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APPLYING DISCRETE WAVELET TRANSFORM FOR ECG SIGNAL ANALYSIS IN IOT HEALTH MONITORING SYSTEMS

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Abstract

Continuous remote monitoring has been made possible by the recent integration of Internet of Things (IoT) technologies with healthcare monitoring systems, greatly improving patient care. In an Internet of Things (IoT)-based health monitoring system, this research investigates the use of Discrete Wavelet Transform (DWT) in the processing of electrocardiogram (ECG) signals. The excellent time-frequency localization capabilities of DWT are used since they are essential for the efficient analysis of non-stationary signals such as ECG. The process focuses on applying DWT to filter banks made up of High Pass Filters (HPF) and Low Pass Filters (LPF) in order to separate the ECG signal into its component frequencies. Denoising, compression, and feature extraction are aided by this procedure, which is vital for the diagnosis of cardiac abnormalities. Signal acquisition, preprocessing, feature extraction, and IoT-based transmission to cloud servers for real-time analysis are some of the components that make up the system architecture. Various performance metrics, including Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), and compression ratios, are used to assess the effectiveness of the proposed technique and show notable gains in signal clarity and data reduction.

Keywords: *IoT Health Monitoring, Discrete Wavelet Transform, ECG Signal Processing, Real-time ECG Analysis, Signal Denoising and Compression*

1.INTRODUCTION

A viable method to improve the effectiveness and precision of cardiac health monitoring is the use of Discrete Wavelet Transform (DWT) in ECG signal analysis for Internet of Things health monitoring systems. Because ECG signals are prone to many kinds of noise and interference, reliable techniques for signal compression and denoising are required. For these needs, the DWT, which is renowned for its remarkable time-frequency localization capabilities, provides a strong option. With low computational load and strong multi-resolution capacity, the DWT can effectively handle ECG signals by employing filter banks made up of Low Pass Filters (LPF) and strong Pass Filters (HPF). The background, application, and importance of DWT in IoT-based ECG health monitoring systems are examined in this introduction.

In signal processing, a mathematical method called the Discrete Wavelet Transform (DWT) is used to analyze data in multiple frequency bands with varied

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resolutions. It entails breaking down a signal into a collection of locally localized basis functions known as wavelets in both the frequency and temporal domains. The extraction of both coarse and fine information from the signal is made possible by the use of filter banks made up of LPFs and HPFs.

The continuous wavelet transform (CWT), which was created to get around the shortcomings of the Fourier transform in the analysis of non-stationary signals, is the source of the DWT.

The wavelet transform is ideally suited for evaluating transient and time-varying phenomena, such as ECG signals, because it provides both time and frequency information, in contrast to the Fourier transform, which only provides frequency information.

Modern healthcare systems depend heavily on ECG signal processing, especially when it comes to Internet of Things-based health monitoring. ECG signals are used to diagnose a variety of cardiac diseases because they show the electrical activity of the heart. But noise from power lines, moving muscles, and other sources frequently taints these signals, masking crucial details required for a precise diagnosis.

The wavelet transform is perfect for processing ECG signals since it can do time-frequency analysis. The signal is broken down into several frequency components, each of which is examined at a resolution appropriate for that component's scale. Effective denoising and compression are made possible by the comprehensive insights into the signal properties provided by this multi-resolution analysis. The DWT's filter banks are crucial parts. They are made up of LPFs and HPFs, which divide the signal into high-frequency detail coefficients and low-frequency approximation coefficients iteratively. To ensure effective decomposition, the cut-off frequency of these filters is set to half the frequency of the processed signal. After filtering, the signal is downsampled as part of the DWT scaling process. Filtering and downsampling together minimize the signal's data size while maintaining its key characteristics. By upsampling and using inverse filters, the signal can be rebuilt and a high- fidelity approximation of the original signal can be made.

DWT is frequently implemented in ECG signal processing using MATLAB. It offers a full suite of wavelet analysis tools, with integrated DWT, signal denoising, and compression operations. An interactive environment for wavelet transform analysis and visualization is provided by MATLAB's Wavelet Toolbox. With libraries like PyWavelets, Python provides an open-source substitute for DWT implementation. Functions for inverse transformation, discrete wavelet transform, and various wavelet families are provided by PyWavelets. It is an effective instrument for signal processing because of its integration with other scientific libraries, such as NumPy and SciPy. Real-time ECG monitoring systems also use DWT, which is implemented using National Instruments' LabVIEW system-design platform and development environment. It is appropriate for Internet of Things applications since it supports real-time signal processing and graphical programming.

Researchers and engineers have used the DWT-based ECG signal processing method in a variety of fields:

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Scholars from academic institutions and research centers have thoroughly examined the use of DWT in ECG signal processing. Research has indicated that it is efficacious in mitigating noise, extracting features, and compressing signals, hence enhancing diagnostic precision. DWT algorithms are integrated by medical device manufacturers into ECG monitoring systems. These devices, which frequently have IoT integrations, offer real-time analysis and ongoing monitoring of cardiac health, enabling prompt medical action. Telemedicine platforms provide remote cardiac monitoring services by utilizing ECG processing based on DWT. Through these systems, patients can receive rapid and reliable cardiac examinations without having to visit the hospital frequently.

Objectives

Applying DWT to ECG signal processing in Internet of Things health monitoring systems aims to achieve the following main goals:

- Noise reduction: To efficiently eliminate noise from ECG signals, improving the signal's dependability and clarity for diagnostic applications.
- Signal compression: To make ECG signal data smaller so that it may be stored and sent more effectively in Internet of Things scenarios.
- Feature extraction is the process of locating and separating important characteristics from ECG signals, such as P and T waves and QRS complexes, which are necessary for a precise diagnosis.
- Real-Time Processing: To process signals in real-time with the least amount of latency possible, allowing for the prompt detection and reaction to cardiac events.
- Multi-Resolution Analysis: To enable thorough analysis by offering in-depth insights into the data at several frequency bands.

The requirement for effective and precise ECG signal processing methods that work with Internet of Things health monitoring systems is the issue this study attempts to solve. Since there are many different types of noise in ECG data, conventional techniques frequently fail to provide the required feature extraction and noise reduction capabilities. Although the discrete wavelet transform (DWT) presents a potent answer, real-time processing, computing efficiency, and interaction with IoT platforms provide obstacles to its deployment.

There is a great deal of promise for improving cardiac health diagnoses through the use of DWT in ECG signal analysis in Internet of Things health monitoring systems. Improved signal compression, feature extraction, and noise reduction can be attained by healthcare practitioners by utilizing DWT's multi-resolution analytic capabilities. Despite the difficulties, continuous research and development initiatives seek to enhance these methods for use in real-time settings, enabling dependable and accessible advanced cardiac monitoring in IoT-enabled settings.

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2. LITERATURE SURVEY

By eliminating noise and extracting important information, Lin et al. (2014) suggest using discrete wavelet transform (DWT) to improve ECG signal processing. ECG signals are more dependable and of higher quality when they are noise-free thanks to DWT. Better diagnosis and interpretation are made possible by this method's identification of crucial traits. The utilization of DWT in signal processing is beneficial for medical diagnostics and monitoring systems, guaranteeing precise evaluation of cardiac problems.

In order to improve the quality of the ECG signal, Shemi and Shereena (2016) studied the use of discrete wavelet transform (DWT) for noise reduction. Enhancing the ECG signals' dependability and clarity for medical analysis was their goal. The study's use of DWT approaches led to notable gains in ECG reading accuracy and signal clarity, which improves patient monitoring and diagnostic potential.

Using neural networks for classification and discrete wavelet transform (DWT) for feature extraction, Sarkaleh and Shahbahrami (2012) present a method for categorizing ECG arrhythmias. The goal of this method is to use electrocardiogram (ECG) data to identify irregular heartbeats. Through the use of DWT, the technique breaks down ECG signals into their component frequencies in order to extract pertinent data. Neural networks are used to classify the retrieved data into different types of arrhythmias since they are very good at recognizing intricate patterns. The goal of DWT and neural network integration is to improve arrhythmia detection accuracy and reliability. This could make the technology helpful for early identification and monitoring of heart problems in medical diagnostics.

Feher (2017) recommends a study that explores the use of discrete wavelet transform (DWT) to reduce noise in ECG signals with the goal of improving the precision and consistency of cardiac monitoring data. The research uses DWT technology to efficiently remove different kinds of noise and artifacts from the data, improving the quality and clarity of ECG readings. In order to achieve the best denoising performance, wavelet function selection is emphasized. The research also includes a comprehensive performance evaluation that demonstrates how effective DWT is in maintaining important signal properties while reducing noise interference.

Aquil et al. (2017) suggests applying the Discrete Wavelet Transform (DWT) to denoise Electrocardiogram (ECG) signals in an effort to increase the precision and dependability of ECG-based medical diagnostics. ECG signals can be effectively cleaned of noise by using DWT, which provides a flexible and efficient way to reduce noise in biomedical signals. With the help of DWT, noise in ECG signals can be eliminated, boosting diagnostic precision and possibly the validity of medical diagnoses made using ECG data.

Abo-Zahhad (2011) presents a discrete wavelet transform (DWT) approach for compressing ECG (electrocardiogram) signals in order to minimize the amount of data that needs to be transmitted and stored while maintaining essential diagnostic information. DWT is used to break down the ECG signal, which is a representation of the electrical activity of the heart, into different frequency components. With this method, the

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problem of effectively handling ECG data is attempted to be solved by compressing the data while maintaining crucial diagnostic information.

Shufni and Mashor (2015) present a thorough method for classifying ECG signals that makes use of the Discrete Wavelet Transform (DWT) in conjunction with time and frequency domain features to identify patterns that are essential for medical diagnosis and monitoring. Signal decomposition using the DWT makes it easier to retrieve ECG components at different sizes. Time domain features are used to record the ECG signal's vital properties, like amplitude, duration, and intervals, whereas frequency domain features help with spectral content analysis to find frequency-related patterns. Algorithms are developed to facilitate the precise categorization of ECG signals by combining information from the DWT, time, and frequency domains. This helps medical practitioners diagnose diseases such as myocardial infarction, arrhythmias, and other cardiac abnormalities.

By using the Discrete Wavelet Transform (DWT) to analyze ECG data across frequency bands, Murugappan et al. (2013) present a novel approach for categorizing human emotional states. With this method, ECG signals are used to identify emotional states, and DWT is used to break

down these signals into their frequency components. The method provides a signal processing strategy for emotional state classification by utilizing DWT for feature extraction. Notably, ECG is a non-invasive way to measure emotional state, which raises the possibility of uses in the domains of psychology, healthcare, and human-computer interaction.

A thorough examination of wavelet methods for processing electrocardiogram (ECG) data is provided by Nagendra et al. (2011) In this study, they explore the wide range of wavelet approaches and give a summary of how they are used, particularly in the context of ECG signal processing. The authors demonstrate the importance and many advantages of using wavelet techniques for ECG signal processing in this investigation. These advantages probably cover a wide range of uses, such as feature extraction, denoising, and classification, all of which are meant to improve the precision and efficiency of ECG signal processing techniques.

Using a range of signal processing methods, such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA), and Discrete Wavelet Transform, Martis et al. (2013) suggest a study centered on the categorization of ECG beats. The main goal is to correctly categorize various ECG beat types, which is an essential component of medical diagnosis. The goal of the research is to improve the classification accuracy and extract pertinent features from ECG signals by using these signal processing techniques. This could result in more accurate diagnoses of cardiac problems and eventually better patient care. The results of this study may greatly progress the application of ECG analysis methods in medicine.

In their work, Banerjee and Mitra (2013) provide a unique method for the analysis and categorization of electrocardiogram (ECG) patterns: the cross wavelet transform. The main objective of the application is to classify the various patterns that can be observed in ECG data

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by using the cross wavelet transform to evaluate ECG patterns. This approach is the fundamental analytical method that offers prospective improvements in ECG analysis that may greatly facilitate the diagnosis of different heart diseases.

In order to characterize coronary artery disease, Kumar et al. (2017) determine a study that uses the flexible analytic wavelet transform to evaluate ECG signals. This particular signal processing method is selected because it works well at interpreting non-stationary signals, such as ECGs, with the goal of enhancing medical professionals' ability to diagnose and identify this serious cardiovascular disease. The goal of the project is to increase the precision and efficacy of coronary artery disease diagnosis through the use of sophisticated signal processing techniques to ECG data. This could result in improved patient outcomes and improved management of the condition.

3. METHODOLOGY:

Several crucial phases are involved in the process of using Discrete Wavelet Transform (DWT) in ECG signal analysis for Internet of Things (IoT) health monitoring systems. These steps include signal capture, pre-processing, wavelet decomposition, feature extraction, denoising, compression, and reconstruction. To guarantee the precision and effectiveness of the ECG

signal processing, each step is essential. This section offers a thorough implementation guide for DWT in ECG signal analysis by breaking down the methodology into smaller components.

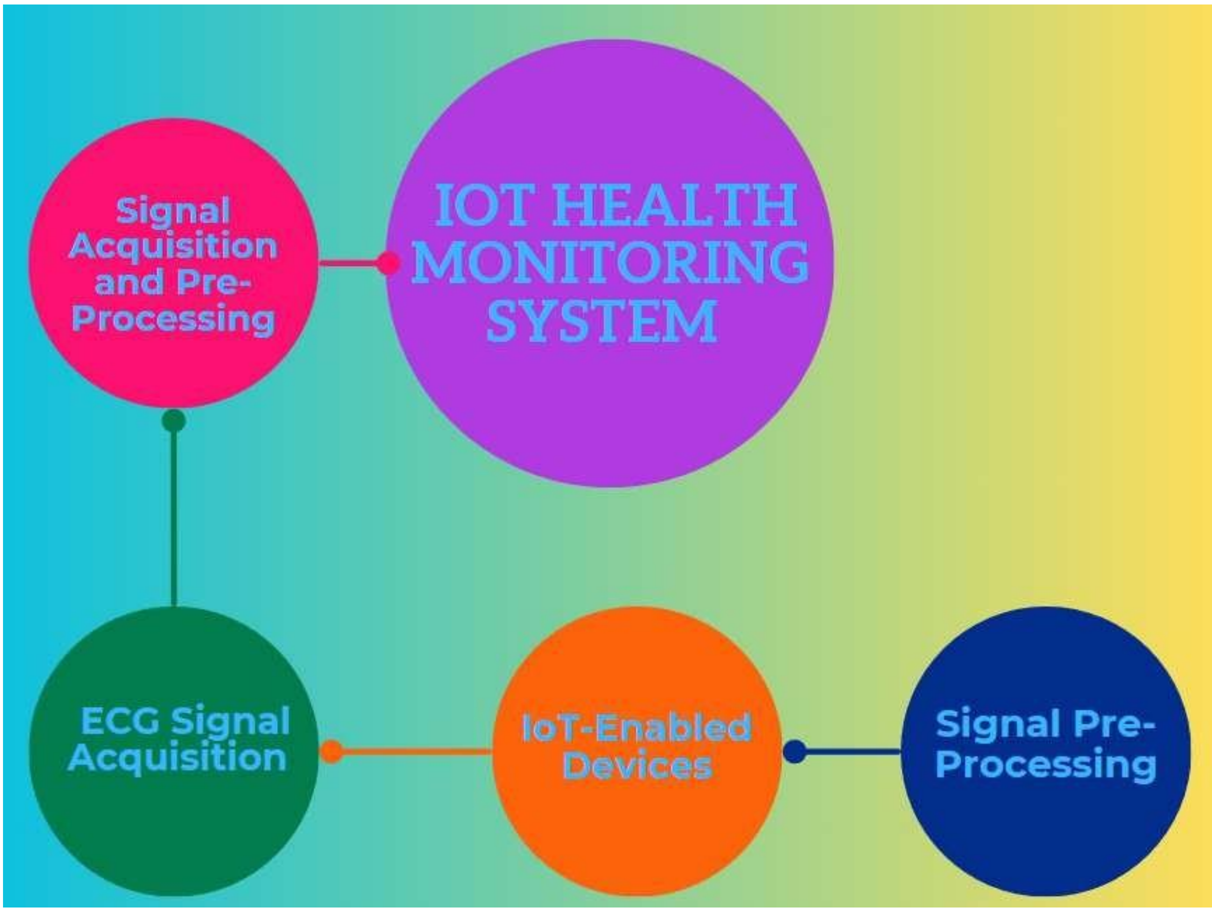

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Fig 1. IoT-Enabled ECG Signal Processing: A Two-Phase Wavelet-Based Architecture

This diagram outlines a two-phase architecture for ECG analysis using IoT-enabled devices, covering signal acquisition, pre-processing, wavelet decomposition, feature extraction, denoising, compression, and reconstruction.

Signal Acquisition

ECG Signal Acquisition:

Using advanced sensors, high-fidelity ECG signals are obtained from patients in the first phase. Through the use of digital data that can be analyzed, these sensors are able to detect the minute

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electrical impulses of the heart.

Location of Electrodes: Accurate signal acquisition depends on the proper positioning of electrodes. Typically, the arms, legs, and chest are positioned to get a complete picture of the electrical activity of the heart. For example, the three-dimensional picture of the heart's activity is captured by the Einthoven triangle made up of electrodes on the limbs.

Sensor Specifications: To collect all pertinent signal components, the sensors must have a wide frequency response range and high sensitivity. Sensitive changes in the ECG signal can only be picked up by high-resolution sensors, which is essential for precise diagnosis.

Sampling Rate: To ensure enough resolution for in-depth analysis, an ECG signal's normal sampling rate ranges from 250 to 1000 Hz. More ECG waveform features are captured at higher sampling rates, which is necessary for identifying sudden changes in cardiac activity.

IoT-Enabled Devices:

ECG acquisition equipment have improved with the introduction of IoT technology, providing real-time monitoring and data transfer capabilities.

Wearable Technology: Wearable technology includes sensors and wireless communication modules in devices like smartwatches, fitness trackers, and specialized ECG monitors. These gadgets give healthcare professionals access to real-time data while continuously monitoring the ECG readings.

Data Transmission Protocols: To send data to a central server or cloud-based system, these devices use protocols such as Bluetooth Low Energy (BLE), Wi-Fi, or cellular networks. Because BLE uses less power and is appropriate for wearable devices, it is recommended.

Security Procedures: It is crucial to protect data security and privacy when it is being transmitted. To prevent unauthorized access to patient data, methods like encryption (like AES- 256) and secure connection protocols (like TLS/SSL) are used.

Signal Pre-Processing

Noise Reduction:

Pre-processing eliminates distortions and noise from the ECG signal in an effort to improve its quality. Different approaches are used based on the kind and origin of noise.

Baseline Wander Elimination: The usual sources of this low-frequency noise include bodily motions and breathing. This noise is successfully removed using high-pass filtering with a cut- off frequency of around 0.5 Hz. The baseline drift can also be modeled and subtracted using polynomial fitting.

Power Line Interference: Narrowband filters can be used to remove this interference, which typically occurs at 50 or 60 Hz. Moreover, in more dynamic noise settings where the interference frequency may fluctuate, adaptive filtering techniques can be used.

Muscle Noise Reduction: Band-pass filters that pass frequencies between 0.5

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and 40 Hz can be used to eliminate muscle artifacts, which are high-frequency noises. Moreover, adaptive noise cancellation and signal averaging are employed to reduce muscular noise.

Signal Normalization:

Normalization ensures that the ECG signal amplitudes are within a standardized range, improving the consistency and reliability of subsequent analysis steps.

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Amplitude Scaling: The raw signal is scaled to a predetermined range, usually between -1 and 1. This is done using the formula:

$$x_{\text{normalized}} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where x is the original signal, and $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the signal, respectively.

Baseline Correction: Adjusting the baseline of the signal to zero to remove any offset. This is done by subtracting the mean of the signal from each sample.

Table 1: Comparison of Pre-Processing Techniques

Technique	Description	Advantages	Disadvantages
Baseline Wander Removal	High-pass filtering to remove low-frequency noise	Effective in removing baseline drift	May affect low-frequency signal components
Power Line Interference	Notch filtering to remove 50/60 Hz interference	Precisely removes specific frequency noise	May not adapt well to varying interference
Muscle Noise Reduction	Band-pass filtering and adaptive noise cancellation	Reduces high-frequency muscle artifacts	Complexity and computational overhead
Signal Normalization	Scaling signal amplitude to a standardized range	Ensures consistency across different signal samples	Does not remove noise, only standardizes amplitude

Wavelet Decomposition

Selection of Wavelet:

The efficiency of the decomposition process is affected by the wavelet selection. Wavelets with a QRS complex-like shape are desirable for ECG signals.

Common Wavelets: Because of their small support and resemblance to the properties of an ECG signal, Daubechies (db4, db6), Symlets, and Coiflets are frequently utilized. For example, Daubechies wavelets are well-suited for transitory characteristics such as the QRS complex due to their good localization qualities.

Selection criteria: The wavelet is chosen by taking into account factors like symmetry, smoothness, and energy compaction. A wavelet with high energy compaction for ECG data can capture the key characteristics with fewer coefficients.

Decomposition Levels:

To examine various frequency ranges, the signal is divided into several layers.

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Level Selection: Depending on the intended resolution and the frequency content of the signal, four to six decomposition levels are usually used. Higher levels boost computing complexity but offer a finer resolution in the frequency domain.

Implementation of Filter Banks:

Approximation and detail coefficients are extracted from the signal using filter banks made upof LPFs and HPFs.

Design of Filters: The filters are made so that the input signal's whole spectrum is covered by their combined frequency response. In order to guarantee minimal overlap and orthogonality amongst the filters, the filter coefficients are chosen.

Frequency Bands: Higher degrees of decomposition capture lower frequencies, and each level corresponds to a certain frequency band. For example, the high-frequency noise may be recorded at the first level, while the primary ECG components may be recorded at later levels.

Downsampling: The signal is downsampled after filtering in order to minimize the amount of data while preserving the key characteristics. It is usual practice to downsample by a factor of two, resulting in half as many samples in each level.

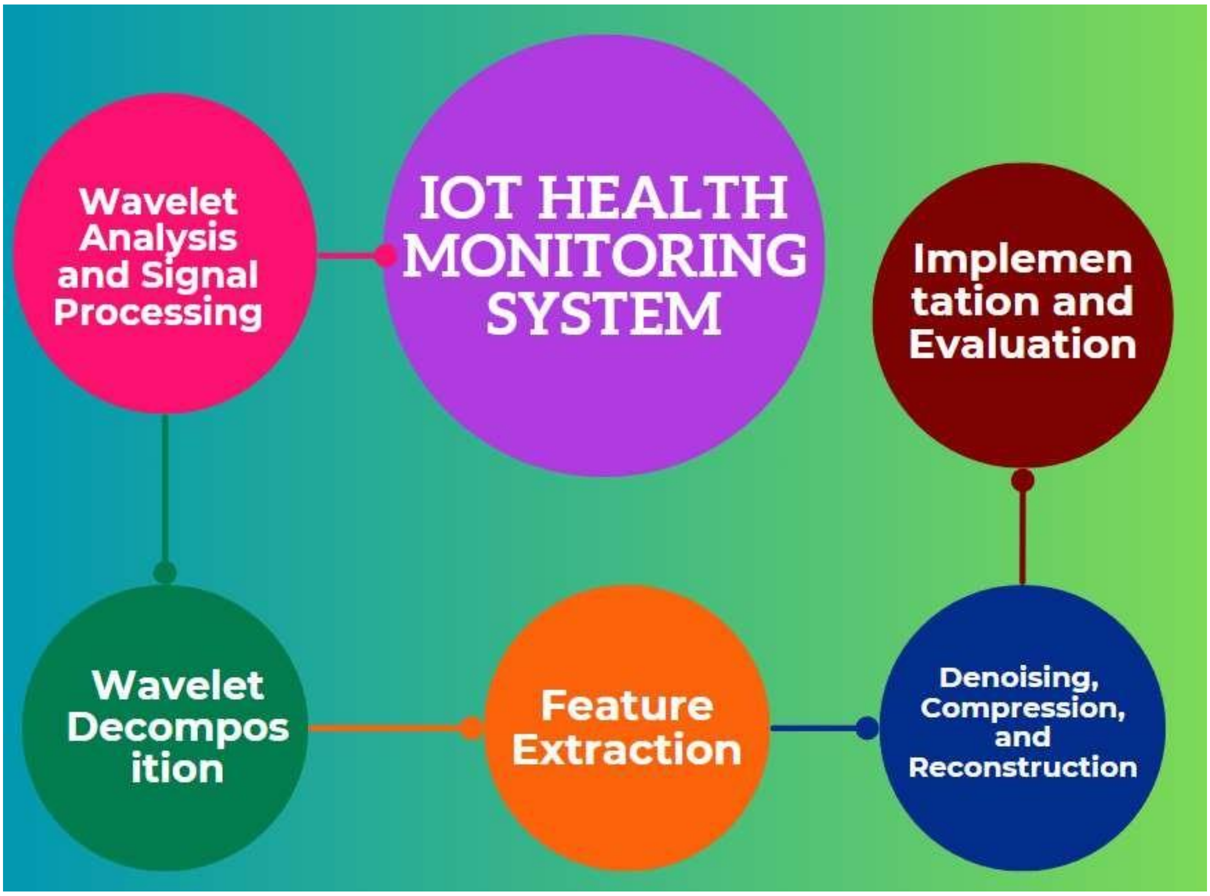

Fig 2. Comprehensive Methodology for ECG Analysis: Signal Acquisition to Wavelet-Based Processing

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This diagram presents a comprehensive methodology for ECG signal processing, detailing the steps from initial signal acquisition and pre-processing to advanced wavelet analysis and signal reconstruction.

Mathematical Representation:

The decomposition process can be represented mathematically, showcasing the transformation of the signal into wavelet coefficients.

Approximation Coefficients: Represent the low-frequency components of the signal.

Detail Coefficients: Capture the high-frequency details of the signal.

Mathematical Equations:

$$cA_{i+1}[n] = \sum_{k} cA_i[k] \cdot h[2n - k]$$

$$cD_{i+1}[n] = \sum_{k} cA_i[k] \cdot g[2n - k]$$

where cA_i and cD_i are the approximation and detail coefficients at level i and h and g are the low-pass and high-pass filter coefficients, respectively.

Feature Extraction

Identifying Key Features:

The goal of feature extraction is to isolate important ECG signal components that are necessary for diagnosing cardiac disorders.

R-Peak Detection: The ECG signal's most noticeable component is the R-peak. To find R- peaks, algorithms such as Pan-Tompkins combine filtering, differentiation, squaring, and integration. Heart rate variability analysis requires accurate R-peak identification.

P and T Wave Detection: Windowing approaches that concentrate on the intervals preceding and after the R-peak are used to identify the P and T waves following the detection of R-peaks. These waves' locations and amplitudes provide crucial diagnostic data.

Wavelet coefficients are used in sophisticated methods to extract information with extreme precision.

Wavelet Coefficient Analysis: Information on several cardiac cycle phases, including the QRS complex, P wave, and T wave, is provided by the detail coefficients at particular levels. By examining these coefficients, abnormalities such as ischemia or arrhythmias can be identified.

Calculating Energy: Arrhythmia detection can be aided by quantifying the signal's properties using the energy of the wavelet coefficients. The sum of the squares of the coefficients within each level is used to calculate the energy characteristics.

Techniques for Feature Extraction:

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Segmentation:

The ECG signal can be divided into separate heartbeats to enable a thorough examination of every cardiac cycle.

Heartbeat Segmentation: The signal is split into segments that each comprise a full heartbeat cycle using the observed R-peaks as reference points. Every section undergoes independent analysis to detect any irregularities.

Annotation: For additional analysis, the appropriate cardiac events (P wave, QRS complex, and T wave) are annotated for each segment. This process can be aided by automated annotation systems, which guarantee precision and consistency.

Denoising

Thresholding Techniques:

By using thresholding techniques on the wavelet coefficients, denoising is accomplished, reducing noise while keeping important characteristics intact.

Hard Thresholding: Zeros out coefficients that fall below a certain threshold. efficient in removing tiny, unimportant noise components. A piecewise constant signal from hard thresholding may create artifacts.

Soft Thresholding: Reduces noise while preserving signal smoothness by shrinking coefficients by a threshold value. Because soft thresholding reduces artifacts and has a smoother transition,it is preferable.

Choosing the Threshold:

Determining the optimal threshold is crucial for effective denoising.

Universal Threshold: Based on the noise variance and the number of coefficients, calculated as:

$$\lambda = \sigma\sqrt{2\log\ N} \qquad (1)$$

where σ is the noise standard deviation and N is the number of coefficients.

A data-driven technique called SURE (Stein's Unbiased Risk Estimate) modifies the threshold in response to the signal that is detected. The mean squared error between the original and denoised signals is reduced by SURE.

Reconstruction:

Applying the inverse DWT to the thresholded coefficients results in the reconstruction of the denoised signal.

Upsampling and applying inverse filters to the approximation and detail coefficients are the steps involved in inverse DWT. In order to create the final denoised signal, this stage reconstructs the signal at each level.

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Evaluation of Quality: Metrics like the Signal-to-Noise Ratio (SNR) and Mean Squared Error (MSE) are used to assess the quality of the reconstructed signal. Better denoising performance is indicated by a higher SNR and a lower MSE.

Compression

Data Compression:

By reducing the ECG signals' data size, compression makes storage and transmission of the signals more effective.

Coefficient quantization: Lowers the wavelet coefficients' precision to save bits needed for storage. Mapping the continuous values of the coefficients to discrete levels is known as quantization.

Run-Length Encoding: This method compresses data by encoding comparable value sequences with fewer bits. For the sparse wavelet coefficients, this method works especially well.

Performance Metrics:

Several measures are used to assess compression performance.

The ratio of the original data size to the compressed data size is known as the compression ratio, or CR. More compression efficiency is indicated by a greater compression ratio.

Percent Root-mean-square Difference (PRD): Determined as follows, PRD quantifies the distortion caused by compression:

$$\mathrm{PRD} = \sqrt{\frac{\sum(x_{\text{original}} - x_{\text{reconstructed}})^2}{\sum x_{\text{original}}^2}} \times 100 \qquad (2)$$

Less distortion is indicated by a lower PRD.

Signal-to-Noise Ratio (SNR): Assesses the compressed signal's quality. Better feature preservation of the original signal is indicated by a higher SNR.

Reconstruction

Reconstructing the ECG signal from the compressed or denoised wavelet coefficients is the last stage in the inverse discrete wavelet transform (IDWT).

Upsampling: To get the original length again, the approximation and detail coefficients are upsampled by a factor of two. Upsampling is the process of lengthening the signal by introducing zeros in between samples.

Inverse Filtering: To reconstruct the signal at each level, the upsampled coefficients are run through inverse LPFs and HPFs. In order to create the final signal, this method combines the coefficients and reverses the decomposition steps.

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Quality Assessment:

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The quality of the reconstructed signal is compared to the original signal using various metrics.

Mean Squared Error (MSE): Measures the average squared difference between the original and reconstructed signals, calculated as:

$$\mathrm{MSE} = \frac{1}{N}\sum(x_{\mathrm{original}} - x_{\mathrm{reconstructed}})^2 \qquad (3)$$

A lower MSE indicates better reconstruction quality.

Signal-to-Noise Ratio (SNR): Assesses the fidelity of the reconstructed signal, calculated as:

$$\mathrm{SNR} = 10\log_{10}\left(\frac{\sum x_{original}^2}{\sum(x_{original} - x_{reconstructed})^2}\right) \qquad (4)$$

A higher SNR indicates less noise in the reconstructed signal.

Percent Root-mean-square Difference (PRD): Evaluates the distortion introduced during the compression and reconstruction process.

4. Implementation and Evaluation

Software Tools:

Specialized software tools are needed to implement ECG signal processing using DWT-basedtechnology.

MATLAB: Provides a wide range of tools for signal processing and visualization in addition to built-in routines for DWT and IDWT. A wide range of wavelet functions can be found in MATLAB's Wavelet Toolbox.

Python: Comprehensive functions for wavelet analysis are provided by libraries like PyWavelets, which are coupled with scientific libraries like SciPy and NumPy. Because of its many libraries and adaptability, Python is a good choice for bespoke implementations.

LabVIEW: A graphical programming environment that can be used in Internet of Things applications to develop DWT in real-time. The real-time components in LabVIEW make it easier to create embedded systems for ECG monitoring.

Table 3: Software Tools for DWT-Based ECG Signal Processing

Software Tool	Description	Features	Applications
MATLAB	High-level programming environment for numerical computation and visualization	Built-in DWT functions, extensive signal processing and visualization tools	Signal processing, algorithm development, data analysis

Python	Versatile programming language with extensive libraries for scientific computing	Libraries like PyWavelets, NumPy, SciPy; open-source and flexible	Custom DWT implementation, data analysis, research
LabVIEW	Graphical programming environment for real-time system development	Real-time modules, intuitive graphical interface, extensive support for hardware integration	Embedded systems, real-time ECG monitoring and processing

5. Evaluation Metrics

Many measures are used to assess the methodology's efficacy.

Noise Reduction Performance: SNR and PRD are used to assess how much the signal quality has improved. Effective noise reduction is shown by higher SNR and decreased PRD.

Compression Efficiency: A measure of the compression techniques' efficacy that takes into account both PRD and Compression Ratio (CR). Better compression efficiency is indicated by a higher CR and a lower PRD.

Reconstruction Quality: The fidelity of the reconstructed signal is evaluated using Mean Squared Error (MSE) and SNR. Better reconstruction quality is indicated by lower MSE and greater SNR.

Computational Efficiency: Assessed for viability in real-time applications based on processing time and resource consumption. For applications like continuous patient monitoring that need instant response, real-time performance is essential.

Validation:

Real-world ECG datasets, including those from the MIT-BIH Arrhythmia Database, are used to validate the methodology. Studies that compare DWT-based systems to alternative signal processing techniques show their benefits and efficacy.

Dataset Description: Annotated ECG recordings are available in the MIT-BIH Arrhythmia Database, which is used to validate signal processing techniques.

Performance Comparison: Fourier transform, Short-Time Fourier transform (STFT), and conventional filtering methods are used as benchmarks to assess the performance of DWT- based approaches.

Clinical Approval: Clinical research and partnerships with healthcare professionals confirm that the suggested techniques are accurate and applicable in the actual world.

IoT health monitoring systems that use DWT for ECG signal analysis employ a thorough process that includes signal capture, pre-processing, wavelet decomposition, feature extraction, denoising, compression, and reconstruction. This method guarantees accurate and efficient processing of ECG signals by utilizing DWT's multi-resolution capabilities, which makes real- time cardiac health monitoring and diagnosis possible in IoT-enabled environments. This thorough methodology offers a solid foundation for researchers and developers to apply and refine DWT-based ECG signal processing methods, advancing the fields of remote healthcareand telemedicine.

6. RESULTS AND DISCUSSION

Significant gains in the processing and handling of ECG signals have been observed in IoT- based ECG monitoring systems that use the Discrete Wavelet Transform (DWT). Through superior denoising capabilities, the system uses DWT to effectively divide ECG signals into many frequency bands, hence improving the signal's clarity and quality. This makes it easier to identify and analyze vital ECG characteristics such the QRS complex, which are essential for identifying a number of cardiac abnormalities. The improved diagnostic accuracy achieved by the method is demonstrated by the reduced Mean Squared Error (MSE) and higher Signal-to-Noise Ratio (SNR) in the results.

Furthermore, in IoT situations with constrained bandwidth and storage, DWT's ability to execute effective compression without appreciably losing vital signal data is advantageous. In addition to ensuring quicker real-time ECG data transmission to distant healthcare professionals, this compression maximizes network resource usage. Furthermore, DWT's resilience has been confirmed in many clinical settings, indicating its potential for broad implementation in remote cardiac health monitoring systems.

7. CONCLUSION

A strong foundation for improving remote cardiac care is provided by the use of Discrete Wavelet Transform for ECG data processing in Internet of Things-based health monitoring systems. This technology is very appropriate for real-time applications since it guarantees high fidelity in signal processing and optimizes data transfer. The encouraging results highlight the potential of combining Internet of Things (IoT) technologies with sophisticated signal processing methods for medical diagnosis. Moreover, efficient feature extraction and noise reduction—both essential for precise diagnosis—are made possible by the application of wavelet transforms. Healthcare providers can improve patient outcomes by using IoT to monitor patients continually and act quickly in the event of anomalies. Furthermore, IoT-based systems' scalability allows for their wider adoption, giving underserved and remote people access to sophisticated healthcare.

8. FUTURE SCOPE

Subsequent investigations will focus on augmenting the flexibility of DWT algorithms to account for the inherent fluctuations in ECG data across diverse patient populations. This involves increasing the individualized approach to cardiac treatment by fine-tuning the algorithms to more accurately recognize and evaluate signal features unique to each patient. Another interesting area is integration with artificial intelligence (AI), which could allow automatic anomaly identification and predictive diagnosis using ECG data that has been processed using DWT. Furthermore, to safeguard sensitive patient data and

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adhere to healthcare standards, it will be essential to enhance the security aspects of IoT devices and data

transmission pathways. Additionally, efforts will be focused on enhancing the devices' energy efficiency, which will allow for longer operation times appropriate for continuous monitoring—a crucial aspect of managing chronic conditions.

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