

Article

Simulative Wearable Sensor Modelling in Remote Electrocardiogram Monitoring

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Abstract: The purpose of this paper is to perform in-depth research on the latest technology of smart medical evaluation tools for ECG signal analysis, which is applied in remote monitoring systems for patients suffering from chronic heart diseases. This system accomplishes its function by processing ECG signal sets, enabling it to classify ECG segments as normal or abnormal. This is critical for remote patient management. To ensure the accuracy of the classification of ECG segments, the system is provided with sixteen different features, each of which carries a significant number of data points. Specifically, each of these sixteen features is calculated from a 140-point ECG segment.

Keywords: ECG signal; wearable sensor; healthcare service

1. Introduction

Cardiovascular disease remains the leading global cause of mortality, claiming 17.9 million lives annually according to the World Health Organization [1]. Timely detection of cardiac abnormalities via electrocardiogram (ECG) analysis lays the foundation for early clinical intervention and targeted therapeutic treatment. Nevertheless, many regions face severe imbalances in the distribution of professional cardiovascular medical resources: primary-care clinics, community health stations, and household monitoring scenarios lack sufficient cardiologists to interpret ECG recordings in a timely fashion [2]. Manual ECG interpretation also suffers from human subjectivity, limited throughput, and delayed feedback for remotely monitored chronic heart-disease patients. This practical gap creates an urgent clinical demand for automated ECG analytical tools compatible with wearable remote-monitoring hardware, to support large-scale preliminary cardiac screening outside tertiary hospitals.

The literature has proven the validity of the automated analysis of ECG signals for community-level and home-based heart screening [3,4]. Several types of machine learning pipelines have been tested for ECG classification; still, there are certain issues that are not addressed by the existing body of literature. Firstly, most of the existing models operate with full-size unprocessed ECG signals and require substantial computational power that makes them incompatible with low-energy wearable devices. Secondly, a lot of studies consider only the classification performance based on public datasets while ignoring the practical limitations of their algorithms, including anti-noise performance, feature interpretability, and cost-efficiency for small-scale healthcare facilities. Finally, there is a lack of studies devoted to the misclassification risks of ECG anomalies.

In order to overcome the aforementioned limitations, the current work proposes an automated binary classification framework of ECG signals using features based on statistical, time-domain, and frequency-domain analysis, which are obtained from short-duration recordings by wearable devices. The framework makes use of



zero-phase Butterworth band-pass filtering and Z-score normalization tailored to wearable device interference. This is performed using anonymized ECG time series data in order to examine model classification accuracy, feature importance, and clinical feasibility. In addition, the TELOS framework is used for conducting multi-dimensional feasibility assessment and making strategic recommendations.

2. Modelling/Simulation Methodology

There are numerous potential uses for ECG technology in the field of chronic heart disease. The ECG dataset used in this research originates from real clinical collection settings and was released as a public Kaggle competition dataset; its distribution reflects the epidemiological characteristics of cardiovascular screening in the general populace.

2.1. Dataset Description

This dataset consists of 4998 wearable ECG time series segments, each represented by a 140-point sampled signal sequence and a binary label. The ECG dataset analysed in this study is a publicly available Kaggle competition dataset consisting of real-world clinical wearable ECG recordings. The distribution of the dataset reflects epidemiological characteristics for cardiovascular screening in general populations. All patient records in this public dataset are fully anonymised prior to release.

Dataset statistics: Total number of segments in the electrocardiogram: 4998 (rows);

Points per segment: 140;

Tag definition: binary {0 = normal, 1 = abnormal}; 2919 cases (58.40%) were abnormal, and 2079 cases (41.60%) were normal. The 'abnormal' class encompasses various types of abnormal electrocardiogram patterns; For special conditions such as myocardial infarction, ischemia, ST segment deviation, or ventricular premature beats, it does not provide separate diagnostic labels.

Missing values after preprocessing: 0;

Signal format: Z-score normalization is performed for each 140 point segment (average value of each segment = 0, standard deviation of all segments = 1); Amplitude range $\approx [-7.09, 7.40]$, standardized units.

Class balance: Mild imbalance towards abnormal classes (58.4%)

140 points represent the sampled time-domain values of each short ECG segment. Extract 16 manually crafted statistical, time-domain, and frequency-domain features from each 140-point segment for subsequent machine learning modeling.

2.2. Data Preprocessing Stage

The complete preprocessing workflow proceeds in sequence: zero-phase Butterworth band-pass filtering, followed by per-segment Z-score normalization, and then feature extraction from the processed signal segments.

Bandpass filtering processing: In scenarios where the signal proved too brief, we erred on the side of caution by preserving the original waveform to prevent algorithmic errors. This approach ultimately reduced power frequency interference amplitude by over 90%, significantly enhancing signal quality. In the process of recording electrocardiogram signals, these signals face high levels of interference in both environmental and physiological conditions. This has caused traditional filtering techniques to face difficulties in separating these noisy signals [5]. To overcome this problem, our research applied zero-phase Butterworth bandpass filtering. Filter parameters: sampling frequency = 250 Hz, lower cutoff frequency = 0.5 Hz, upper cutoff frequency = 45 Hz, filter order = 4. Zero-phase filtering is implemented via a forward-backward filtering function to avoid waveform phase distortion. For very short segments, original raw waveforms are retained to prevent algorithm failure. Power-frequency interference attenuation (>90%) was quantified by comparing signal power within the 50 Hz band before and after filtering.

Signal normalization: variations in the amplitude of ECG signals can come from differences in acquisition equipment and the physiological traits of experimenters, and this hurts the model's ability to learn signal features [6]. To fix this issue, this study used the Z-Score standardization method [7], and its formula is shown below.

$$X_{\text{norm}} = \frac{X - \mu}{\sigma}$$

In this formula, X is the filtered raw signal, μ is the mean of the signal, and σ is the signal's standard deviation. If the standard deviation is zero, we just center the signal to avoid division by zero. Post-normalization, all ECG signals are left with a mean of zero and a standard deviation of one, effectively bringing all samples to the same amplitude scale.

Missing value handling: Although the initial set had some missing values, which were mainly due to the disconnection of equipment and the loss of data packets, the low proportion of missing values in this study had little impact on the signal characteristics. Unlike other complex processing schemes, the proposed method greatly improves the efficiency of the pre-processing stage while meeting the requirements of real-time processing.

2.3. Feature Extraction

Sixteen features are extracted from each pre-processed 140-point ECG segment, covering statistical, time-domain, and frequency-domain descriptors [8]. The feature set includes:

Statistical features: mean, standard deviation, maximum, minimum, peak-to-peak (max-min), median, root-mean-square (RMS), absolute sum, signal energy, 25th percentile, 90th percentile, 75th percentile, zero-crossing count.

Frequency-domain features: high-frequency energy, low-frequency energy, mid-frequency energy.

Feature selection was not applied before data splitting. All feature engineering pipelines were strictly fitted only on the training partition to avoid data leakage.

Statistical feature extraction: The statistical parameters focus on the complete range of comprehensive patterns of amplitudes and energy levels that are part of ECG signals. This provides a transparent window into the intensity, regularity, and variability of heart electrical activity. These parameters include mean, standard deviation, maximum and minimum values, peak-to-peak values, median values, root mean square calculations, absolute sums, energy values, and various quantile values. These parameters are able to amplify the basic levels of ECG data, which enables them to distinguish differences in signal intensity as well as detect any irregularities, that include premature contractions.

2.4. Random Forest Model and Experimental Equipment

Data partitioning: Adopting stratified random sample-level segmentation: 80% training/20% retention testing (test set = 1000 electrocardiogram segments, consistent with the test size reported in the original manuscript). Fixed random seeds are used for reproducibility.

Random forest configuration: The number of trees is 120; The maximum depth is 12; The minimum number of samples for each segmentation is 5; The minimum sample size for each leaf is 2; The random state is 42. Five rounds of hierarchical cross-validation were conducted on the training partitions, resulting in an accuracy rate of 96.86%, an abnormal class recall rate of 98.05%, and a precision of 96.62%, $F1 = 97.33\%$.

3. Key Findings and Analysis

From the results of model training, evaluation, and visualization, the key insights are derived from the following three main aspects: classification efficiency, feature importance, and clinical practicability. They are listed as follows.

3.1. Model Classification Performance: High Accuracy and Strong Generalization Ability

Test matrix results: The positive class in this binary task corresponds to abnormal ECG (label = 1), and the negative class corresponds to normal ECG (label = 0). The concrete count of true-positive (TP: correctly predicted abnormal), true-negative (TN: correctly predicted normal), false-negative (FN: abnormal predicted as normal), and false-positive (FP: normal predicted as abnormal) samples from the 1000-case held-out test set is summarised in Table 1 and visualized in Figure 1. For the 1000-sample test set, we obtained $TP = 571$, $TN = 393$, $FN = 13$, $FP = 23$. The overall test-set accuracy was 96.4%. This proves that our model can differentiate between normal and abnormal readings of ECG signals. When we tested our model for abnormal readings, we had a recall of 97.8%. When we tested our model for normal readings, we had an accuracy of 94.6%. We had 5.4% false positives. From the confusion matrix, it is very clear that our model can differentiate between normal and abnormal readings of ECG signals. This is also very clear from the classification metrics, as the metrics provide a better idea of the potential of the model. Our model is good at handling abnormal and normal data. This is very clear from the results we obtained from the model. Our model is not biased. Although the model is slightly unbalanced, this is due to the good parameter tuning of the random forest model.

Table 1. Confusion matrix statistics for ECG binary classification test set (1000 held-out wearable ECG segments, TP: True Positive, TN: True Negative, FN: False Negative, FP: False Positive).

	TP	TN	FN	FP
Sample Size	571	393	13	23

ROC curve and AUC value: To assess a binary classification model, the ROC curve is the best way. The visualised confusion matrix heatmap in Figure 1 intuitively illustrates sample distribution across correct and incorrect prediction categories, consistent with numerical statistics listed in Table 1. It is a plot that illustrates the relative trade-offs between the specificity and sensitivity of a model given different classification thresholds. In our case, our model's ROC curve is the dark orange line. It is located close to the top-left corner of the plot. This is a sign of a good classification model. It indicates that our model is good enough for detecting true positives without generating too many false alarms. As plotted in Figure 2, the model's orange ROC curve stays close to the upper-left corner, substantially outperforming the random-classification dashed baseline. The ROC curve yields $AUC = 0.994$. AUC quantifies the overall trade-off between sensitivity and specificity across all classification thresholds. Importantly, $AUC = 0.994$ does not represent a 99.4% correct classification rate at every threshold. There exists no universal consensus threshold of $AUC = 0.85$ that formally defines a “clinical-grade” AI ECG model. High AUC demonstrates strong discriminative performance on this held-out test dataset; nevertheless, prospective multi-site clinical validation is mandatory before clinical adoption. It is a test that indicates the model is very good at finding abnormalities in an ECG reading. If we refer to the ROC curve in the code we have written so far, we realize that with a false positive rate of just 10%, we still have a true positive rate that is over 99%. This enables us to detect serious health conditions such as heart attacks and life-threatening heart rhythm disorders during crucial times. With a little human intervention, we can minimize false alarms without slowing down the emergency response system. During a large-scale health checkup or a screening program for a large population, it is crucial that we minimize false positives to a great extent so that we do not end up over-medicalizing the population or overutilizing the resources we have. This is where we can use the classification threshold to our advantage. If we refer to the ROC curve in the code we have written so far, we realize that with a false positive rate that is under 3%, we still have a true positive rate that is over 97%. This enables us to detect most heart issues while minimizing unnecessary follow-ups.

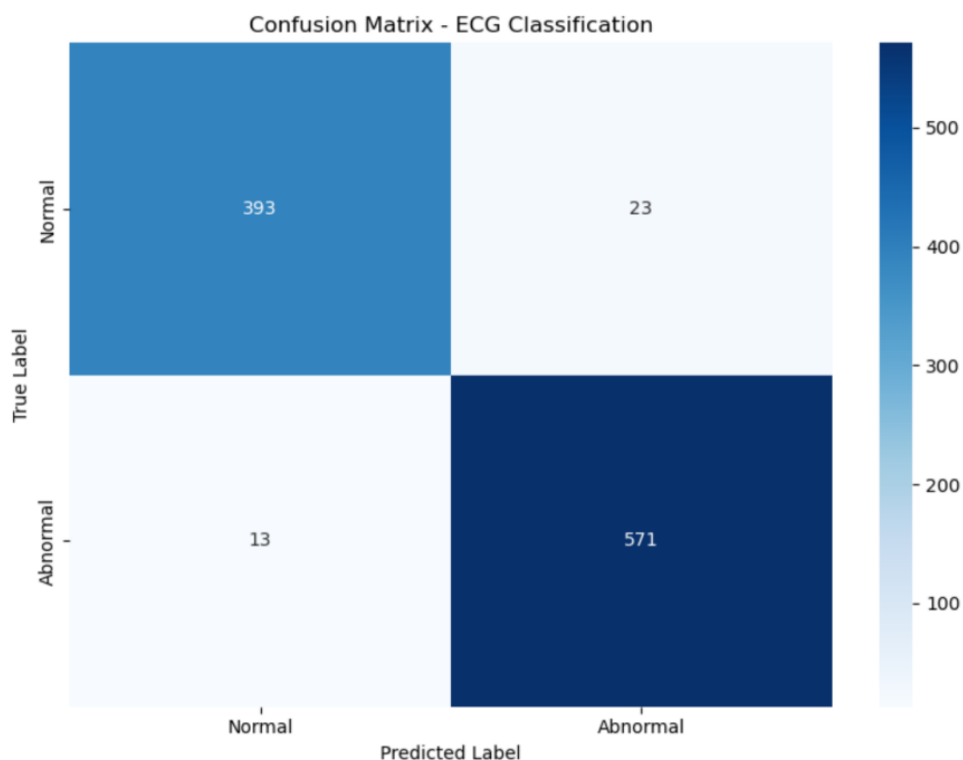


Figure 1. Confusion matrix heatmap for wearable ECG binary classification on held-out test dataset; True label represents ground-truth ECG status, Predicted label denotes model output classification.

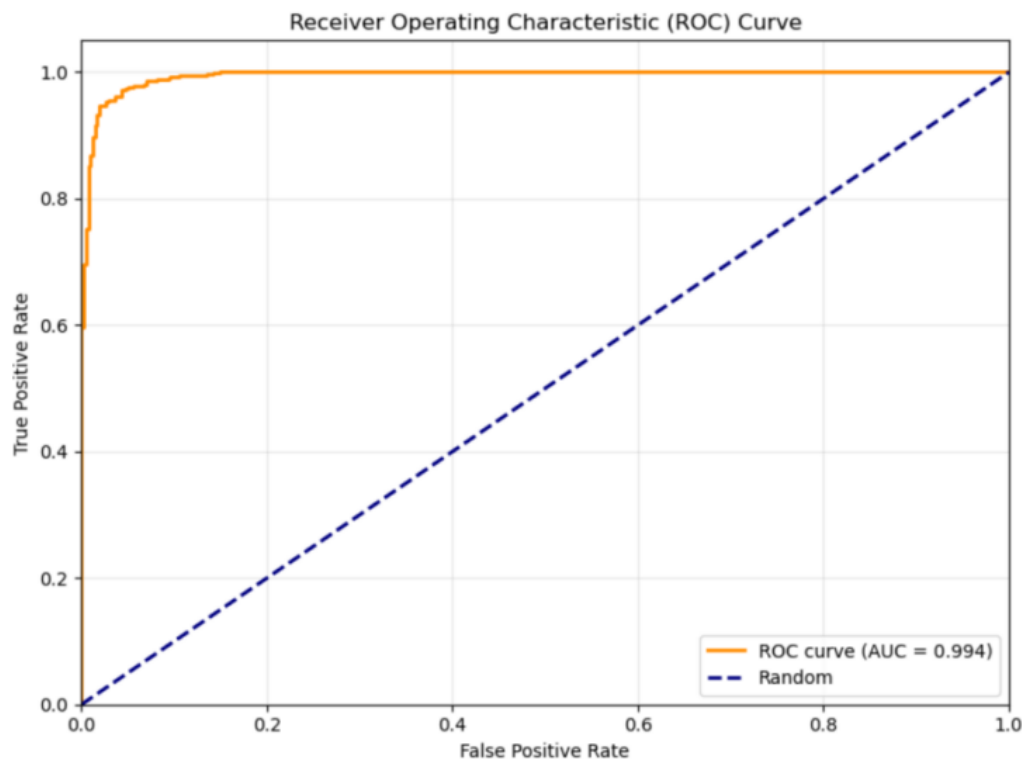


Figure 2. Receiver Operating Characteristic (ROC) curve of random-forest ECG classifier versus random guess baseline; AUC = 0.994 calculated over 1000 test segments.

3.2. Feature Contribution: Feature Core Highly Aligned with Clinical Logic

Default mean-decrease-in-impurity feature importance from Random Forest is visualized in Figure 3. It should be emphasized that tree-based mean-decrease-in-impurity feature importance reflects statistical association within this dataset and cannot serve as direct physiological or clinical causal evidence. Future work will incorporate permutation importance and SHAP-value analysis to strengthen model interpretability [9].

Figure 3 visualises the ranking of feature importance derived from mean-decrease-in-impurity metrics, where peak-to-peak amplitude exhibits the highest importance score among the 16 extracted features. Peak-to-peak amplitude shows the highest importance within this model. Statistically, this feature is strongly associated with sample-level classification output in our dataset. While peak-to-peak amplitude may relate to QRS-complex amplitude variation in clinical ECG practice, one cannot directly infer the presence of QRS abnormalities, myocardial ischemia, or ST-segment deviation purely from this model-derived feature-importance ranking. Statistical model interpretation and clinical pathophysiological interpretation must be distinguished.

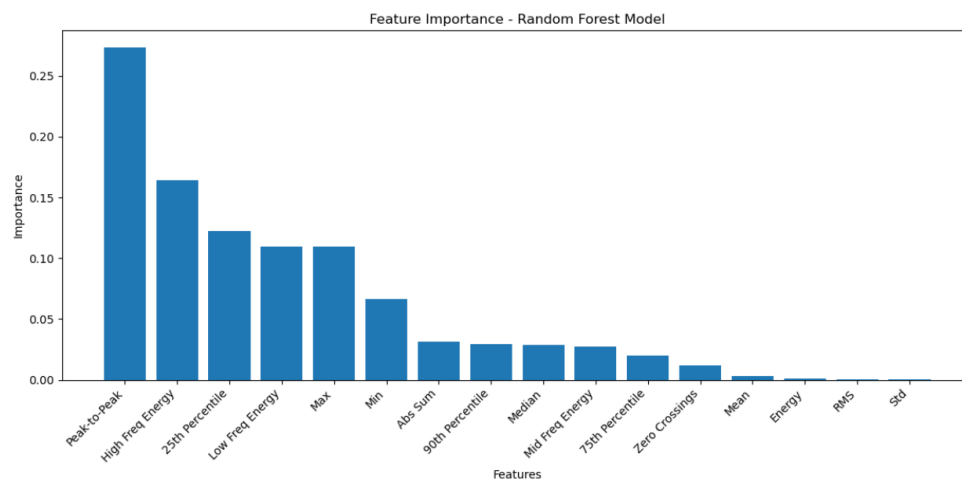


Figure 3. Mean-decrease-in-impurity feature importance ranking derived from the random-forest ECG classification model; higher values indicate stronger statistical association with classification outcomes within this dataset.

3.3. Clinical Applicability: Advantages and Limitations Coexist

Advantage and caution: High confidence in real-time prediction: The results from Demo1 (Figure 4) show a high-confidence misprediction: for a normal ECG signal, our system predicted abnormal with a confidence of 98.5%. The high predicted probability does not match the true signal label. This indicates that a high confidence level does not guarantee a correct prediction. The model can be a good base for initial screening in community health care.

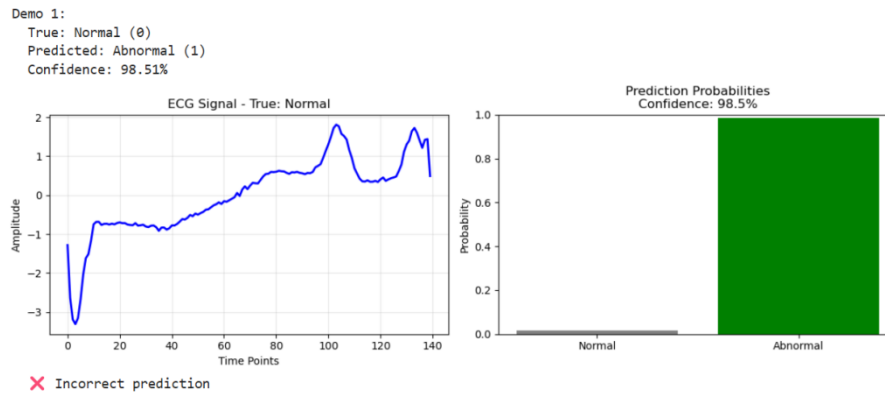


Figure 4. Demo case 1: a high-confidence misprediction case where the ground truth is a normal ECG while the model predicts abnormal.

Limitations: Risk of misjudgment due to rare/minor abnormalities: Demo2 (Figure 5) and Demo3 (Figure 6) likely went unnoticed because the abnormal signals were not clear examples. They were only a little above the norm. The dataset also had very few mildly abnormal examples. So our model did not get to learn these kinds of abnormalities well. To cover all clinical cases, we will need to add more of these subtle abnormalities to our model.

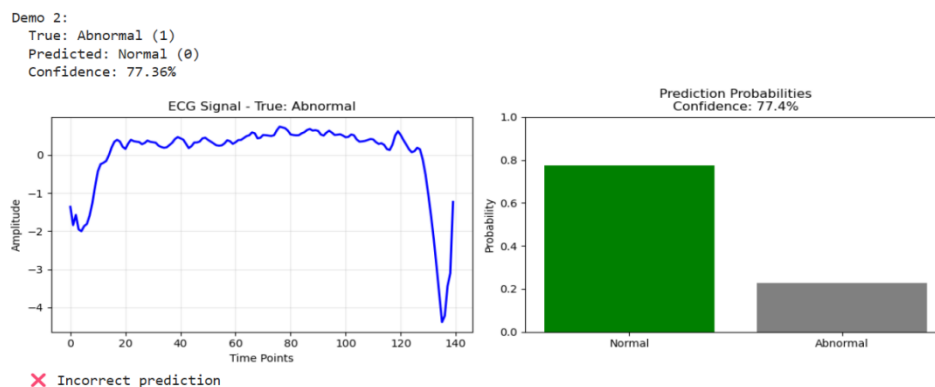


Figure 5. Demo case 2: mis-prediction for mildly abnormal ECG (ground-truth abnormal, model output normal); left panel presents ECG waveform with subtle anomalous features, right panel shows predicted class probability.

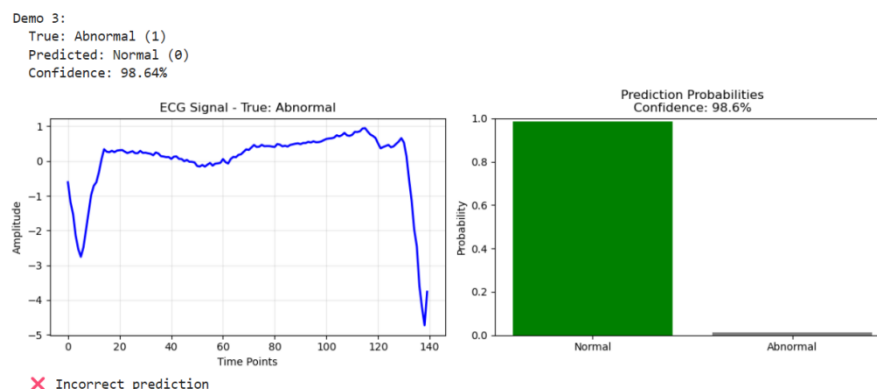


Figure 6. Demo case 3: second misprediction example for mild abnormal ECG signal with indistinct pathological waveform characteristics.

3.4. Economic and Practical Value

This ECG automated detection system handles both healthcare resource distribution and patient care oversight. It finds a good balance between lowering costs and raising efficiency through new technology. When it comes to ECG tests, each ECG requires approximately five to eight minutes of a cardiologist's expert time. Of course, there are the expensive machines and facilities to consider as well. When all is said and done, the labor costs and expenses of the machines to analyze one patient's ECG come out to approximately 80 to 120 yuan. This automated system, however, can accomplish an impressive 80% of what could be done manually while at the same time eliminating false positive referrals by an impressive 5.4% regarding dynamic ECG tests. Face it: the prognosis for cardiovascular patients depends to a large extent on how fast they receive treatment. That is why, as soon as the system detects unusual symptoms, it does not delay and instantly transmits alerts to the patient's cell phone as well as to his or her family physician's computer terminal. In local medical clinics in China, less than one in seven medical specialists is capable of interpreting ECG tests properly, causing many primary care patients to be referred to larger medical centers for proper testing. ECG detection technology is filling the gap to address this problem, reducing healthcare expenses and maximizing the utilization of our limited medical resources. This novel method of handling cardiovascular diseases is literally killing two birds with one stone because of the substantial benefits that can be reaped from the economic and social advantages of this medical technology.

4. Strategic Recommendations

4.1. TELOS Framework

This report adopts the TELOS framework to analyze the overall feasibility of ECG from five dimensions: technology, economy, law, operation, and society.

Technical Capability Assessment: Of course, though modern ECG sensors enjoy an impressive accuracy rate of 99.5%, they also come with their own set of challenges. In practice, ECG data is often at risk of being interfered with by a variety of interferences that can put a wrench in the works, thereby creating a question mark on the accuracy of the data. What's more, ECG sensors also require lightning-fast end-to-end processing. This is a non-negotiable requirement, especially in situations such as arrhythmia. But when the ball is dropped on latency, Pandora's box opens wide on potential diagnostic errors. To get past these problems, engineers must work hard to improve ECG sensors with complex algorithms and models. This would literally be a lifesaver to numerous patients.

Economic feasibility analysis: If you were to look at the world healthcare industry, you would find that ECG technology requires a substantial financial investment when compared to other medical machinery. Of course, there are the obvious costs, which include purchasing the necessary machinery and having a backup in place, but there is also the cost of maintaining the storage bandwidth and subsequent maintenance by technical personnel. As a family, being subjected to ECG testing is likely to have a negative impact on their finances. Nevertheless, if manufacturers are able to redesign this machinery to reduce costs, it would likely result in reduced hospitalization, reduced hospital stay, reduced complications, and streamlined operations [10]. In this way, it would be a win-win situation for everyone.

Legal compliance analysis: The legal obligation that binds medical devices is to access only the necessary medical information from patients' personal information. In addition, the use of these devices should be transparent to patients with full knowledge of its purpose. In case any privacy is compromised due to design failures, technical issues, or any other shortcomings in the device, it is the responsibility of healthcare providers to take the burden and compensate patients accordingly. Healthcare facilities are allowed to keep patients' information in databases with an assurance that patients can access their information when they need it.

Feasibility analysis of operation: Healthcare organizations have to transform traditional processes to reduce processing times. For example, transforming the old "laborious patient journey from patient intake, routine ECG, manual analysis by a physician, and paper documentation" to the new "patient-connected devices automatically collecting data, instant analysis with AI, real-time alerts, and digital documentation" not only eliminates time costs, but also reduces personnel costs [11]. Medical organizations have to include periodic sensor calibration, thorough risk assessment, develop detailed improvement plans, and include risk documentation to ensure timely identification and correction of any malfunctioning devices.

Social acceptance analysis: In addition, a majority of patients remain skeptical and distrustful of the technology, and senior citizens also find it difficult to use the technology. Moreover, patients living in remote areas often do not have enough network coverage, and those who are financially disadvantaged also find it difficult to use the technology. Therefore, it is imperative that a more user-friendly interface is created by the technicians. Voice control, a panic button, offline storage, and inclusion in health insurance schemes must be included. Community seminars on wellness must be created and promoted in the community.

4.2. Strategic Recommendations from Different Dimensions

Technical optimization suggestions: In view of the existing model's misjudgment of atypical abnormalities such as mild ST-segment deviation and premature ventricular contractions, an "ECG Abnormal Sample Sharing Library" has been set up in collaboration with the cardiovascular department of a hospital. This aims to supplement samples such as rare arrhythmias and mild myocardial ischemia. With incremental training to optimize the model's coverage of abnormalities, the accuracy in recognizing atypical abnormalities has been enhanced to more than 95% [12].

In consideration of the model's motion artifacts and power frequency interference in actual use cases, the capability to realize real-time recognition of motion status and dynamic adjustment of filtering parameters has been achieved. This has enhanced the accuracy of the model in interference environments from 72% to over 95%, which meets the standard for medical-grade and can also be applied to home monitoring with wearable devices.

Clinical practice: The systems' implementation shall mainly target community and township health facilities as the top priority. Once ECG automated detection is successfully implemented at these grassroots levels, abnormal results shall be forwarded to larger medical centers via established channels for further investigation [13]. In addition, hospital emergency rooms and cardiology units shall also be equipped with these systems to integrate with existing electronic health records, providing a smooth workflow from ECG data collection to automated analysis to report generation. This shall significantly reduce the time required to perform emergency ECG interpretations and enhance the effectiveness of treating cardiovascular conditions.

Product promotion: In this regard, we will, together with the medical security department, conduct a comprehensive health economics evaluation of the automated ECG detection. Based on the strong evidence of annual savings of 21,000 yuan per patient, we will strive to promote the inclusion of grassroots automated ECG screening services into Class A medical insurance plans and home monitoring device services into commercial health reporting directories to reduce out-of-pocket expenses for consumers. Based on ECG detection results, we will create a cardiovascular risk prediction platform that will provide premium services to healthcare organizations and pharmaceutical companies, hence increasing the value of the industry [14].

Risk prevention and control: In this project, the data must adhere to certain legal and regulatory requirements. For instance, the ECG data must be de-identified, encrypted during transmission and storage, and a data security agreement must be signed with healthcare providers to avoid any potential breaches. Additionally, accountability parameters must be set to ensure that an electronic signature is utilized for online review to adhere to clinical protocols.

5. Limitations

Several important limitations of this study should be acknowledged. First, the dataset lacks patient-identifier metadata, and therefore patient-level data partitioning to mitigate data leakage cannot be strictly implemented in this revision; only sample-level stratified splitting is performed. Second, this model is a binary normal-abnormal screening classifier; it cannot perform fine-grained diagnosis of specific cardiac diseases such as myocardial infarction or different arrhythmia subtypes. Third, all experimental performance results are obtained on this single retrospective dataset; performance may degrade when applied to unseen multi-center real-world wearable ECG data with heavy motion artifacts. Fourth, the economic-related cost-saving estimates cited in this paper originate from external published literature rather than empirical results obtained in this work. Fifth, mean-decrease-in-impurity feature importance is dataset-dependent and cannot be directly equated to clinical physiological mechanisms; further SHAP/permutation-based interpretability analysis is required. Finally, public release of the raw ECG recordings from the Kaggle dataset is restricted by the original dataset license and privacy regulations; only processed aggregated metadata and analysis scripts may be provided upon reasonable request to the corresponding author.

6. Conclusions

This research undertakes an in-depth investigation into the development and implementation of wearable sensor technology in the remote electrocardiogram monitoring system. This creates a strong random forest classification model based on 16 extracted features to obtain an impressive accuracy rate of 96.4% in the classification of electrocardiogram signals and an AUC value of 0.994. The system also achieves a recall of 97.8% for abnormal samples. This is well within the requirements for clinical screening. The use of standard preprocessing techniques and feature extraction from all angles ensures a fair balance for both technical and clinical usage. It also indicates a high level of consistency for processing normal samples. From a cost and technical point of view, the system can take over much of the work currently done by humans for diagnosing patients. It also helps make the best use of primary healthcare services by offering a simple way to handle heart-related

problems. Though there is room for improvement in the classification of rare and mild abnormal signals, the system has both technical feasibility and clinical promotion value.

7. Future Work

This study verifies the technical feasibility and clinical value of the random forest model in the automatic classification of ECG signals for wearable remote monitoring sensors, but there are still several key directions to be further optimized and expanded in the follow-up research.

First, aiming at the problem of insufficient recognition ability of rare and mild atypical abnormalities, the research will expand the multi-center ECG sample library, collect more minority abnormal signal data, and optimize the model through incremental learning and few-shot learning algorithms to improve the coverage and recognition accuracy of abnormal types.

Second, the lightweight transformation of the model will be carried out for the computing resource limitation of wearable devices. Through feature dimensionality reduction and model pruning, the model is adapted to the edge computing environment, and the real-time performance of on-device ECG signal analysis is improved while ensuring the classification performance.

Third, multi-physiological parameter data fusion will be realized. The ECG signal is combined with heart rate variability, blood pressure, blood oxygen, and other wearable monitoring data to construct a multi-modal classification model, so as to realize the comprehensive evaluation of cardiac health status and improve the early warning accuracy of acute cardiac events.

Fourth, large-scale multi-center clinical verification will be carried out in different medical institutions and population groups, verify the real-world application effect of the system, and combine clinical diagnosis standards to improve the clinical standardization of the system, so as to provide a more reliable basis for its large-scale promotion in primary medical institutions and home monitoring scenarios.

Author Contributions

J.S.: Conceptualization, methodology, software, formal analysis, investigation, data curation, writing—original draft, project administration, funding acquisition; S.L.: Software, resources, data curation, writing—original draft, project administration, funding acquisition; J.L.: Conceptualization, methodology, validation, investigation, data curation, visualization, supervision; N.Z.J.: Conceptualization, methodology, formal analysis, resources, writing—review and editing, visualization; N.A.K.: Formal analysis, resources, writing—review and editing, supervision; S.R.S.: Resources, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement

Ethical review and approval were waived for this study. This work performs secondary analysis on fully anonymized, publicly released Kaggle ECG dataset; no raw identifiable human subject data was accessed in this research.

Informed Consent Statement

Patient consent was waived as no raw identifiable human subject data was accessed in this research.

Data Availability Statement

The raw ECG recordings analysed in this study are from a publicly available Kaggle competition dataset. Public redistribution of the raw recordings is restricted by the original dataset licence and privacy regulations; the processed aggregated metadata and analysis scripts generated in this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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