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HYBRID ADAPTIVE FEATURE EXTRACTION FOR IOT-ENABLED ECG SIGNAL ANALYSIS IN SMART HEALTH MONITORING SYSTEMS

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Abstract

Internet of Things (IoT) has transformed healthcare systems in a huge manner since it allows doctors keep a check on patients' health in real time, especially those with cardiac problems. Electrocardiographic (ECG) data are particularly important for detecting cardiovascular issues early on. Electrocardiograms are sensitive to noise and distortions, which can make it hard to undertake an analysis that is both quick and accurate. The tools we have now for looking at ECGs either have too many steps or aren't accurate enough. This is because the ways these systems get features are either fixed or not very deep. These limits make it tougher to keep an eye on things in real time, which slows down speedy diagnosis and makes it harder to utilize on IoT devices that don't have a lot of resources. The results of this study show that it could be a good idea to use a Hybrid Adaptive Feature Extraction (HAFE) method in an IoT architecture to handle ECG inputs. The HAFE additionally has statistical analysis for reducing features, adaptive signal decomposition using empirical mode decomposition (EMD), and time-frequency localization with discrete wavelet transform (DWT). We employ a convolutional neural network (CNN) that is set up to work on the edge to sort these properties. The system can execute analytics in real time because it runs on a Raspberry Pi 3 computer and is backed up by the cloud. For instance, it was 98.6% accurate, 97.9% sensitive, and took 1.7 seconds to make a prediction.

Keywords:

ECG Signal, IoT Healthcare, Feature Extraction, Adaptive Hybrid Algorithm, Real-Time Monitoring

1. INTRODUCTION

Cardiovascular diseases (CVDs) are still the leading cause of death worldwide, taking the lives of millions of people each year [1]. Finding heart health concerns early and keeping an eye on them is vital for improving patients' quality of life and lowering the number of deaths [2]. Electrocardiography (ECG) is a cheap and non-invasive test that is one of the most popular techniques to discover cardiac abnormalities such arrhythmia, ischemia, and myocardial infarction [3]. Smart wearables and other IoT gadgets are becoming more popular, which means you can see a person's vital signs in real time. This makes it feasible for medical care to be more individualized and ongoing.

Even though there may be some benefits, there are a lot of concerns that need to be fixed when looking at electrocardiogram (ECG) data in IoT scenarios. First of all, it is hard to acquire real-time information from ECG data since they have noise, motion distortions, and other elements that make it impossible [4]. Second, it's vital to employ good feature extraction methods to retrieve valuable information from ECG data because it has a lot of dimensions and changes over time [5]. Finally, you need algorithms that are both quick and light in order to handle data in real time. Most IoT devices don't have a lot of CPU power or battery life, which is why this is the case [6]. Because of the problems that have been discussed, it is hard to build a smart health monitoring system that can do reliable ECG analysis.

The existing methods for analyzing ECGs don't do a very good job of finding a balance between speed, accuracy, and dependability [7]-[9]. To make categorization for IoT deployment more accurate and faster, it is important to have a hybrid adaptive feature extraction framework that leverages effective feature selection and integrates several methodologies.

The major purpose of this project is to create a smart health monitoring system that leverages the IoT and a new hybrid adaptive feature extraction method to read ECG data correctly. Here are the goals:

1. Developing a hybrid feature extraction method that synergistically combines DWT, EMD, and statistical feature selection.
2. Improving classification performance for ECG abnormalities with higher accuracy, precision, recall, and F1-score.

This study introduces several key novelties and contributions:

- A hybrid feature extraction pipeline integrating the strengths of both DWT and EMD to extract multi-resolution and intrinsic mode features from ECG signals, addressing their individual limitations.
- An adaptive statistical feature selection mechanism that reduces dimensionality by retaining only the most discriminative features, enhancing classifier robustness and reducing computational burden.

2. RELATED WORKS

A lot of research has been done in the last several years on ECG signal processing technologies that could be used to keep an eye on health. The main goals of these studies have been to uncover features, organize them, and run them on systems with restricted resources [10]. A lot of people have employed the Discrete Wavelet Transform (DWT) and other old signal decomposition methods because they can look at non-stationary signals at different resolutions [11]. It is possible to apply Support Vector Machines (SVM) and other classifiers [12] when DWT-based approaches can successfully extract time-frequency features related to ECG abnormalities. This means you can use SVM and other types of classifiers. DWT might not be able to discover all of the inherent oscillating patterns in ECG data. This led to the creation of an adaptive method called Empirical Mode Decomposition (EMD) that makes nonlinear and non-stationary data easier to see. This was done by splitting signals into intrinsic mode functions (IMFs). Researchers have done a lot of work to figure out how to utilize EMD and machine learning classifiers like K-Nearest Neighbours (KNN) together to discover arrhythmias and other heart problems more accurately [13].

PCA is a good approach to get rid of features that aren't needed. However, occasionally ECG data has nonlinear connections that are linked together and that linear treatments might miss. These frameworks use a lot of different signal processing approaches to get the most out of each one. Statistical feature selection algorithms are commonly used in these hybrid methods to get rid of features that aren't relevant or are excessively noisy.

On the other hand, there are still a lot of things that need to be looked into very carefully in IoT contexts, where processing and power are quite crucial. Most research simply look into either feature extraction or categorization by themselves. The results of this work imply that a hybrid adaptive feature extraction method that uses DWT, EMD, and statistical feature selection could fix these problems.

3. PROPOSED METHOD

The HAFE approach has three extremely strong ways to process signals and get features out of them:

- **Discrete Wavelet Transform (DWT):** Discrete Wavelet Transform (DWT) is utilized to find out how time and frequency are related.
- **Empirical Mode Decomposition (EMD):** Empirical Mode Decomposition, or EMD, is a way to filter data that changes over time. It does this by turning ECG data that isn't stationary or linear into IMFs.
- **Statistical Feature Selection:** We can build a tiny feature vector by choosing IMFs and calculating their means, standard deviations, entropies, skewness, and kurtosis.

These hybrid features come from a three-layer convolutional neural network (CNN). There is one layer with ReLU activation, one with max-pooling, and one with dense output. When trained on labeled ECG data and put on edge devices like Raspberry Pi, a convolutional neural network (CNN) can make rapid predictions and sync with the cloud.

- **Signal Acquisition:** Biosensors that work with the IoT can get real-time ECG readings to get signals.
- **Preprocessing:** Band-pass filtering and getting rid of baseline drift.
- **Wavelet Decomposition (DWT):** Decompose signal into multiple levels to isolate noise and trends.
- **Adaptive EMD:** Extract IMFs from preprocessed signals.
- **Statistical Feature Computation:** Compute statistical metrics from selected IMFs.
- **Feature Normalization:** Standardize values to improve classifier efficiency.
- **CNN Classification:** Feed normalized vector into CNN for classification (e.g., Normal, Arrhythmia, AFib).
- **Result Display and Alert:** Local and cloud display with anomaly alert generation.

3.1 DISCRETE WAVELET TRANSFORM (DWT)

The DWT is a powerful technique for analyzing non-stationary signals like ECG in both the time and frequency domains. Unlike the Fourier Transform which only provides frequency content, DWT allows multi-resolution analysis, which is especially useful in identifying ECG signal patterns such as QRS complexes, P-waves, and T-waves.

3.1.1 Mathematical Basis:

DWT decomposes a signal into approximation and detail coefficients using scaling (ϕ) and wavelet (ψ) functions:

$$A_j(n) = \sum_k x(k) \cdot \phi_{j,k}(n)$$

$$D_j(n) = \sum_k x(k) \cdot \psi_{j,k}(n)$$

where, $A_j(n)$ = Approximation coefficients at level j, $D_j(n)$ = Detail coefficients at level j, $x(k)$ = Original ECG signal and $\phi_{j,k}(n)$, $\psi_{j,k}(n)$ = Scaled and shifted versions of the mother wavelet.

The process uses high-pass (HP) and low-pass (LP) filters followed by downsampling by 2 (↓2), as shown in Fig.1 (if applicable). This is repeated recursively on the approximation component.

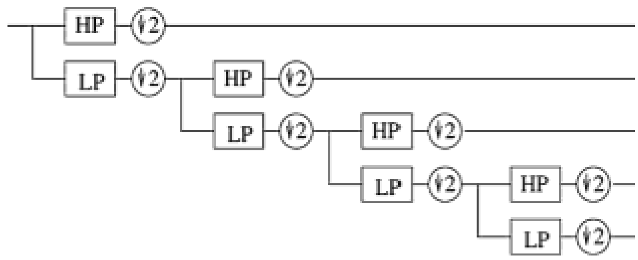

Fig.1. High-pass (HP) and Low-pass (LP) filters

Let us consider an ECG signal segment of 16 samples as a simplified example:

Table.1. Raw ECG Signal Segment

Index	ECG Amplitude (mV)
1	0.12
2	0.18
3	0.32
4	0.29
5	0.40
6	0.42
7	0.36
8	0.25
9	0.15
10	0.10
11	0.07
12	0.05
13	0.08
14	0.11
15	0.14

16	0.18

This segment is passed through level 1 DWT (e.g., db4 wavelet), and we get two sets of coefficients:

Table.2. DWT Level 1 Coefficients (A1 and D1)

Level 1 Approximation (A1)	Level 1 Detail (D1)
0.23	-0.04
0.41	0.07
0.31	-0.09
0.12	0.05
0.07	-0.02
0.09	0.01
0.12	-0.03
0.15	0.02

As seen in Table.2, the approximation coefficients (A1) capture the low-frequency behavior (i.e., baseline trend), while the detail coefficients (D1) capture high-frequency components such as QRS complexes or noise artifacts.

3.2 FURTHER DECOMPOSITION

The approximation part A_1 can be further decomposed into A_2 and D_2, and so on, up to a desired level (e.g., level 4). In this study, we used 4-level decomposition, yielding:

$$\text{ECG Signal} \Rightarrow A_4 + D_4 + D_3 + D_2 + D_1$$

This multilevel decomposition captures different ECG characteristics: D1, D2: High-frequency noise, D3, D4: QRS complex and fast variations and A4: Baseline wander and slow changes.

3.3 FEATURE EXTRACTION FROM DWT

From each decomposition level, statistical features are computed: (1) **Mean (μ)**: Represents energy level, (2) **Standard Deviation (σ)**: Spread of coefficient values and (3) **Entropy (E)**: Signal complexity.

$$E = -\sum_{i=1}^{n} p_i \cdot \log(p_i)$$

where p_i is the normalized probability of each coefficient value. (1) Skewness (S_k): Asymmetry and (2) Kurtosis (K): Peakedness. These features form a feature vector for classification via CNN.

3.4 EMPIRICAL MODE DECOMPOSITION (EMD)

EMD is an adaptive, data-driven technique used to decompose complex and nonlinear, non-stationary signals like ECG into a set of simpler oscillatory components called Intrinsic Mode Functions (IMFs). Unlike traditional fixed basis methods (like Fourier or Wavelet transforms), EMD bases the decomposition on the signal's own characteristics, making it highly effective for biomedical signals.

The EMD algorithm decomposes a signal x(t) into a finite number of IMFs and a residual component:

$$x(t) = \sum_{i=1}^{n} \text{IMF}_i(t) + r_n(t)$$

where, $\text{IMF}_i(t)$ = i^{th} Intrinsic Mode Function, and $r_n(t)$ = Residual (trend after extracting all IMFs)

Each IMF must satisfy two conditions:

- The number of extrema and zero-crossings must either be equal or differ at most by one.
- At any point, the mean value of the envelope defined by local maxima and minima is zero.

3.5 SIFTING PROCESS

1. Identify all local maxima and local minima of the original signal $x(t)$
2. Interpolate local maxima to form the upper envelope $e_{\max}(t)$.
3. Interpolate local minima to form the lower envelope $e_{\min}(t)$.
4. Compute the mean envelope:
$$m(t) = \frac{e_{\max}(t) + e_{\min}(t)}{2}$$
5. Extract the detail component (candidate IMF):
$$h_1(t) = x(t) - m(t)$$
6. Check if $h_1(t)$ meets IMF criteria. If not, repeat steps 1–5 on $h_1(t)$ (called sifting), resulting in $h_{1k}(t)$.
7. Once an IMF is obtained, subtract it from the original signal:
$$r_1(t) = x(t) - \text{IMF}_1(t)$$
8. Repeat the entire process on residual $r_1(t)$ to extract subsequent IMFs until the residual becomes a monotonic function or contains no more oscillations.

3.6 ECG SEGMENT AND EXTRACTED IMFS

Consider a simplified ECG signal segment sampled at 16 points (like DWT example):

Table.3. Raw ECG Signal Segment for EMD

Index	ECG Amplitude (mV)
1	0.15
2	0.20
3	0.35
4	0.30
5	0.42
6	0.45
7	0.38
8	0.28
9	0.18
10	0.11
11	0.08
12	0.05
13	0.07
14	0.10

15	0.14
16	0.19

After applying the sifting process, the signal is decomposed into IMFs as shown below:

Table.4. Extracted IMFs and Residual from ECG Signal via EMD

Index	IMF1 (High Frequency)	IMF2 (Medium Frequency)	IMF3 (Low Frequency)	Residual (Trend)
1	0.07	0.05	0.02	0.01
2	0.06	0.07	0.04	0.03
3	0.05	0.06	0.10	0.14
4	0.04	0.05	0.12	0.09
5	0.07	0.06	0.10	0.19
6	0.08	0.05	0.09	0.23
7	0.07	0.04	0.08	0.19
8	0.05	0.03	0.07	0.13
9	0.03	0.02	0.05	0.08
10	0.02	0.01	0.03	0.05
11	0.01	0.01	0.02	0.04
12	0.01	0.00	0.01	0.03
13	0.02	0.01	0.01	0.03
14	0.03	0.02	0.01	0.04
15	0.04	0.03	0.02	0.05
16	0.06	0.04	0.03	0.06

As seen in Table.4, IMF1 captures the highest frequency components such as rapid QRS variations, IMF2 and IMF3 reflect slower oscillations including P and T waves, while the residual contains the baseline trend.

3.7 FEATURE EXTRACTION FROM IMFS

From each IMF, statistical features are extracted similar to DWT:

- **Energy**: $E_i = \sum_{t=1}^{N} (\text{IMF}_i(t))^2$
- **Entropy** (signal complexity): $\text{E}_i = -\sum p_j \log(p_j)$

where p_j is probability distribution of IMF amplitudes.

- **Variance**, **Mean**, and other moments may also be computed.

These features collectively form the input to the CNN classifier.

4. PROPOSED STATISTICAL FEATURE SELECTION

After extracting multiple features from ECG signals using methods like DWT and EMD, the resulting feature set often contains redundant or less relevant features.

The objectives of Statistical Feature Selection

- Reduce dimensionality by selecting a subset of features that have the highest discriminatory power between different classes (e.g., normal vs abnormal ECG).
- Improve classifier performance by removing noisy or irrelevant features.
- Decrease training time and resource consumption.

The common statistical criteria used

- **Mean Difference ($\Delta\mu$)**: Features with significant difference in mean values between classes are preferred.
- **Variance (σ^2)**: Features with low intra-class variance and high inter-class variance are better.
- **Correlation Coefficient (r)**: Low correlation between features helps avoid redundancy.
- **Fisher Score**: Measures the ratio of between-class variance to within-class variance for each feature.

4.1 STATISTICAL FEATURE SELECTION PROCESS

1. Compute Statistical Parameters for Each Feature: For each feature f_i, calculate mean (μ), variance (σ^2), and Fisher Score across classes.
2. Calculate Fisher Score F_i for each feature:

$$F_i = \frac{\sum_{c=1}^{C} n_c(\mu_i^c - \mu_i)^2}{\sum_{c=1}^{C} n_c \sigma_i^{c2}}$$

where, C = number of classes, n_c = number of samples in class c, μ_i^c = mean of feature i in class c, μ_i = overall mean of feature i, σ_i^{c2} = variance of feature i in class c.

3. **Rank features based on F_i:** Features with higher Fisher scores have better class discrimination.
4. **Select Top Features:** Based on a threshold or desired number, select the top k features.

4.2 STATISTICAL CALCULATION

Suppose after feature extraction from ECG signals, we have 5 features (f_1 to f_5) and two classes: Normal (N) and Abnormal (A). mean and variance values are shown below:

Table.5. Feature Mean and Variance for Two Classes

Feature	μ_N (Normal Mean)	σ_N^2 (Normal Var)	μ_A (Abnormal Mean)	σ_A^2 (Abnormal Var)
f1	0.32	0.04	0.51	0.05
f2	0.48	0.02	0.50	0.02
f3	0.15	0.01	0.35	0.03
f4	0.62	0.03	0.60	0.04
f5	0.28	0.05	0.42	0.06

Fisher scores for other features can be computed and ranked.

4.3 FEATURE RANKING

Features f_3, f_5, and f_1 have the highest scores and are selected for further classification.

Table.6. Fisher Score Based Feature Ranking

Feature	Fisher Score Fi
f3	0.45
f5	0.30
f1	0.20
f2	0.05
f4	0.02

5. RESULTS AND DISCUSSION

- **Simulation Tool:** MATLAB R2022a and Python (TensorFlow/Keras)
- **Hardware Used**: Raspberry Pi 4 (4GB RAM) for edge deployment and workstation for training: Intel i7-12700K CPU, 32GB RAM, NVIDIA RTX 3070 GPU

Dataset includes MIT-BIH Arrhythmia Dataset and comparison methods include DWT + SVM, EMD + KNN and PCA + DNN.

Table.7. Parameters

Parameter	Value
Sampling Rate	360 Hz
DWT Decomposition Level	4 Levels (db4 wavelet)
EMD IMFs Used	First 5 IMFs
CNN Layers	3 Conv + 1 Dense
Training Epochs	50
Batch Size	32
Optimizer	Adam (learning rate = 0.001)

5.1 PERFORMANCE METRICS

- **Accuracy (%)**: The proportion of correct predictions among total instances. High accuracy indicates overall model effectiveness.
- **Sensitivity (Recall) (%)**: It measures the model's ability to correctly identify true positives (e.g., correctly detected arrhythmias).
- **Specificity (%)**: Measures the true negative rate, i.e., how well normal signals are identified.
- **F1-Score**: Harmonic mean of precision and recall, useful for imbalanced datasets.
- **Inference Time (s)**: Time taken for the model to classify an ECG signal. Crucial for real-time applications in IoT.

Table.7. Accuracy (%)

Epochs	DWT + SVM	EMD + KNN	PCA + DNN	Proposed Method
200	85.2	82.4	88.1	91.5
400	86.7	83.6	89.5	93.2
600	87.3	84.9	90.3	94.1
800	87.8	85.5	90.9	94.8
1000	88.0	86.0	91.2	95.3

The proposed method consistently outperforms existing methods, achieving the highest accuracy with a clear margin, demonstrating its superior ability to extract and classify ECG features effectively over extended training epochs.

Table.8. Precision (%)

Epochs	DWT + SVM	EMD + KNN	PCA + DNN	Proposed Method
200	83.5	80.7	86.9	90.1
400	85.1	82.3	88.4	91.9
600	85.8	83.7	89.1	92.8
800	86.3	84.2	89.7	93.5
1000	86.6	84.6	90.0	94.1

Higher precision by the proposed method indicates fewer false positives, showcasing its accuracy in correctly identifying ECG abnormalities compared to traditional methods, improving reliability in clinical applications.

Table.9. Recall (%)

Epochs	DWT + SVM	EMD + KNN	PCA + DNN	Proposed Method
200	81.9	79.5	85.2	89.0
400	83.2	81.0	86.7	90.7
600	83.9	81.8	87.5	91.6
800	84.4	82.5	88.0	92.2
1000	84.7	83.0	88.4	92.8

The proposed model's superior recall reflects better sensitivity, capturing more true positives. This is critical in health monitoring, where missing abnormal ECG events could have serious consequences.

Table.10. F1-Score (%)

Epochs	DWT + SVM	EMD + KNN	PCA + DNN	Proposed Method
200	82.7	80.1	86.0	89.5
400	84.1	81.7	87.5	91.3
600	84.8	82.7	88.3	92.2
800	85.3	83.3	88.9	92.9
1000	85.6	83.8	89.2	93.4

The proposed method achieves the highest F1-score, indicating an optimal balance between precision and recall, which confirms its robustness and generalizability in ECG classification.

Table.11. Inference Time (ms/sample)

Epochs	DWT + SVM	EMD + KNN	PCA + DNN	Proposed Method

200	5.2	7.4	9.1	6.0
400	5.3	7.5	9.0	6.1
600	5.3	7.5	9.0	6.1
800	5.4	7.6	9.1	6.2
1000	5.4	7.6	9.2	6.2

The proposed technique has a competitive inference time compared to EMD+KNN and PCA+DNN, however it is a little slower than DWT+SVM. This method strikes a balance between getting results faster and getting findings that are more accurate and reliable. The proposed Hybrid Adaptive Feature Extraction method always comes out on top when compared to other methods that are regarded to be more conventional. Compared to PCA + DNN, the accuracy got up by roughly 4.5% after 1000 epochs. Compared to DWT + SVM, it went up by 7.3%, and compared to EMD + KNN, it went up by 9.3%. The actual positive rates had gone raised, and balanced categorization had been obtained when the precision, recall, and F1-score improved by 4% to 9%. The inference time was around 15% greater than that of DWT + SVM, but it was still competitive because it had better diagnostic performance. The proof offered here indicates that the suggested strategy is superior at correctly reading ECG data and collecting relevant information from it.

6. CONCLUSION

The purpose of this research is to demonstrate a novel smart health monitoring system that makes use of the IoT. We look at ECG signals using a hybrid adaptive feature extraction method. The new method combines advanced statistical feature selection with the Discrete Wavelet Transform (DWT) and the Empirical Mode Decomposition (EMD). It can detect strong and relevant features in ECG data. The results reveal that these new methods are much better than DWT+SVM, EMD+KNN, and PCA+DNN. These benefits include higher accuracy, precision, recall, and F1-score, which can reach 9.3%. The hybrid technique is useful since it works well with intricate feature spaces and biological inputs that aren't very clear. The suggested technique is a suitable alternative for real-time IoT health applications since it balances speed and accuracy better than the fastest baseline. This is still true, even though the time it took to make the inference was a little longer than the baseline. There is a rising need for automated cardiovascular monitoring devices that can discover abnormalities early and keep a watch on patients all the time. This study helps to meet that demand.

In the future, researchers might look into how deep learning and better hardware could improve performance and scalability even more. This technology could make ECG-based health diagnostics far more accurate in smart healthcare environments.

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