



Indian Institute of Technology,
Guwahati

DA312 Course Project Presentation

Personalized Zero-Shot ECG Arrhythmia Monitoring
System

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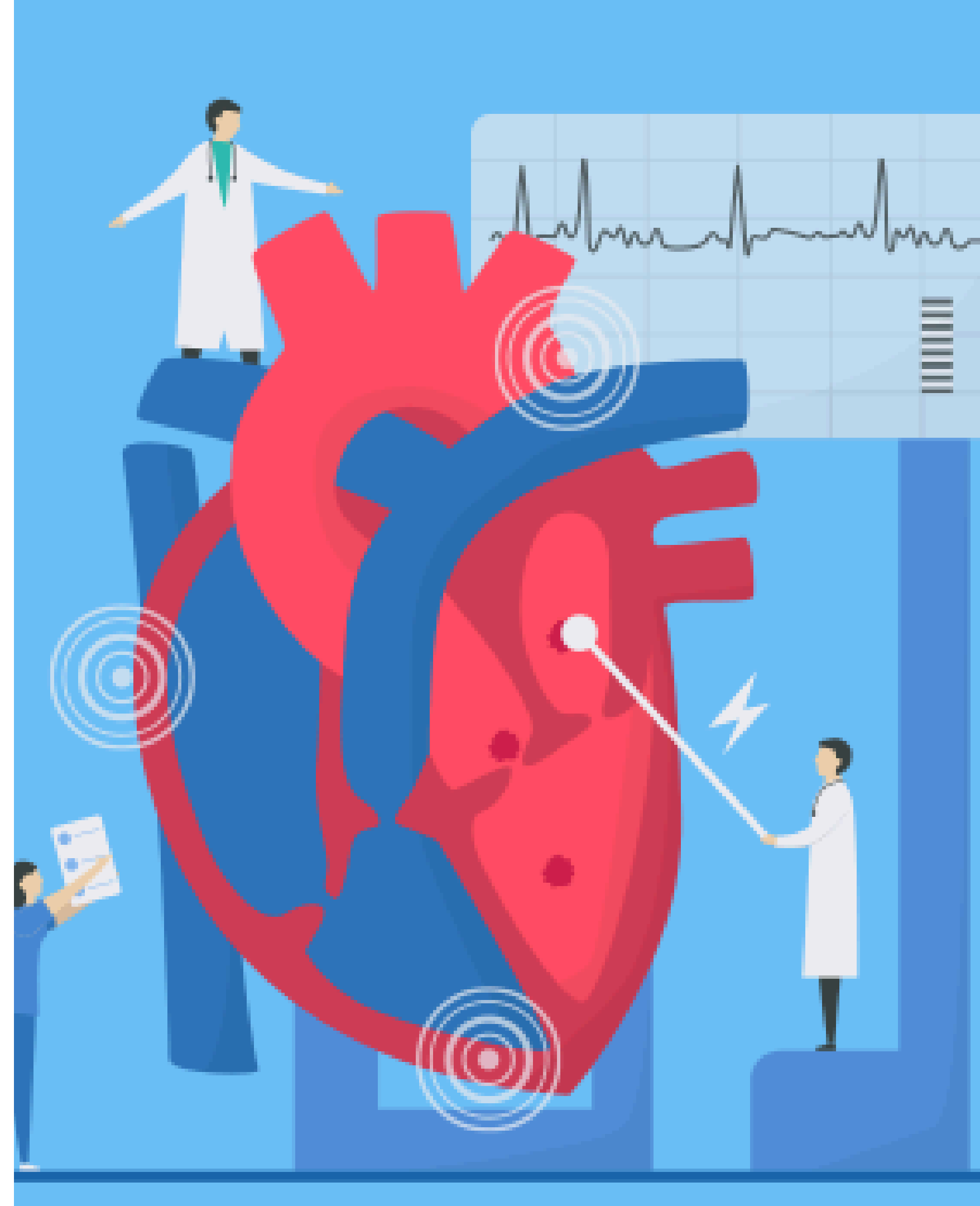
Motivation

Cardiovascular diseases remain the #1 cause of death globally.

Approximately 32.84% of all deaths in 2019 were caused by cardiovascular diseases.

Early detection of cardiac arrhythmias can significantly reduce casualties.

Traditional monitoring systems cannot serve as early warning systems for healthy individuals.



Abstract

Numerous methods have been proposed for the identification of electrocardiogram (ECG) waveforms using machine learning and signal processing, such as support vector machines (SVMs), frequency analysis, and statistical analysis.



Goal of the Project

The goal of this project is to create a low-cost and highly accurate ECG monitoring system to detect ECG arrhythmias for wearable mobile sensors.

Relevance of the Project

A sparse representation-based domain adaptation technique is used to project other existing users' normal and abnormal signals onto the new user's signal space, allowing training the classifier without having any abnormal heartbeat of the new user.



Results

The project achieved SOTA performance on the MIT-BIH Arrhythmia Database with 99.0% accuracy and 96.3% F1-Score using sparse representation-based domain adaptation for personalized zero-shot ECG arrhythmia detection.



Introduction

Global Health Challenge

Cardiovascular diseases remain the leading cause of death globally, accounting for approximately 32.84% of all deaths in 2019. Early arrhythmia detection can significantly reduce casualties.



Current Limitations

Traditional monitoring systems require both normal and abnormal heartbeat data from patients, making them unsuitable for healthy individuals with no history of cardiac disorders.

Personalization Need

ECG morphology varies between individuals due to differences in cardiovascular systems, necessitating person-specific monitoring approaches rather than generic detection methods.

Introduction

Zero-Shot Learning Approach

Our system requires only normal heartbeats from new users, eliminating the need for abnormal data collection and enabling early warning capabilities for healthy individuals.



Null Space Projection Based Classifier

We employ null space analysis on healthy signal space via sparse dictionary learning, providing 20x faster computation without compromising performance.

Domain Adaptation Method

Novel sparse representation-based domain adaptation projects existing users' data onto new users' signal space, enabling personalized classification without synthetic data generation.

Related Work: Sparse Representation-Based Classification

Core Concept

Normal ECG beats can be accurately represented using a dictionary learned from a user's own healthy beats, where $s = D^p \cdot x + e$ (D^p is the user-specific dictionary, x is sparse coefficient vector, e is residual error)

Mathematical Formulation

The l_0 -minimization problem is relaxed to convex l_1 -minimization using Lasso: $\min_x ||s - D^p x||_2^2 + \lambda ||x||_1$, enabling stable solutions even with noise

Classification Mechanism

Normal beats have low Sparse Approximation Error (SAE) when reconstructed with the dictionary, while abnormal beats produce higher errors, making classification possible based on reconstruction performance

Related Work: Abnormal Beat Synthesis

Challenge Addressed

For healthy users with no history of cardiac disorders, no abnormal beats are available for training personalized detection systems.

Linear Transformation Model

Abnormal beats are modeled as linearly degraded versions of normal beats: $s^I_A = s^I_N \otimes h^I$, where h^I represents the filter coefficients of a Linear Time-Invariant system.

Synthesis Process

When a new user registers, their average normal beat s^p_N is computed, then filters from existing users are applied to generate synthetic abnormal beats: $s^p_A = s^p_N \otimes h^I$, enabling training of a conventional classifier like 1-D CNN.

Proposed Solution: NPE Based Classifier

Core Concept

Normal ECG beats can be accurately represented using a dictionary learned from a user's own healthy beats, where $s = D^p x + e$ (D^p is the user-specific dictionary, x is sparse coefficient vector, e is residual error)

Mathematical Formulation

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Computational Advantage

Rather than solving sparse recovery iteratively, NPE directly projects error components onto the null space of D^p using the left annihilator matrix F^p , achieving up to 20x faster computation without compromising performance.

Proposed Solution: NPE Based Classifier

Dictionary Learning

A Lasso-based dictionary learning method is used: $\min_{\{X^p, D^p\}} ||S^p - D^p X^p||_2^2 + \lambda ||X^p||_1$ to learn dictionary D^p and sparse coefficients X^p from normal beats S^p .

Classification Mechanism

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Threshold Determination

Simple thresholding on reconstruction error enables anomaly detection without requiring abnormal training data, making it suitable for early warning systems for healthy individuals.

Proposed Solution: Sparse Representation Based Domain Adaptation

Challenge Addressed

ECG morphology varies between individuals due to differences in cardiovascular systems, making personalized classification difficult without user-specific abnormal data.

Proposed Solution

linear transformation matrix $Q^{\{l \rightarrow p\}}$ maps ECG signals from existing users (l) to match the morphology style of a new user (p).

Morphology Transformation Matrix (MTM)

Designed specifically to transform both normal and abnormal beats from source users to target user's ECG morphology space while preserving diagnostic characteristics.

Proposed Solution: Sparse Representation Based Domain Adaptation

MTM Learning Problem

Formulated as finding $Q^{\{I \rightarrow p\}}$ that results in transformed signals being sparsely represented in the target dictionary: $Q^{\{I \rightarrow p\}}, X^I = \arg \min_{\{Q^{\{I \rightarrow p\}}, X^I\}} ||Q^{\{I \rightarrow p\}} S^I - D^p X^I||_2^2 + \lambda ||X^I||_1 + \gamma ||S^I - Q^{\{I \rightarrow p\}} S^I||_2^2$.

Optimization Strategy

Iterative algorithm alternates between updating sparse coefficients and refining the transformation matrix with a trade-off parameter γ balancing transformation fidelity and sparse representation.

Training Data Generation

After transformation, both normal and abnormal beats from existing users can be included in the new user's training set, enabling personalized classification without synthetic data generation.

Proposed Solution: Ensemble Learning Approach

Probabilistic Model

Null space projection errors (NPEs) for both normal and abnormal beats are used to fit two probability distributions using maximum likelihood estimation.

Distribution Selection

Normal NPEs are modeled with an exponential distribution (PDF: $f(x;\beta) = e^{(-x/\beta)}/\beta$ for $x \geq 0$) while abnormal NPEs follow a Gaussian distribution (PDF: $f(x;\mu,\sigma) = e^{-(x-\mu)^2/2\sigma^2}/(\sigma\sqrt{2\pi})$).

Parameter Estimation

For exponential distribution, $\beta = \sum x_i/n$ (sample mean); for Gaussian, $\mu = \sum x_i/n$ (sample mean) and $\sigma^2 = \sum (x_i - \mu)^2/n$ (sample variance).

Proposed Solution: Ensemble Learning Approach

Confidence-Based Decision

CNN output is passed through softmax function to determine classification confidence; if confidence exceeds threshold C , CNN prediction is used.

Fallback Mechanism

When CNN exhibits low confidence (below threshold C), the probabilistic model based on NPE is used for final classification decision.

Performance Results

The ensemble approach achieves state-of-the-art performance with 99.0% accuracy and 96.3% F1-Score on MIT-BIH benchmark, significantly outperforming previous methods while requiring no abnormal heartbeats from new users.

Experiments: Experimental Setup

Dataset Selection

- MIT-BIH Arrhythmia Database containing 2-channel ECG records from 48 different patients, each approximately 30 minutes long, with annotated beat labels.
- Following AAMI recommendations, 34 patient records were used (excluding patients 102, 104, 107, 217 with pacemakers and patients 105, 114, 201, 202, 207, 209, 213, 222, 223, 234 showing high beat variations)

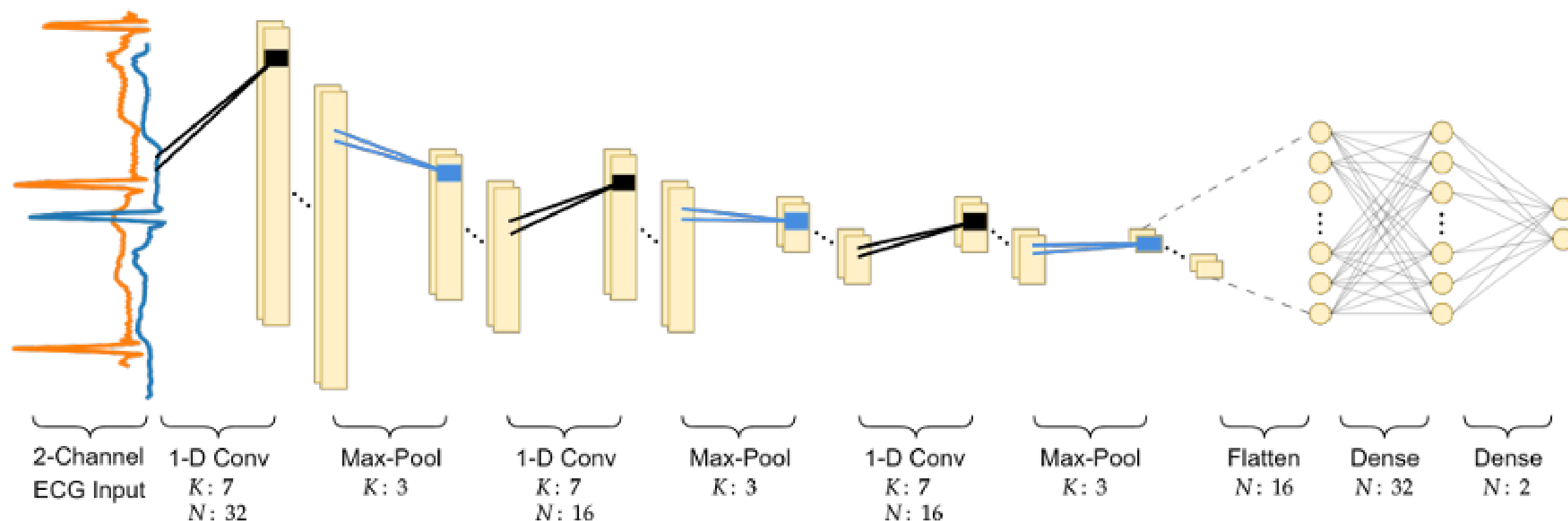
Data Preparation

- Each beat represented by 128 samples through resampling
- Two representation formats used: single beat (centered on R-peak) and beat-trio (including adjacent R-peaks)
- For single beat: nearby R-peaks located, 10% inward movement toward central peak, segment extracted and resampled
- For beat-trio: adjacent R-peaks located, 10% outward movement, segment extracted to capture temporal morphological features

Experiments: Experimental Setup

Training Protocol

- Following AAMI guidelines, only normal heartbeats from the first five minutes are used for training
- Test data: abnormal beats during the first five minutes plus all beats from the next 25 minutes
- 80–20 train-validation split with early stopping (15 epochs) based on validation loss
- CNN architecture: three convolutional layers (kernel size 7, stride 1) with max-pooling, followed by two fully connected layers.



Experiments: Evaluation Metrics

The performances of the proposed methods are compared using the following metrics:

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}},$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}},$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}},$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}},$$

where a positive response corresponds to an abnormal beat, and true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are computed from the predicted and ground-truth binary labels.

Experiments: Evaluation Methodology

Macro-averaging is used for overall performance metrics.

Confusion matrices accumulated over 10 independent training runs to reduce randomness

Positive response corresponds to abnormal beat classification

Comparative analysis against state-of-the-art methods including global classifiers, one-shot classifiers, and personalized approaches

Results

Method	Accuracy	Specificity	Precision	Recall	F1-Score
CNN					
Kiranyaz <i>et al.</i> [5] \diamond	0.959	0.971	0.842	0.888	0.864
Zhai <i>et al.</i> [16] \diamond	0.968	0.976	0.879	0.920	0.899
Li <i>et al.</i> [17]	0.920	0.918	0.628	0.933	0.751
SR-based \diamond*					
SAE-based	0.947	0.968	0.779	0.794	0.786
NPE-based (ours)	0.947	0.968	0.779	0.80	0.79
CNN \diamond*					
ABS [9]	0.977	0.995	0.956	0.825	0.886
Baseline (ours) \diamond *	0.965	0.987	0.899	0.809	0.852
Domain Adaptation (ours)	0.990	0.991	0.940	0.987	0.963
Ensemble (ours)	0.990	0.991	0.939	0.983	0.961
Ensemble (avg.) (ours)	0.988	0.990	0.933	0.979	0.955

Table 1: Comparison of other CNN methods, NPE-Based (ours) Baseline (ours), Domain Adaptation (ours), and Ensemble Classification (ours) methods. The classification performances of former studies, including global and one-shot classifiers, are presented. The results show that our personalized zero-shot ensemble classifier surpasses in F1-Score all the other methods.

\diamond Personalized classifiers.

* Zero-shot classifiers.

Conclusion

The personalized zero-shot ECG arrhythmia monitoring system requires no abnormal heartbeats from new users, enabling early detection for healthy individuals with no cardiac history.

The null space projection (NPE) approach offers 20x faster computation by directly projecting error components onto the dictionary's null space, making it suitable for wearable devices.

The ensemble classifier combines CNN and probabilistic models based on NPE, achieving 99.0% accuracy and 96.3% F1-Score on the MIT-BIH benchmark, significantly outperforming previous methods.

Sparse representation-based domain adaptation transforms ECG signals from existing users to match new users' morphology, enabling personalized classification without user-specific abnormal data.



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Thank You

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