

Enhancement of Sparse Spasmodic Sampling using Novel Machine Learning Fusion Technique

Umesh Mahind*, Deepak Karia**(C.A.), Vijay Kapure*** and Sankit Kassa****

Abstract: This research explores the demands of compressive sensing (CS) and Machine learning (ML) in biomedical signal processing. The sparse spasmodic sampling (SSS) technique has gained significant attention in compressive sensing. The SSS samples the signal irregularly and spasmodically. Combining machine learning (ML) with Sparse Spasmodic Sampling (SSS) enhances accuracy and improves anomaly detection in biomedical signals. We propose a machine learning-based novel fusion technique that enhances sparse spasmodic sampling (ML-SSS). Mathematical analysis, extensive simulations, and experimental results show notable improvements in reconstruction accuracy and precision. The reconstruction using the proposed model achieves a high signal-to-noise ratio (SNR) of up to 42 dB at a high compression factor of 10%. The achieved accuracy is approximately 95%, and the precision is about 93.3% when detecting abnormalities. This approach paves the way for advanced applications in signal processing and medical imaging, where efficient data acquisition and processing are critical. The proposed framework offers a promising direction for bridging the gap between compressive sensing and intelligent algorithms in anomaly detection.

Keywords: Compressive Sensing, Electrocardiogram (ECG), Sparse Spasmodic Sampling, Machine Learning, Anomaly Detection, Fusion Technique.

1 Introduction

In the biomedical domain, Electrocardiography (ECG) is a crucial monitoring tool which provides essential insights into cardiac health. In ECG signals, there are three different stages: P wave, QRS complex,

and T segment, which represent atrial contraction, ventricular contraction, and relaxation [1], [2]. From the morphological features of the ECG, the detection of various cardiac conditions, including heart blocks, is possible, as shown in Table 1.

Table 1. Morphological features in normal ECG.

Characteristics	Amplitude (mV)	Duration (sec)
P	0.25	0.11
R	1.6	-
Q	0.4	0.03
T	0.1-0.5	0.16
S	1.8-3	
PP	-	0.6 - 1.04
PR	-	0.12 - 0.2
QT	-	0.35 – 44
ST	-	0.05 - 0.15
QRS	1	0.08 - 0.1
RR	-	0.6 - 1.2

Iranian Journal of Electrical & Electronic Engineering, 2026.
Paper first received 10 Jan. 2025 and accepted 06 Aug. 2025.

* The author is with the Electronics Engineering Department, Sardar Patel Institute of Technology, Mumbai - 400058, India.
E-mail: umahind10@gmail.com

** The author is with the Electronics and Telecommunication Engineering Department, Sardar Patel Institute of Technology, Mumbai - 400058, India

E-mails: deepak_karia@spit.ac.in

Corresponding Author: Deepak Karia.

*** The author is with the Applied Sciences and Humanities Department, Xavier Institute of Engineering, Mumbai - 400016, India

E-mails: vijaykapure777@gmail.com

**** The author is with the Electronics and Telecommunication Engineering Department, Symbiosis Institute of Technology, Symbiosis International Deemed University, Pune - 412115, India
E-mails: sankit.kassa@sitpune.edu.in

Heart block is a cardiac conduction disorder classified into three types: first-degree, second-degree, and third-degree [3], [4], [5]. ECG analysis of these blocks facilitates the early detection of conditions such as heart failure or cardiac arrest.

In the first-degree block, the PR interval exceeds 0.2 seconds, but conduction to the ventricles remains intact. It is often benign and requires no treatment. The second-degree block involves intermittent failure of ventricular conduction, seen as dropped QRS complexes. It includes: Mobitz I (Wenckebach): Gradual PR prolongation followed by a missed QRS. Mobitz II: Constant PR intervals with sudden QRS drops. 2:1 or 3:1 conduction: One or two missed QRS complexes after regular cycles. The third-degree block shows complete AV dissociation. P waves and QRS complexes occur independently, with a slow but regular rhythm maintained by a junctional or ventricular pacemaker [2].

In all types, R-R interval patterns reflect disrupted atrioventricular conduction: regular but prolonged in first-degree, irregular in second-degree, and regular but slow in third-degree blocks.

Recent advances in signal processing and computing have improved ECG analysis. Detecting heart block is now more accurate. New methods enable the detection of more precise abnormality detection [1]. Recent studies have focused on utilising advanced techniques, such as compressive sensing (CS) and machine learning (ML), to enhance ECG acquisition, noise reduction, feature extraction, and interpretation. CS is particularly useful in addressing limitations in resource-constrained settings and strengthening overall performance [6].

Nowadays, researchers are focusing on applying compressed sensing techniques to biomedical signals. Compressive Sensing (CS) has evolved as a crucial signal-processing technique [6], [7], [8], [9], [10], [11]. The CS enables the acquisition and reconstruction of sparse signals using fewer samples than the traditional Nyquist-Shannon sampling theorem.

Compressed sensing (CS) exploits the sparsity of signals in certain transformed domains. At the receiver end, CS uses mathematical models to reconstruct the original signal [12], [13], [14], [15], [16]. This framework is widely applied in biomedical signal acquisition, reconstruction, feature extraction, and classification. CS helps overcome significant challenges by enabling faster signal acquisition, higher accuracy, and better energy efficiency [17], [18], [19], [20], [21], [22], [23], [24], [25], [26].

Recent advances in compressive sensing (CS) use machine learning (ML) to boost signal reconstruction, robustness, and efficiency. ML-based sparse representation learning also improves resistance to noise

and outliers. However, challenges in generalization and computational efficiency remain, necessitating hybrid approaches for broader applicability [27], [28], [29], [30], [31]. This paper focuses on the use of machine learning (ML) enhanced sparse spasmodic sampling (SSS). The SSS samples the sparse signal irregularly.

Additionally, ML has excellent potential in handling sparse, noisy, and irregular data. These models are capable of learning basic patterns from the data and help identify abnormalities. The ML-based SSS can overcome the traditional signal reconstruction methods.

The remainder of the paper is organized as follows. Section 2 proposed a novel ML-enhanced Sparse Spasmodic sampling technique. Section 3 has the experimental results of the proposed algorithm on ECG signal. The paper concluded in section 4.

2 ML-enhanced sparse spasmodic sampling (ML-SSS)

Compressive Sensing (CS) is a signal processing technique that enables the acquisition and reconstruction of sparse signals using compressed samples [21], [22], [23], [24]. Sparse Spasmodic Sampling (SSS) is a compressive sensing-based technique used in signal processing. It samples the signal intermittently using sparsity criteria, which lowers the number of samples needed for accurate reconstruction. This method is particularly beneficial in applications such as wireless sensor networks and medical devices.

Sparse Spasmodic Sampling (SSS) focuses on irregularly spaced sampling intervals. This unique strategy differentiates it from non-uniform sampling and random sampling techniques. It samples the data intelligently whenever a zero-to-non-zero component occurs or vice versa. Hence, the SSS technique does not miss the non-zero elements in the sparse signal, which is not possible in non-uniform or random sampling techniques [23], [24]. It concentrates on capturing significant signal features at selected time points. The SSS has shown promise in various domains, including biomedical, communications and sensor networks. The main advantage of SSS is its ability to reconstruct signals with minimal data, reducing storage and transmission costs. It is especially effective when the signal is sparse, with most of the information concentrated in a few components. The detailed steps of the algorithm are outlined below in Algorithm 1.

The flowchart in Fig. 1 illustrates the sparse spasmodic sampling process. The process begins with the initialisation of input data, followed by normalisation and quantisation. Further, it checks for availability for further processing. The level detection compares previously stored data with current data. Based on this comparison, it stores the samples irregularly. The process continues until it meets a specific stopping

condition, at which point it terminates. This structured approach enables data to be processed iteratively.

Algorithm 1: Sparse Spasmodic Sampling (SSS)

Input:

- x: input data sample

Output:

- y: measurement vector

Steps:

1. Store the starting point and its index position
2. Check the next value which differs from the first value (if the starting point is 0, then store the next value if it is '1' and vice versa)
3. If the next value is stored, then store its index position.
4. Continues until transitions occur from 0 to 1 and 1 to 0; otherwise, skip points.
5. Store all the sampled points till the last value occurred.
6. Store the last value as sampled points
7. Return y

In various fields, such as healthcare, anomaly detection is a crucial task. To identify anomalies, it is essential to identify irregular patterns in data. Researchers have proposed various anomaly detection algorithms, including DBSCAN [28], hierarchical clustering [29], K-means and SVD [4], Isolation Forest [32], and Local Outlier Factor [33], [34], [35], [36], [37].

Clustering-based methods, such as K-Means, are effective for grouping data into regular patterns. However, it may be difficult for them to detect high-dimensional outliers. The Isolation Forest (IF) identifies anomalies by measuring the separation between data points. The Isolation Forest (IF) is a tree-based model that identifies global anomalies but struggles to capture local variations in the data. Density-based techniques, such as Local Outlier Factor (LOF), are susceptible to parameter tuning; hence, large datasets may result in inefficient scaling. The comparison of traditional Anomaly detection ML algorithms is given in Table 2.

Where, n is number of data points, k is number of clusters, d is dimensionality, i is number of iterations, t is number of trees, ψ is subsample size (typically $\psi \ll n$)

Table 2. Comparison of Traditional Anomaly detection ML Algorithm

Approach	Time Complexity	Space Complexity	Pros	Cons
k-mean Clustering	$O(n.k.d.i)$	$O(n.d + k.d)$	Fast, Simple	Assumes Spherical clusters
Isolation Forest	$O(t.\psi.\log(\psi))$	$O(t.\psi)$	Scalable	Random Sampling
Local Outlier Factor	$O(n^2)$	$O(n)$	Local sensitivity	Expensive for large data

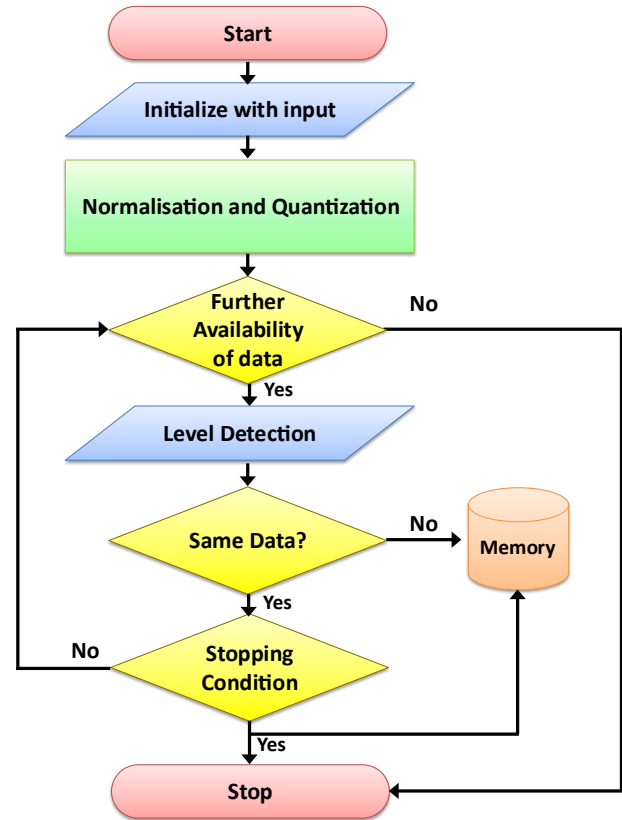


Fig 1. Flow chart of Sparse Spasmodic Sampling

This paper proposes a novel fusion-based approach that combines K-Means, Isolation Forest (IF), and Local Outlier Factor (LOF). This fusion technique helps to detect anomalies. The fusion technique addresses all the limitations of the individual algorithms. Machine learning can effectively handle sparse, noisy, and irregular data. Learning underlying patterns can improve sparse signal reconstruction. The detailed steps of the algorithm are outlined in Algorithm 2 below. The flowchart in Fig. 2 outlines the steps for detecting

anomalies in ECG signals using a fusion-based algorithm. It begins with sampled data from the SSS technique. It calculates the R-R interval and labels it as normal or abnormal. Then, a fusion-based algorithm is applied to detect anomalies from R-R intervals.

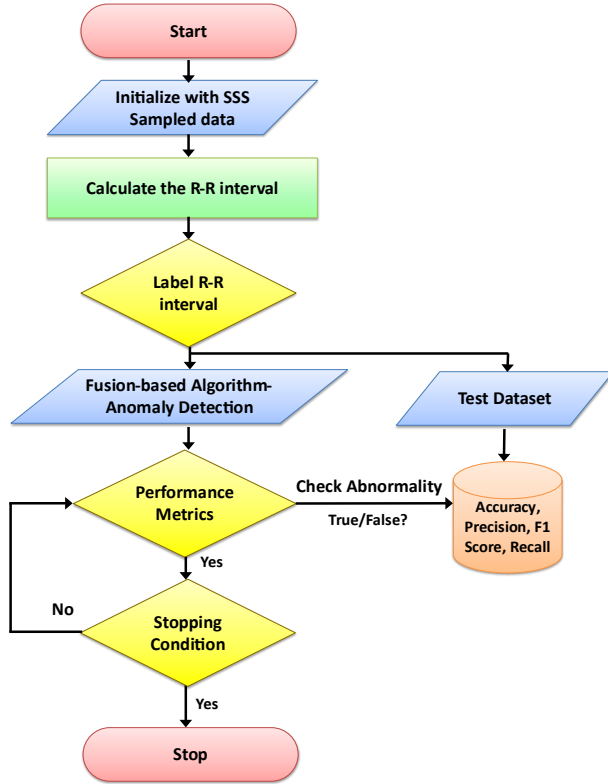


Fig 2. Flow chart of Fusion-based anomaly detection

Algorithm 2: Fusion-based anomaly detection algorithm (ML- SSS)

Input:

- y: measurement vector

Output:

- x: input data sample
- Abnormalities

Steps:

1. Initialise with measurement vector
 2. Calculate RR interval at each occurrence
 3. Label RR interval as normal or abnormal interval
 4. The fusion technique detects abnormal RR intervals from the SSS output.
 5. Returns x with abnormalities
-

An ECG signal $x \in R^N$ is sparse in its time domain, has only $k \ll N$ where k is the number of non-zero coefficients and N is the total measurements, as in Eq. (1).

$$[n] \dots n = 1, 2, 3 \dots N \quad (1)$$

Using the SSS technique, compressed samples were achieved as in Eq. (2)

$$x_{SSS}(i) : \text{where } i \in \text{non-uniform} \quad (2)$$

and sparse indices

The sparse signal x have k non-zero elements. Then, the signal can be equivalently represented as a pair of vectors, as in Eq. (3):

$$x_i = \begin{cases} x', & \text{compressed samples} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Compressed Samples (x') as

$$x' = [0, x_{i1}, 0, x_{i3}, 0, \dots]$$

Support set (index position of sampled values)

$$i = [i_0, i_1, i_2, i_3, i_4, i_5, \dots]$$

The sensing process is incoherent in CS. The measurement vector y sparsely represents the x using the sensing metric ϕ [22], as in Eq. (4).

$$y = \phi x \quad (4)$$

The SSS detects the R-peaks from the ECG signal which further process with the Vandermonde sensing matrix [24]. The sparse signal can be reconstructed by placing the values from x' at the positions specified in i , and setting all other positions to zero.

For example, if sparse signal x_i

$$x_i = [0, 0, 0, 1, 0, 0, 1, 0, 0, 0]$$

$$x'_1 = \begin{cases} 1, & \text{if row } i \text{ in } y_{inner} \text{ has non-zero element} \\ 0, & \text{otherwise} \end{cases}$$

$$x'_1 = [any(y_{inner}[i, :] \neq 0)]_{i=1}^5$$

Vectorized as

$$x'_1 = \left(\sum_{i=1}^5 |y_{ij}| > 0 \right) \forall i \in \{0, \dots, 5\}$$

$$x' = [0, 1, 0, 1, 0, 0]$$

Support set (i) is

$$i = [0, 3, 4, 6, 7, 9]$$

In the Compressive sensing-based novel Sparse Spasmodic Sampling (SSS) reconstruction approach, the reconstruction of the ECG signal is accurately possible due to the Vandermonde sensing matrix. The measurement vector y can be reconstructed by multiplying the index locations of non-zero components with the Vandermonde matrix of compressed sampled components (x') from x , as in Eq. (5).

$$y = V(x') * i \quad (5)$$

For mathematical calculation, we can derive $V(x')$, as in Eq. (6)

$$V_{m,n} = \begin{bmatrix} 1 & x_1 & x_1^2 & \dots & x_1^n \\ 1 & x_2 & x_2^2 & \dots & x_2^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & x_n^2 & \dots & x_n^n \end{bmatrix} \quad (6)$$

For above example, $V(x')$ can derived as

$$V(x') = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$y = V(x') * i = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 9 \\ 0 & 3 & 4 & 6 & 7 & 9 \\ 0 & 0 & 0 & 0 & 0 & 9 \\ 0 & 3 & 4 & 6 & 7 & 9 \\ 0 & 0 & 0 & 0 & 0 & 9 \\ 0 & 0 & 0 & 0 & 0 & 9 \end{bmatrix}$$

While reconstructing x' and i from above equation is with inner vector and binary vector

$$y_{inner} = y[:,1:5] \\ y_{inner} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 3 & 4 & 6 & 7 \\ 0 & 0 & 0 & 0 \\ 3 & 4 & 6 & 7 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

We want a binary vector $x' \in \{0, 1\}^5$ where:

$$x'_1 = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

The indicator function $1_{(\cdot)}$ Is

$$x'_i = 1_{(\sum_{i=1}^5 |y_{ij}| > 0)}$$

The support set is

$$supp(x) = \{i \in \{0, 1, \dots, n-1\} \mid x_i \neq 0\}$$

In vector form,

$$supp(x) = indices(x \neq 0)$$

The derived equation for the support vector for the vector length n is as in Eq. (7)

$$supp(x) = \{i \in \mathbb{Z} \mid x_i \neq 0, 0 \leq i < n\} \quad (7)$$

For above example,

$$supp(x) = \{0, 3, 4, 6, 7, 9\}$$

Using zero interpolation method, indicator function can extend with unknown value with zero. SSS yields near-optimal performance as the signal characteristics remain consistent. Sparse data is often sufficient for accurate interpolation and detection. Sampling does not amplify noise or cause loss. Adaptive Vandermonde matrix calculation repetitively preserves data in its columns and rows. Hence, the impact of noise is very low. However, SSS is inherently well-suited for any sparse signal. It is less affected by noise because it focuses on capturing only the most informative portions of the data. This selective sampling approach reduces redundancy while preserving key features. As a result, SSS offers a robust and efficient method for signal acquisition and processing.

Compressed Sensing (CS) traditionally employs random sampling (e.g., Gaussian or Bernoulli measurement matrices) to ensure incoherence between the sampling basis and the sparsity basis, which is critical for accurate signal recovery. However, for real-world sparse signals, particularly those that are structured, event-driven, or physiological, irregular sampling often provides distinct advantages. Then, the sampling rate (R_s) is defined as in Eq. (8):

$$R_s = \frac{\text{Number of Samples Taken}}{\text{Total length of original signal}} \times 100\%$$

$$R_s = \frac{M}{N} \times 100\% \quad (8)$$

A comparison of state-of-the-art compressive sensing reconstruction algorithms is presented in Table 3, which shows dominance of Sparse Spasmodic Sampling (SSS) over other approaches for sparse signals.

Table 3. Comparison of Compressive Sensing Reconstruction Algorithms

Algorithm	Computational Complexity	Measurement Number	Sampling Rate (M/N)
OMP	$\mathcal{O}(kmn)$	$\mathcal{O}(k \log(n))$	13.3%
CoSaMP	$\mathcal{O}(mn)$	$\mathcal{O}(k \log(n))$	16.6%
IHT	$\mathcal{O}(mn)$	$\mathcal{O}(k \log(n/k))$	20.1%
SSS	$\mathcal{O}(m)$	$\mathcal{O}(k)$	10%

The motivation for combining these algorithms lies in their complementary strengths. Hence, using SSS, sparse signal acquisition and reconstruction can be performed accurately.

For experimentation purposes, data from patient record 232 in the MIT-BIH database have been selected, along with the associated abnormality label.

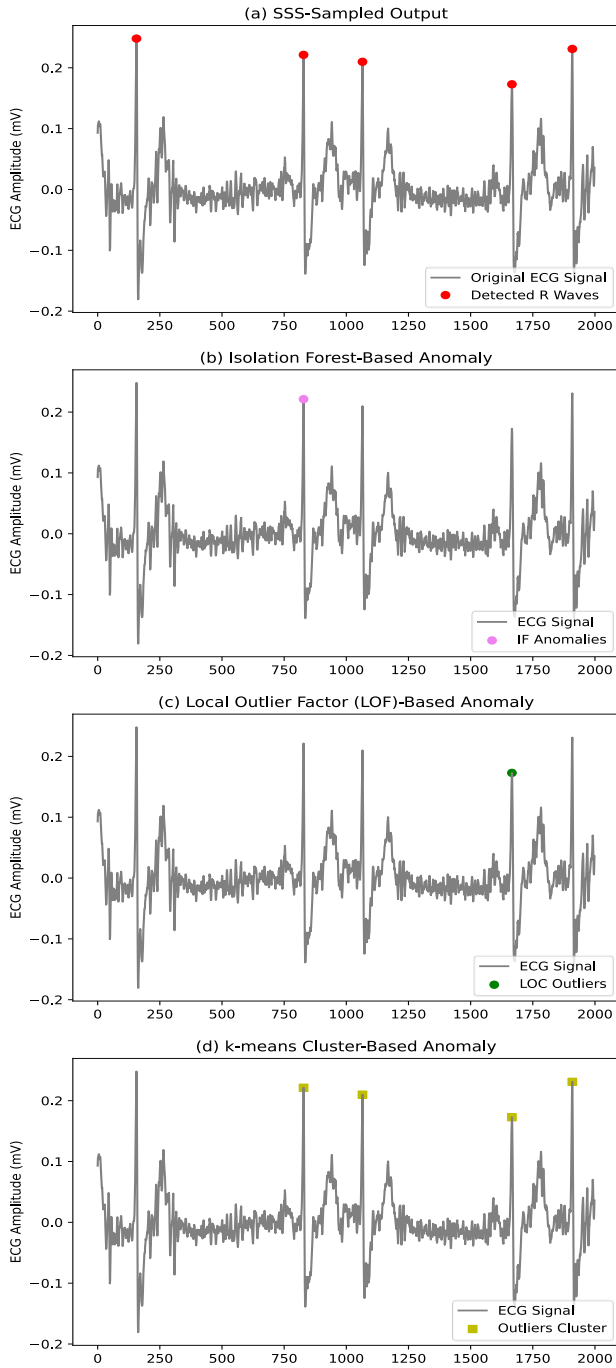


Fig 3. (a) SSS-Sampled Output, (b) Isolation Forest-Based Anomaly, (c) Local Outlier Factor (LOF)-Based Anomaly, (d) k-means Cluster-Based Anomaly

In this example, the total number of data points (N) is 2000, and the number of non-zero components (k), after normalising the data. Using the SSS sampling technique, sampled points are in the range of $(2k+2)$, as shown in Fig. 3(a).

The k-means clustering, isolation forest, and local outlier factor models were used to detect anomalies in the ECG signal. Using the label and predicted data, the calculated performance of the individual model is not highly accurate, as there are a smaller number of True positive cases and more false negative cases, as shown in Fig. 3 (b), (c), and (d). The same signal was tested with the fusion technique. Therefore, in the presence of such abnormal data, a novel fusion technique can detect the abnormality more accurately, as tabulated in Table 4.

Table 4. Performance Comparison of Anomaly Detection Approaches

Approach	True Positive	True Negative	False Positive	False Negative
k-mean Clustering	87	380	0	27
Isolation Forest	24	378	2	90
Local Outlier Factor	36	372	8	72
Fusion Technique	96	372	7	18

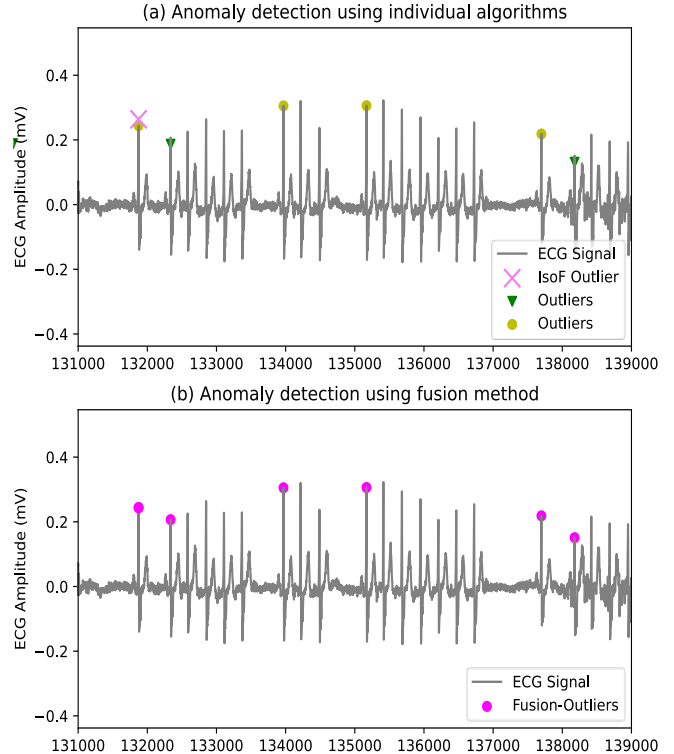


Fig 4. (a) Anomaly detection using individual algorithms, (b) Anomaly detection using fusion method.

Fig. 4(a) illustrates the anomaly detection capabilities of individual state-of-the-art algorithms, clearly highlighting their pros and cons. None of the algorithms gives highly accurate anomaly prediction. In Fig. 4(b), the anomaly detection using the proposed fusion-based algorithm is illustrated.

3 Experimental Results

The proposed ML-enhanced Sparse Sampling technique was tested on ECG signals using the MIT-BIH Arrhythmia database. Experiments were conducted in a Python environment using standard biomedical formats from PhysioNet. The ML-SSS model supports modular design and integrates well with Python-based signal processing tools. The Python-based simulation was implemented using libraries like NumPy for data manipulation, SciPy for signal processing, and Matplotlib for result visualisation. The ECG signals were preprocessed to normalise amplitude and remove noise, ensuring consistency across tests. The random data frame of patient record 232 is used, which has multiple abnormalities. All experiments were conducted on a standard computational setup, and results were averaged over multiple iterations for reliability and statistical significance. Fig. 5 and Fig. 6 show that the detected R-peak from the SSS technique is further classified as normal and abnormal signals for samples 1 and 2, respectively. The abnormalities are highlighted with high accuracy by the fusion outlier. In both figures, a different set of data is used.

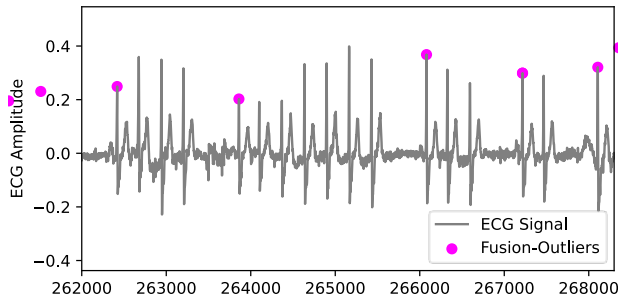


Fig 5. Fusion Technique based Anomaly - Sample 1

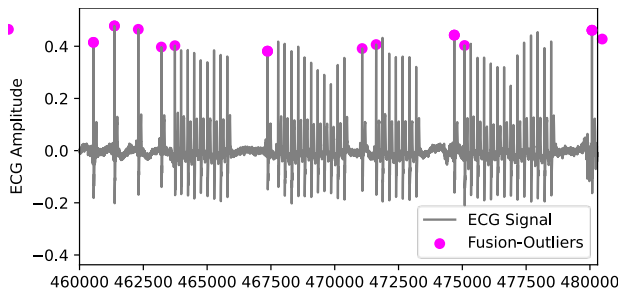


Fig 6. Fusion Technique based Anomaly- Sample 2

Accuracy, precision, recall, and F1 score are essential performance metrics used to evaluate the effectiveness of models. To evaluate the performance of the proposed algorithm, the label data of abnormal ECG signals is used. Using labelled data, the detected anomalies from the proposed algorithm have been tested and validated.

Accuracy measures the proportion of correctly predicted instances out of the total instances, as given in Eq. (9). It gives an overall view of model performance, but can be misleading when dealing with imbalanced datasets.

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{Total\ Instances\ (TP + TN + FP + FN)} \quad (9)$$

Precision measures how many of the predicted positive instances are actual positive, as given in Eq. (10). High precision indicates fewer false positives, which is crucial in medical diagnosis applications.

$$Precision = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Positive\ (FP)} \quad (10)$$

Recall (also known as Sensitivity or True Positive Rate (TPR)) measures the percentage of actual positive instances that were correctly predicted, as given in Eq. (11). High recall is essential in cases where missing positive instances (false negatives) are costly in biomedical applications.

$$Recall = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Negative\ (FN)} \quad (11)$$

The F1 score is the harmonic mean of precision and recall, providing a balanced measure when there is an uneven class distribution, as given in Eq. (12). It is especially useful when precision and recall are in conflict, allowing for a balanced trade-off between the two.

$$F1\ score = 2 * \frac{Precision * Sensitivity}{Precision + Sensitivity} \quad (12)$$

The comparison of the individual model with the fusion technique depicts that the overall accuracy, precision, F1 score and Sensitivity have increased as given in Fig. 7 and Table 5. Among all performance metrics, the fusion technique outperformed the others in the three metrics when compared with k-means, Isolation Forest, and Local Outlier Factor. The precision is better than that of the isolation forest and local outlier factor. Additionally, accuracy, F1 score, and Sensitivity are higher than those of the other algorithms. Hence, the Fusion technique is a more promising technique than the other existing algorithms.

To quantify the uncertainty in our performance metrics, we report 95% confidence intervals (CIs) for accuracy, precision, recall, and F1-score. A confidence interval provides a range within which the actual population parameter (e.g., the accuracy of a model) is likely to lie. Specifically, a 95% confidence interval means that if the experiment were repeated many times under the same conditions, approximately 95% of those intervals would contain the True mean value.

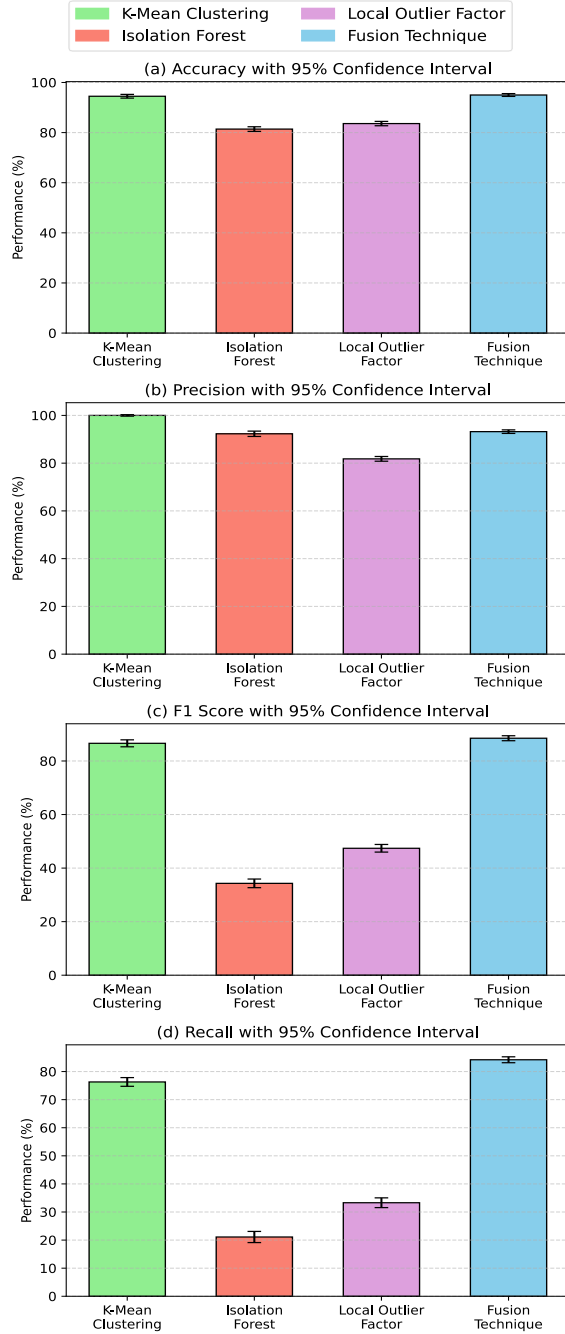


Fig 7. Comparison of Anomaly Detection Methods with Confidence Interval 95% (a) Accuracy, (b) Precision, (c) F1 Score, (d) Recall

The confidence intervals (CI) are calculated using Eq. (13).

$$CI = \bar{x} \pm z \frac{\sigma}{\sqrt{n}} \quad (13)$$

$$CI = \bar{x} \pm 1.96 \frac{\sigma}{\sqrt{n}}$$

where $\bar{x}$ is the sample mean, σ is the sample standard deviation, and n is the number of runs (for 95% Confidence interval, $z=1.96$ and $n=10$ for experimentation count). This statistical measure helps assess the reliability and consistency of our model's performance across different runs, as shown in Fig. 7.

Table 5. Confusion Matrix table for different Algorithms

Approach	Accuracy (95% CI)	Precision (95% CI)	F1 Score (95% CI)	Recall (95% CI)
k-mean Clustering	94.5% (93.7-95.2%)	100% (99.6-100%)	86.6% (85.3-87.9%)	76.3% (74.7-77.8%)
Isolation Forest	81.4% (80.4-82.3%)	92.3% (91.1-93.4%)	34.3% (32.6-35.9%)	21.1% (19.1-23.1%)
Local Outlier Factor	83.6% (82.7-84.4%)	81.8% (80.8-82.8%)	47.4% (45.9-48.8%)	33.3% (31.5-35.0%)
Fusion Technique	95% (94.4-95.5%)	93.2% (92.4-93.9%)	88.5% (87.5-89.4%)	84.2% (83.1-85.2%)

As shown in Fig. 8, the proposed fusion technique for anomaly detection achieved a high Area Under the Curve (AUC) score of 0.91. It indicates robust performance in distinguishing anomalies from normal data. This result demonstrates the effectiveness of the method in maintaining a strong balance between the True Positive Rate (TPR) and False Positive Rate (FPR) across various thresholds. The AUC reflects the model's ability to detect anomalies while minimising false alarms accurately.

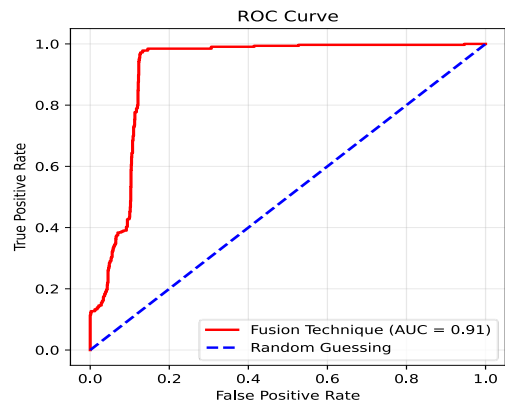


Fig 8. ROC Curve for Fusion technique

In extended experiments, the ML-SSS algorithm was applied to a randomly selected sparse ECG signal and compared with state-of-the-art methods, such as Compressive Sampling Matching Pursuit (CoSaMP) and Adaptive Reduced-Set Matching Pursuit (ARMP) [36]. In this experiment, we evaluated computational complexity, signal-to-noise ratio (SNR), compression factor (M/N), and reconstruction time.

As shown in Table 4, both ML-SSS and ARMP have a computational complexity of (M) , which is lower than that of CoSaMP. ML-SSS achieves the highest SNR of 42 dB, outperforming both ARMP and CoSaMP. It also operates at the highest compression ratio of 10%, while ARMP and CoSaMP operate at 25% and 50%, respectively. ML-SSS delivers faster reconstruction and better overall performance, making it the most efficient method. A summary of performance metrics is provided in Table 6.

Table 6. Comparison of performance metrics of different algorithms

Algorithms	Computational Complexity	SNR (dB)	Compression (M/N)	Reconstruction Time (s)
CoSaMP	$O(MN)$	35	50%	2.65
ARMP	$O(M)$	35	25%	0.06
ML-SSS	$O(M)$	42	10%	0.05

Fig. 9 shows that the SNR for ARMP and CoSaMP improves as the compression rate decreases. This indicates that the reconstructed signal contains minimal noise at lower compression. In contrast, ML-SSS maintains a high SNR across both low and high compression ratios, demonstrating its robustness and efficiency.

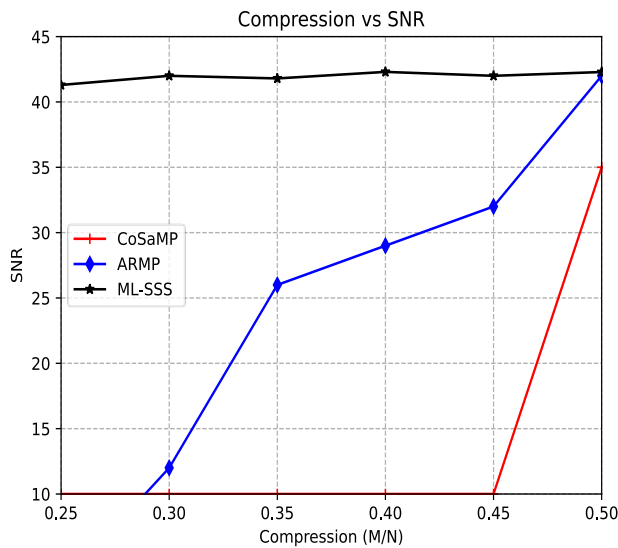


Fig 9. Algorithm Comparison: Compression vs. SNR

4 Conclusion

This research introduces a novel Sparse Spasmodic Sampling (SSS) framework integrated with a fusion-based machine learning (ML) approach, referred to as ML-SSS. The framework combines sparse sampling with adaptive learning to enhance signal reconstruction and anomaly detection. It demonstrates clear improvements over existing compressive sensing methods.

ML-SSS achieves accurate signal recovery with just a 10% sampling rate, outperforming baseline techniques by 5–10% in both accuracy and efficiency. It also requires fewer measurements than traditional methods, such as OMP, CoSaMP, and IHT, with computational complexities of $O(m)$ and $O(k)$, respectively.

The method achieves high performance in both reconstruction and anomaly detection tasks. The model achieves 95% accuracy, 93.3% precision, and an AUC of 0.91 in the experiments so far. It consistently maintains a high signal-to-noise ratio (SNR) of 42 dB across various compression levels, ensuring robust signal quality. With its low reconstruction time and reduced computational load, the method proves to be efficient and suitable for real-world applications.

The results of our research demonstrate significant advancements in reconstruction quality, making the ML-SSS framework highly suitable for real-world sparse signal processing applications. While the model was primarily trained and tested on ECG signals, its design is not inherently limited to this data type. The study lays the groundwork for applying the ML-SSS framework to a wide range of biomedical time-series signals, including EEG, EMG, and respiratory data. The promising results, however, call for further experimental validation to ensure the generalizability of the framework to these diverse signals.

While the ML-SSS technique performs well on benchmark datasets, such as MIT-BIH, clinical implementation presents several challenges that remain for clinical deployment. Real-world data is often noisy and varies across patients. The model must be validated on diverse populations and environments. Resource-limited clinical systems need optimised real-time processing. Regulatory compliance and data privacy must be ensured.

In this research paper, we show the clinical value of the ML-SSS framework. However, successful adoption into clinical practice requires clinician trust and model interpretability. Ensuring model interpretability is a crucial aspect of our ongoing research.

The model's focus on ECG signals may limit its immediate applicability to other types of biomedical signals. For real-time clinical use, API development and

performance optimization may be required. Integration must also meet medical device standards and ensure interoperability with existing healthcare systems. The approach still needs testing under noisy, variable, or real-world conditions to confirm its robustness. Its computational framework is also not yet validated for real-time use on limited-resource devices. Real-time clinical deployment will need API development and system optimization. Integration must also meet medical regulations and interoperability standards.

Future research should improve sparse signal reconstruction and enable real-time use on low-resource devices. Enhancing robustness under noisy and dynamic conditions is also necessary. Integrating sparse sampling with multimodal data fusion may improve diagnostic accuracy. Utilizing deep learning and explainable AI can enhance anomaly detection by improving precision and interpretability. Beyond biomedical applications, extending the framework to environmental, industrial, and financial time series is a promising prospect.

References

- [1] Philip de Chazal, M. O'Dwyer and R. B. Reilly, "Automatic classification of heartbeats using ECG morphology and heartbeat interval features," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 7, pp. 1196-1206, July 2004.
- [2] Anbalagan, T., Nath, M. K., Vijayalakshmi, D., and Anbalagan, A., "Analysis of various techniques for ECG signal in healthcare, past, present, and future" *Biomedical Engineering Advances*, 6: 100089, Nov. 2023
- [3] Sahoo, S., M. Dash, S. Behera, and S. Sabut, "Machine learning approach to detect cardiac arrhythmias in ECG signals: A survey" *Irbm* 41.4 : 185-194, 2020
- [4] Prakash, Allam Jaya, Saunak Samantray, CH Laxmi Bala, and Y. V. Narayana, "An automated diagnosis system for cardiac arrhythmia classification." *Analysis of Medical Modalities for Improved Diagnosis in Modern Healthcare*, CRC Press, pp 301-313, 2021.
- [5] Jayawardhana, Madhuka, Xinqun Zhu, Ranjith Liyanapathirana, and Upul Gunawardana, "Compressive sensing for efficient health monitoring and effective damage detection of structures," *Mechanical Systems and Signal Processing*, vol. 84, pp. 414-430, 2017.
- [6] Balouchestani, Mohammadreza, and Sridhar Krishnan, "Fast clustering algorithm for large ECG data sets based on CS theory in combination with PCA and K-NN methods." *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, 2014.
- [7] Zhang, Zhimin, Xinwen Liu, Shoushui Wei, Hongping Gan, Feifei Liu, Yuwen Li, Chengyu Liu, and Feng Liu, "Electrocardiogram reconstruction based on compressed sensing," *IEEE Access*, vol. 7, pp. 37228-37237, 2019
- [8] Dias, Felipe Meneguitti, Mahdi Khosravy, Thales Wulfert Cabral, Henrique Luis Moreira Monteiro, Luciano Manhaes de Andrade Filho, Leonardo de Mello Honório, Rayen Naji, and Carlos A. Duque, "Compressive sensing of electrocardiogram." *Compressive sensing in healthcare*, pp. 165-184. Academic Press, 2020.
- [9] L. F. Polanía, R. E. Carrillo, M. Blanco-Velasco, and K. E. Barner, "Exploiting prior knowledge in compressed sensing wireless ECG systems," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 2, pp. 508-519, Mar. 2015
- [10] M. M. Abo-Zahhad, A. I. Hussein, and A. M. Mohamed, "Compression of ECG signal based on compressive sensing and the extraction of significant features," *International Journal of Communications, Network and System Sciences*, vol. 8, no. 5, pp. 97-117, 2015
- [11] G. Da Poian, R. Bernardini, and R. Rinaldo, "Separation and analysis of fetal-ECG signals from compressed sensed abdominal ECG recordings," *IEEE Transaction on Biomedical Engineering*, vol. 63, no. 6, pp. 1269-1279, Jun. 2016.
- [12] J. Zhang, Z. Gu, Z. L. Yu, and Y. Li, "Energy-efficient ECG compression on wireless biosensors via minimal coherence sensing and weighted l1 minimization reconstruction," *IEEE journal of biomedical and health informatics*, vol. 19, no. 2, pp. 520-528, Mar. 201
- [13] Dixon, Anna MR, Emily G. Allstot, Daibashish Gangopadhyay, and David J. Allstot, "Compressed sensing system considerations for ECG and EMG wireless biosensors," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 6, no. 2, pp. 156-166, 2012.
- [14] D. Craven, B. McGinley, L. Kilmartin, M. Glavin, and E. Jones, "Adaptive dictionary reconstruction for compressed sensing of ECG signals," *IEEE journal of biomedical and health informatics*, vol. 21, no. 3, pp. 645-654, May 2017
- [15] A. Ravelomanantsoa, H. Rabah, and A. Rouane, "Compressed sensing: A simple deterministic measurement matrix and a fast recovery algorithm" *IEEE Transactions on Instrumentation and Measurement*, vol. 64, no. 12, pp. 3405-3413, Dec. 2015
- [16] Polania, Luisa F., Rafael E. Carrillo, Manuel Blanco-Velasco, and Kenneth E. Barner. "Exploiting prior knowledge in compressed sensing wireless ECG systems." *IEEE journal of*

- Biomedical and Health Informatics* 19, no. 2, pp 508-519, 2014.
- [17] Mamaghanian, Hossein, Nadia Khaled, David Atienza, and Pierre Vanderghenst, "Compressed sensing for real-time energy-efficient ECG compression on wireless body sensor nodes," *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 9, pp. 2456–2466, 2011.
 - [18] H.-T. Li, C.-Y. Chou, Y.-T. Chen, S.-H. Wang, and A.-Y. Wu, "Robust and lightweight ensemble extreme learning machine engine based on eigenspace domain for compressed learning," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 66, no. 12, pp. 4699–4712, Dec. 2019
 - [19] D. Craven, B. McGinley, L. Kilmartin, M. Glavin, and E. Jones, "Compressed sensing for bioelectric signals: A review," *IEEE journal of biomedical and health informatics*, vol. 19, no. 2, pp. 529–540, Mar. 2015
 - [20] Rezaii, Tohid Yousefi, Soosan Beheshti, Mahdi Shamsi, and Siavash Eftekharihar. "ECG signal compression and denoising via optimum sparsity order selection in compressed sensing framework." *Biomedical Signal Processing and Control* 41 (2018): 161-171.
 - [21] Rakshit, Manas, and Susmita Das. "Electrocardiogram beat type dictionary based compressed sensing for telecardiology application." *Biomedical Signal Processing and Control* 47 (2019): 207-218.
 - [22] Donoho, David L. "Compressed sensing." *IEEE Transactions on information theory*, 52(4), pp. 1289-1306, 2006
 - [23] S. Foucart and H. Rauhut, "A mathematical introduction to compressive sensing," *Bulletin of the American Mathematical Society*, vol. 54, pp. 151–165, 2017.
 - [24] Mahind, Umesh, and Deepak Karia. "Novel Sparse Signal Representation using Vandermonde Matrix." *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, pp. 1-5, 2024.
 - [25] Mahind, Umesh, and Deepak Karia, "Development and Analysis of Sparse Spasmodic Sampling Techniques." In *2022 International Conference on Edge Computing and Applications (ICECAA)*, pp. 818-823, 2022.
 - [26] Candès, Emmanuel J., Justin Romberg, and Terence Tao. "Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information." *IEEE Transactions on information theory* 52, no. 2, pp 489-509, 2006.
 - [27] Rauhut, Holger, Karin Schnass, and Pierre Vanderghenst. "Compressed sensing and redundant dictionaries." *IEEE Transactions on Information Theory*, 54(5), pp 2210-2219, 2008.
 - [28] Lal, Bharat, Raffaele Gravina, Fanny Spagnolo, and Pasquale Corsonello. "Compressed sensing approach for physiological signals: A review." *IEEE Sensors Journal* 23, no. 6, pp 5513-5534, 2023.
 - [29] Rani, Meenu, Sanjay B. Dhok, and Raghavendra B. Deshmukh. "A systematic review of compressive sensing: Concepts, implementations and applications." *IEEE access*, 6, pp 4875-4894, 2018.
 - [30] M. Fira, L. Goras, C. Barabasa, and N. Cleju, "On ECG compressed sensing using specific overcomplete dictionaries," *Advances in Electrical and Computer Engineering*, vol. 10, no. 4, pp. 23–28, 2010
 - [31] Ahmadvpour, Seyed-Sajad, Mojtaba Noorallahzadeh, Hamza Mohammed Ridha Al-Khafaji, Mehdi Darbandi, Nima Jafari Navimipour, Bahman Javadi, Noor Ul Ain, Mehdi Hosseinzadeh, and Senay Yalcin. "A new energy-efficient design for quantum-based multiplier for nano-scale devices in internet of things." *Computers and Electrical Engineering* 117 (2024): 109263.
 - [32] Navimipour, Nima Jafari, Seyed-Sajad Ahmadvpour, and Senay Yalcin. "A nano-scale arithmetic and logic unit using a reversible logic and quantum-dots," *The Journal of Supercomputing*, 80, no. 1, pp. 395-412, 2024
 - [33] Nezamabadi, Kasra, Neda Sardaripour, Benyamin Haghi, and Mohamad Forouzanfar. "Unsupervised ECG analysis: A review." *IEEE Reviews in Biomedical Engineering* 16, pp. 208-224, 2022.
 - [34] Wang, Jin, Xiangping Sun, Saeid Nahavandi, Abbas Kouzani, Yuchuan Wu, and Mary She, "Multichannel biomedical time series clustering via hierarchical probabilistic latent semantic analysis," *Computer methods and programs in biomedicine*, vol. 117, no. 2, pp. 238–246, 2014.
 - [35] Xu, Hongzuo, Guansong Pang, Yijie Wang, and Yongjun Wang. "Deep isolation forest for anomaly detection" *IEEE Transactions on Knowledge and Data Engineering* 35, no. 12, pp. 12591-12604, 2023.
 - [36] D. Needell and J. A. Tropp, "CoSaMP: Iterative signal recovery from incomplete and inaccurate samples," *Applied and computational harmonic analysis*, vol. 26, no. 3, pp. 301–321, May 2009.
 - [37] Melek, Michael, and Ahmed Khattab. "ECG compression using wavelet-based compressed sensing with prior support information," *Biomedical Signal Processing and Control*, 68, 102786, 2021

- [38] Karasmanoglou, Apostolos, Marios Antonakakis, and Michalis Zervakis. "ECG-based semi-supervised anomaly detection for early detection and monitoring of epileptic seizures" *International Journal of Environmental Research and Public Health*, 20.6, pp 5000, 2023.

Biographies



Umesh Mahind received B.E. and M.E. degree in Electronics and Telecommunication Engineering from University of Mumbai, Mumbai, India, in 2014 and 2016, respectively. He is currently pursuing PhD in Electronic. He is currently He has published 8 research papers in international and national conferences and 2 research paper published in Scopus indexed

Journals. He is serving as AI/ML Computational Science Associate Manager , Mumbai, India.



Dr. Deepak Karia received the Ph.D. degree in electronics engineering from the Veermata Jijabai Technological Institute, Mumbai india. He is currently an Associate Professor with the Sardar Patel Institute of Technology, Mumbai, India. He has published more than 50 research papers in international and national

journals as well as conferences. His area of interest includes Wireless Communication, Mobile Communication and Networking. He is also a reviewer of various IEEE transactions and conferences.



Dr. Vijay Kapure has completed his PhD in electronics from Sardar Patel institute of technology, Andheri from university of Mumbai, Maharashtra, India. His research interest areas are electromagnetics, Antenna designing and wireless communication. Currently he is working as Head of department at Xavier institute of engineering,

Mahim, Mumbai. He has published his research in various nationals and international Scopus indexed journal papers and conferences.



Dr. Sankit Kassa is currently working as a Sr. Assistant Professor at Symbiosis Institute of Technology, Pune in the department of Electronics and Telecommunication Engineering. He has obtained his Ph.D. from Motilal Nehru National Institute of Technology Allahabad (2016), M.Tech from National Institute of Technology Hamirpur (2011), and

B.Tech from Gujarat University (2009). His research interest focus on Quantum-dot Cellular Automata, VLSI circuits and systems, FPGA system design. He has published more than 60 articles in various national as well as international conferences/journals of repute. He has also published a book titled 'Performance analysis of Femtocells in NGWNs' with ISBN: 9786138268697. In addition to this, he is an active member of IEEE, ISTE, IETE societies.