(X_train_scaled)
```

- Only records with the label SR (Sinus Rhythm) are used to train the model.
- In the feature space, this enables the SVM to learn the "shape" of typical ECG patterns.
- The model may assess fresh data points following training:
  A point is categorized as Normal (1) if it is inside the learned border.
  A point is categorized as an anomaly (-1) if it is outside the boundary.

5. ANALYSIS AND RESULTS

In addition to vital ECG-derived parameters like average ST-segment voltage and QRS peak count, which are directly related to rhythm analysis and ischemia diagnosis, each record includes demographic data like patient age and sex. Demographic tendencies, such as whether tachycardia is more common in younger patients and ST depression is more common in elderly populations, can be the focus of an initial examination of the dataset.

Table 4: Collected Data

patient_id	age	sex	qrs_peak_count	average_st_	segment_mV	diagnosis
2	10016	83	1	14	-0.123	[Tachycardia, ST Depression]
4	1002	87	1	9	-0.094	[SR]
8	10030	23	1	8	-0.035	[SR]
12	1005	74	0	16	0.02	[Tachycardia]
24	1008	69	0	16	-0.083	[Tachycardia]
1596	11001	22	1	13	-0.008	[Tachycardia]
1600	11011	26	1	14	-0.123	[Tachycardia, ST Depression]

1618	11090	18	1	13	-0.048	[Tachycardia]
1620	11103	26	1	14	-0.016	[Tachycardia]
1623	11111	83	0	21	-0.041	[Tachycardia, Arrhythmia]

A subset of patient records that the One-Class SVM model identified as anomalies are shown in Table 3. These abnormalities, which differ from the typical sinus rhythm (SR) patterns utilized for model training, mostly comprise patients with tachycardia, ST depression, and arrhythmia. Features like average ST-segment mV values and QRS peak count are important markers for aberrant ECG patterns; variations from these metrics point to problems with heart function. To illustrate the range of age groups at risk for arrhythmias, patient ID 10016 (age 83) and patient ID 11011 (age 26) both displayed aberrant ST-segment depression in addition to tachycardia. These abnormalities highlight the model's capacity to spot minute but significant differences across patients, providing important information for the early diagnosis of heart disorders.

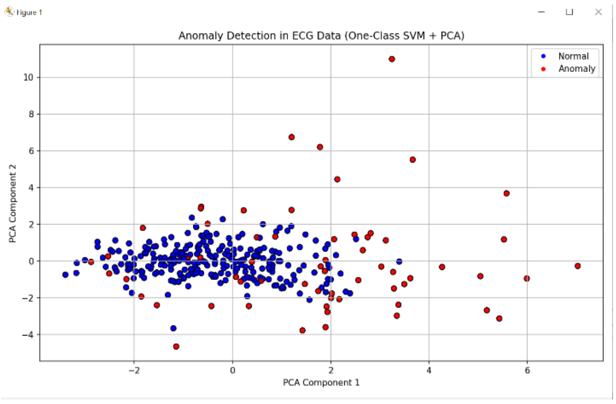


Figure IV. Anomaly Detection in ECG Scatter Plot

The findings of anomaly detection in ECG data using a One-Class Support Vector Machine (SVM) in conjunction with Principal Component Analysis (PCA) are displayed in the plot. While maintaining the majority of the data's variance, PCA simplifies the presentation of high-dimensional ECG characteristics by dividing them into two principle components. Normal ECG signals are shown by blue points in this figure, while anomalies are denoted by red points. To identify the border defining typical cardiac rhythms, the One-Class SVM model is trained mostly on normal ECG data. An anomaly is defined as any data point that deviates from this learned boundary.

These anomalies can include conditions that produce aberrations in ECG waveform aspects such as heart rate, QRS complex, or ST segment levels, such as arrhythmia, tachycardia, bradycardia, or ST-segment depression or elevation. By examining changes in the input ECG feature values and identifying those that deviate noticeably from the typical pattern, the model detects such anomalies.(Fig. IV) As can be seen from the plot, the system successfully separates abnormal cardiac signals from normal ones based on their deviation in the feature space, with normal samples clustering firmly in the center and anomalies dispersed around the periphery.

- Accuracy = 81.22%

The model recognizes normal ECG more reliably.

True positives (detected abnormal samples) also increased significantly.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$

$$Accuracy = ((785 + 534)) / (785 + 534 + 262 + 43)$$

$$= 1319 / 1624$$
$$= 0.8122 \approx 81.22\%$$

The model achieved an accuracy of 81.22%, indicating that it correctly identified the majority of ECG samples in the dataset. This demonstrates a strong overall classification performance after training the One-Class SVM exclusively on normal (SR) data.

- Precision = 0.750 (75%)

Precision= TP/ TP + FP

Precision = 785 / 785+262

= 785/1047
= 0.75

The precision of 0.75 indicates that 75% of the samples the model classified as normal (SR) were actually correct. This shows that the model is reasonably reliable in avoiding false positives when predicting normal ECG signals.

6. CONCLUSION

Using cloud integration and machine learning, the suggested solution offers a clever and effective framework for automated ECG signal analysis and anomaly detection. The PTB-XL Lead-I ECG dataset is used by the system to guarantee accurate input data for analysis. Data management and storage in MongoDB are made possible by the translation of ECG data into PDF format, text extraction using LeaPDF2, and interface with PyMongo. Data transport to the cloud is safe and dependable when secure transmission protocols like HTTPS and MQTT are used. Healthcare applications by integrating anomaly detection, data processing, and storage into a single, automated system. The One-Class SVM (OC-SVM) algorithm efficiently detects and categorizes ECG patterns into tachycardia, sinus rhythm (SR), and ST depression, while cloud ingestion enables scalable data storage and model training.

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