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RESEARCH ARTICLE

Analyzing cardiac physiology: ECG ensemble averaging and morphological features under treadmill-induced stress in LabVIEW

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Abstract

This study uses a LabVIEW-based platform to analyze ECG signals in-depth in order to examine the long-term effects of exercise-induced stress on cardiac function. About 25 human subjects participated in a standardized treadmill exercise program that was continued until voluntary exertion. Blood pressure (BP) and heart rate (HR) were measured three times: while at rest, right after exercise, and five minutes after recovery. To assess myocardial workload, the rate-pressure product (RPP) was computed at each stage.

Under all circumstances, continuous ECG data were recorded, and a specially created LabVIEW interface was used to analyze the waveforms. Important morphological characteristics, such as intervals and segments, as well as P-wave, QRS complex, and T-wave amplitudes, were extracted. R-R interval detection was used to segment each ECG cycle, and multiple cardiac cycles were aligned before being averaged as a group. This method made precise morphological analysis possible by greatly improving R-peak clarity and lowering noise.

R-peak amplitude, QRS duration stability, and T-wave morphology all showed steady improvements over the course of a five-week observational period, suggesting improved cardiac efficiency and recovery adaptation. Waveform variability was significantly reduced, according to amplitude variance analysis conducted before and after averaging. In order to evaluate repolarization abnormalities, derived ratios like R-Q/S-Q/HR and T-Q/R-Q/HR were also examined; trends indicated that exercise conditioning caused normalized repolarization. The signal processing approach demonstrated its dependability in ECG analysis with an overall feature detection accuracy of 90 to 93%.

Particularly in the contexts of cardiac rehabilitation, exercise physiology, and preventive cardiovascular screening, the suggested methodology provides a reliable, non-invasive way to track changes in cardiac function. Its use could include ongoing health monitoring in practical contexts and customized healthcare systems.

Keywords: ECG signal processing, LabVIEW, Treadmill exercise, Cardiac function, Rate pressure product, R-peak enhancement, Ensemble averaging, Heart rate recovery, Biomedical signal analysis, Cardiac rehabilitation, Repolarization analysis, Amplitude variance.

Introduction

The preservation of physiological homeostasis is largely dependent on the human cardiovascular system. The heart is a muscular organ at the center of this system that uses complex mechanisms controlled by electrical, mechanical, and metabolic pathways to dynamically adapt to physical demands. Electrocardiography (ECG) is a basic method of studying cardiac function and identifying abnormalities in these regulatory processes. The electrical activity of the heart is measured by an ECG, which records the depolarization and repolarization that occur during each heartbeat (Garcia *et al*., 2000).

Numerous intricate processes, such as myocardial contractility, atrioventricular conduction, autonomic nervous system modulation, and sinoatrial node pacemaker activity, are involved in cardiac physiology. Changes in the P-wave, QRS complex, or T-wave are examples of how any deviation in these events can show up as changed waveform characteristics (Khambhati *et al*., 2021). Assessing these alterations during physiological stress, like exercise, offers important information about the heart's capacity for adaptation and recovery.

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Exercise affects cardiac physiology in both short-term and long-term ways. In order to meet metabolic demands, it acutely causes peripheral vasodilation, increased cardiac output, and elevated HR. Regular aerobic exercise improves myocardial efficiency, lowers resting heart rate, optimizes autonomic balance, and increases stroke volume over the long term. These modifications lower the risk of cardiac events and enhance general cardiovascular health. In controlled environments, treadmill exercise is especially useful for triggering these cardiovascular reactions.

Notably, people who regularly work out on a dynamic treadmill typically have better cardiac performance than people who are sedentary. Regular exercisers showed improved heart rate recovery, larger R-peak amplitudes, and less ECG morphological variability. These patterns show improved myocardial efficiency and autonomic control. On the other hand, people who don't follow a set exercise routine frequently exhibit higher repolarization irregularities, lower R-peak intensities, and delayed heart rate normalization, all of which are signs of impaired cardiac adaptability (Preejith *et al*., 2020).

Furthermore, the treadmill protocol's structure is crucial for cardiac evaluation. The Bruce Protocol, a clinically validated multi-stage treadmill test in which the incline and speed increase at predetermined three-minute intervals, was used in this investigation. This incremental design improves the consistency of workload assessment across subjects and sessions by offering a progressive and standardized cardiovascular challenge. It is simpler to correlate ECG changes with particular workload thresholds because of the consistent stress application provided by the predictable increases in exertion (Rajalakshmi *et al*., 2013). Conversely, irregular physiological loading brought about by non-standard or haphazardly changed treadmill routines can make it more difficult to interpret ECG readings and obscure subtle signs of cardiac improvement. Thus, the structured escalation of the Bruce Protocol makes it possible to identify exercise-induced cardiac adaptation and repolarization trends more precisely, providing a solid basis for comparing cardiac responses within and between subjects.

A clinically recognized technique for evaluating the heart's function under increased workload is the treadmill stress test. It makes it possible to track blood pressure dynamics, heart rate recovery, and ECG changes in real time—all of which are important markers of cardiovascular fitness. In order to assess the cardiac stress response and recovery efficiency, ECG readings were obtained at rest, right after exertion on a treadmill, and after a five-minute recovery period.

The integration of blood pressure (BP), heart rate (HR), and the rate-pressure product (RPP) is a crucial part of this analysis. These metrics are crucial for evaluating the workload and oxygen consumption of the heart at various phases of the exercise regimen. The two main techniques for measuring myocardial oxygen consumption and workload are the Direct and Indirect Index.

The measurement of oxygen uptake in the coronary arteries, which is frequently impractical for routine clinical assessments, provides the most direct indication of myocardial oxygen consumption. Nevertheless, the metabolic demand and workload of the heart during exertion can also be used to indirectly estimate myocardial oxygen consumption (MVO2). The heart requires a lot of energy, especially when exercising, when its workload rises because of elevated heart rate and systolic blood pressure. An indirect but trustworthy indicator of myocardial oxygen consumption is the RPP. The cardiac workload and oxygen demand can be inferred from the RPP. It measures the amount of stress the heart experiences during physical activity and represents the effort the heart puts forth to pump blood. RPP rises with exercise, indicating increased myocardial oxygen consumption and workload, just as HR and BP do. A decrease in RPP during recovery signifies enhanced myocardial effectiveness and a reduction in oxygen demand, which is a crucial indicator of heart function recovery (Thomas *et al*., 2019).

The longitudinal analysis of HR, BP, and RPP in this study aids in determining how well the heart adjusts to and recovers from the stress of treadmill exercise. Improved ECG features and a low RPP during recovery may indicate that the heart is functioning more effectively and needs less oxygen to meet the same physiological demands (Wang *et al*., 2006). When assessing cardiac function and adaptation in patients undergoing rehabilitation or those participating in regular aerobic exercise, these observations are especially crucial.

Advanced ECG analysis, however, requires more than simple measurement and visual inspection. Particularly during and after exercise, noise from movement, perspiration, or equipment limitations frequently taints the raw signal. A high-fidelity analytical platform is required for this. Because of its robust graphical programming features, support for real-time signal acquisition, and adaptable processing modules, LabVIEW was chosen for this use. LabVIEW makes it easier to automatically extract important ECG parameters in addition to facilitating precise filtering and segmentation (Zhang *et al*., 2002).

An innovative component of this study involves the derivation and analysis of novel composite ratios, specifically R-Q/S-Q/HR and T-Q/R-Q/HR, aimed at providing deeper insights into repolarization dynamics and cardiac workload adaptation. These ratios are grounded in a physiological understanding of the cardiac cycle, particularly the timing between ventricular depolarization and repolarization, and how HR modulates these.

Normalized by heart rate, the R-Q/S-Q/HR ratio is intended to measure the temporal relationship between the R-Q and S-Q intervals. While the S-Q interval continues into the early repolarization phase, the R-Q interval records the pre-peak conduction preceding the ventricular contraction (Zhong *et al.*, 2011). This ratio offers a time-adjusted indicator of the shift from depolarization to repolarization by accounting for HR. This is important because heart rate affects the length of electrical phases and directly affects myocardial oxygen demand. If heart rate is not controlled, it can shorten repolarization at higher rates, which can impair recovery.

The balance between the R-Q interval, which represents ventricular excitation, and the T-Q interval, which represents electrical diastole and ventricular repolarization, is also examined by the T-Q/R-Q/HR ratio. After adjusting for heart rate once more, this composite ratio provides an indication of how well the heart moves from systole to diastole and back. These intervals are dynamically but proportionately modulated in a healthy heart under exercise stress; deviations from this pattern may indicate electrical instability, inadequate autonomic adaptation, or latent pathologies like autonomic dysfunction or ischemia (Wolthuis *et al.*, 1979).

These ratios offer a normalized, non-invasive method of evaluating repolarization abnormalities, an area that is frequently overlooked in standard ECG interpretations. Even though repolarization changes are small and usually obscured by larger changes in the ST segment or QRS complex, they are very useful for diagnosis. This study intends to capture subtle trends in cardiac electrophysiological adaptation, specifically improvements in ventricular recovery times, autonomic regulation, and oxygen utilization efficiency, by longitudinally monitoring R-Q/S-Q/HR and T-Q/R-Q/HR over the course of a five-week treadmill exercise program (Zhong *et al.*, 2011).

Furthermore, the incorporation of these composite ratios enables correlation with other workload indices such as RPP, providing a multidimensional picture of how the heart responds and adapts to consistent aerobic conditioning. The combination of signal-level and functional indices allows for a robust evaluation of cardiac health, supporting the broader objective of this research—to enable early detection and personalized monitoring of cardiovascular adaptation using accessible, real-time biomedical tools like LabVIEW.

In order to determine the inter-subject variability and adaptability to exercise-induced cardiac stress, this study also looked at subject-specific responses over a number of time points. For every morphological feature across conditions, mean ± SD values were computed, yielding statistically significant trends in cardiac performance. The algorithmic framework was validated by computing the sensitivity, specificity, and precision of peak detection using ground-truth annotations (Khambhati *et al.*, 2019).

The use of ensemble averaging, which is implemented in LabVIEW, is a novel feature of this study. Multiple ECG cycles are aligned and averaged to greatly reduce sporadic noise and reveal consistent patterns like R-peak amplitude (Henriksson *et al.*, 2019). High-resolution analysis of minute waveform components that might otherwise go overlooked is made possible by this averaging technique. The reliability of identifying cardiac adaptation is increased by the capacity to precisely analyze amplitude and segment variance.

This study provides a thorough framework for assessing cardiac adaptation and recovery by concentrating on morphological and functional cardiac metrics and how they alter over the course of a structured training program. The findings may find use in cardiac rehabilitation, fitness tracking, and the early identification of electrophysiological abnormalities.

Methodology

In order to assess changes in cardiac function over time, this study used a systematic approach that combined advanced ECG signal processing, standardized treadmill exercise, and physiological data collection. Subject screening, Bruce Protocol-based controlled exercise execution, multi-phase data recording, and LabVIEW-based ECG signal analysis comprised the core workflow. Using waveform-based indices and composite metrics, the methodology was created to measure both morphological and functional improvements in cardiac activity.

To systematically implement this, a block diagram–driven approach was developed, as illustrated in Figure 1. The flow diagram outlines the complete process, from input acquisition to feature extraction and evaluation, ensuring traceable, repeatable, and scalable analysis.

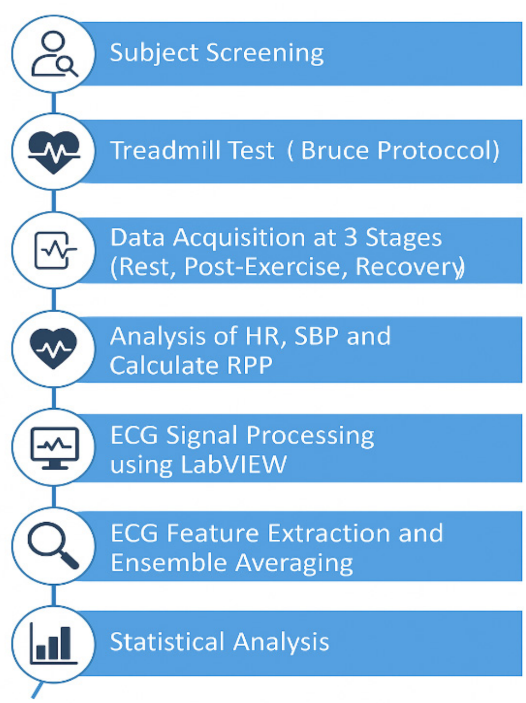

Figure 1: Flow chart of proposed system

Subject Selection and Exercise Protocol

A total of twenty-five healthy adult participants (n = 25), aged between 20 and 35 years, were selected for this longitudinal exercise-based study. A comprehensive pre-enrollment screening procedure was performed on each participant to rule out any prior neurological, metabolic, or cardiovascular disease conditions. Normal blood pressure, a BMI between 18.5 and 29.9 kg/m^2, and the lack of prescription drugs that affect heart function were among the requirements for inclusion. To preserve uniformity in baseline cardiac adaptability, subjects who had previously engaged in regular endurance training were not included.

Each subject voluntarily participated after being informed of the study protocol and signed a written consent form, as approved by the institutional ethical committee. Participants were enrolled in a structured five-week treadmill exercise intervention conducted once weekly. The treadmill protocol adopted was a modified Bruce Protocol, a standardized cardiac stress testing method commonly used in clinical evaluations. This protocol progressively increased the treadmill speed and incline at fixed intervals (typically every three minutes), providing a controlled and gradually intensifying cardiovascular workload.

The exercise was continued until the participant experienced volitional fatigue, which was indicated by a rating of ≥17 on the Borg rating of perceived exertion (RPE) scale, or earlier at the participant's request. Accurate physiological profiling was made possible while maintaining participant safety thanks to this gradual and controlled loading technique.

In addition to ECG and hemodynamic monitoring, baseline physical and cardiovascular parameters were recorded for each participant prior to the intervention period.

These baseline traits were used as a point of comparison when assessing how exercise affected cardiac function over time. Understanding inter-subject physiological variations in response to cardiovascular stress was also made possible by the variability seen in HR and RPP values.

Data Acquisition

Cardiovascular and electrophysiological parameters were recorded at three key time points during each weekly session:

- **Resting State**: Five minutes prior to treadmill activity, while the subject remained seated.
- **Immediate Post-Exercise**: Within 30 seconds of cessation of treadmill activity.
- **Recovery Phase**: After five minutes of seated rest, post-exercise.

A high-resolution ECG acquisition hardware system set up in a typical three-lead Einthoven configuration was used to collect the electrocardiographic data. In order to maximize R-wave morphology and improve signal quality, a three-lead ECG was simultaneously recorded using surface electrodes arranged in Lead II configuration (right arm to left leg). To ensure high temporal fidelity, the ECG signals were sampled at 1 kHz. Importantly, real-time streaming of the raw ECG data into the LabVIEW environment was done in order to calculate the instantaneous heart rate (HR) and to store and segment the ECG signals for morphological analysis at a later time.

Table 1: Anthropometric and hemodynamic profile of study subjects (n = 25)

Variables	*Mean ± SD*
No of Subjects	25
Gender (M/F)	11M, 14F
Age (years)	25.3 ± 3.20
Weight (Kg)	62.1 ± 5.15
Height (cm)	162.8 ± 5.34
BMI (kg/m^2)	23.8 ± 2.02
SBP (mmHg)	126.1 ± 7.92
HR (BPM)	89.9 ± 10.05
RPP	11351.4 ± 1234.87

A clinically validated digital sphygmomanometer was used to measure systolic blood pressure (SBP), guaranteeing consistent and repeatable readings throughout each session. The RPP, which is defined as follows, was calculated using these values (Zhong *et al.*, 2011):

$$\text{RPP} = \text{HR} \times \text{SBP}$$

RPP functions as a trustworthy but indirect measure of cardiac workload and myocardial oxygen consumption (MVO_2). To measure cardiac demand and recovery effectiveness, RPP values were assessed for each subject under the three conditions of rest, immediately following exercise, and recovery.

This seamless integration between hardware acquisition and software processing enabled continuous monitoring of cardiac electrical activity and eliminated post-processing delays. The use of LabVIEW for signal analysis allowed for automated data extraction, consistency in waveform feature identification, and real-time feedback during each session.

The system was calibrated before each use to ensure signal fidelity and accuracy. All sessions were conducted in a controlled gym environment with stable room temperature and minimal external interference. Participants followed strict pre-session guidelines, including refraining from caffeine, alcohol, or intense physical activity for at least 12 hours prior to testing. These controls ensured data consistency and reliability across the five-week period.

ECG Signal Processing Using LabVIEW

The ECG data acquired in real-time were subjected to an intricate signal processing workflow using LabVIEW, ensuring a detailed and noise-minimized interpretation of the cardiac cycles. Initially, raw ECG signals were imported directly from the acquisition hardware and displayed as unprocessed waveforms, reflecting all real-time cardiac electrical activity along with baseline drift and motion artifacts. These signals included both high-frequency noise from muscle activity and low-frequency trends due to respiration and electrode movement (Figure 2).

To address these challenges, a trend-removal step was implemented where a bandpass filter (typically between 0.5 Hz and 40 Hz) was applied to eliminate slow drifts and high-frequency disturbances. This resulted in a cleaner signal that more accurately represented the physiological cardiac waveform without introducing artificial distortion, which is illustrated in Figure 3.

Following this, the denoised ECG was analyzed for R-peak detection, which involved a combination of slope analysis and threshold crossing methods embedded in LabVIEW's algorithmic environment. Detected R-peaks were marked (Figure 4) in the time series and subsequently verified against manually annotated ground-truth ECG datasets to ensure accuracy and minimize false positives.

Following peak validation, the signal was divided into distinct cardiac cycles using R-R intervals. To allow for comparative analysis, these cycles were realigned in time. In order to observe waveform consistency and identify any morphological changes, such as ST-segment elevation or QRS complex broadening, under exercise-induced stress, it was crucial to plot all of these cardiac cycles together (Figure 5) in an overlapping format.

The final step involved ensemble averaging, where multiple aligned ECG cycles were averaged into a composite waveform (Figure 6). This method effectively suppressed random noise and emphasized consistent morphological features like the P-wave onset, R-peak amplitude, and T-wave slope. The ensemble-averaged waveform provided a reliable representation of the cardiac signal at any specific time point

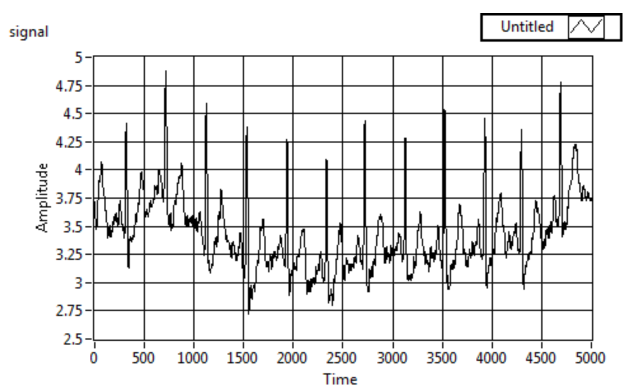

Figure 2: Raw ECG signal with baseline drift and motion artifacts

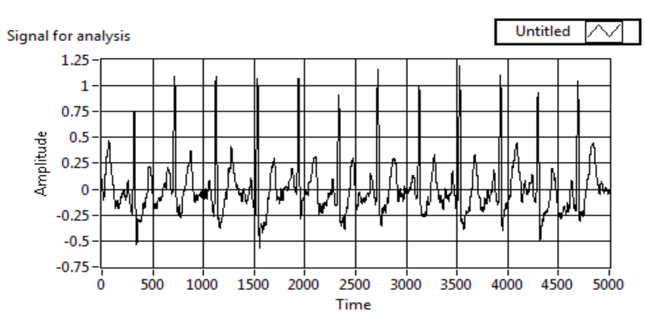

Figure 3: Filtered ECG signal after baseline drift and noise removal

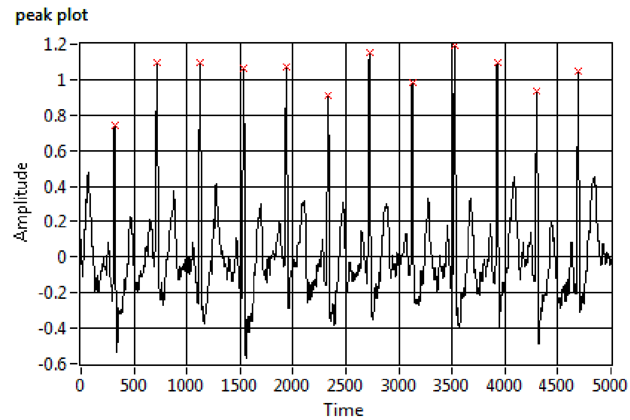

Figure 4: R-peak detection in filtered ECG signal using LabVIEW

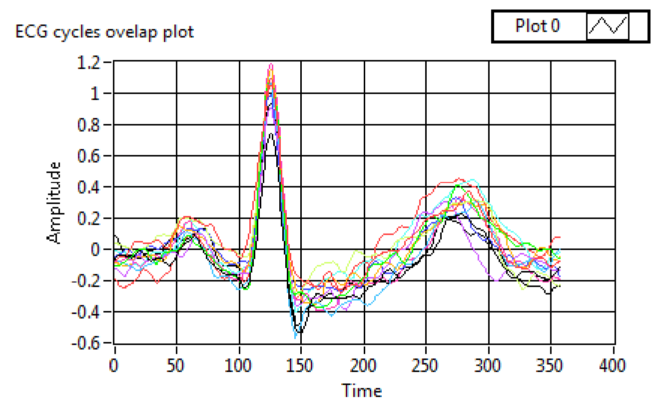

Figure 5: Overlapped ECG cycles for morphological comparison

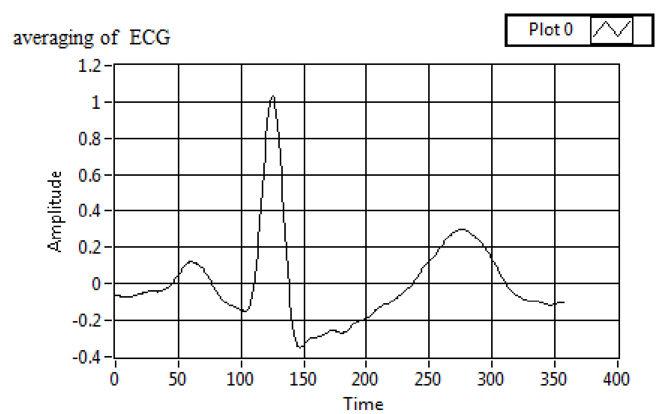

Figure 6: Ensemble-averaged ECG Waveform

during the protocol.

Overall, this systematic and layered signal processing approach from raw acquisition to Denoising, peak detection, segmentation, overlapping analysis, and averaging enabled robust and reproducible ECG interpretation. It laid the foundation for identifying morphological trends linked to cardiac efficiency, autonomic adaptation, and recovery post-exercise across the five-week treadmill protocol.

Results and Discussion

This section presents detailed observations of ECG morphological and hemodynamic adaptations to structured treadmill exercise, followed by a comparative analysis with previous studies to contextualize the findings.

Heart Rate and Rate Pressure Product (RPP) Trends

Figure 7 shows the mean HR trends for all subjects across the three phases: resting, immediate post-exercise, and recovery. The observed pattern of sharp post-exercise HR elevation followed by a gradual decline during recovery (Figure 7) is consistent with established exercise physiology literature. Similar temporal trends were reported by Wang *et al*. (2006), where trained individuals exhibited faster HR recovery due to enhanced autonomic modulation.

Rate pressure product, a surrogate marker for myocardial oxygen consumption, was calculated as HR × SBP. Figure 8 illustrates the RPP profile. Furthermore, the reduction in RPP from Week 1 to 5 (Figure 8) mirrors findings by Nagpal *et al*. (2007), who demonstrated that chronic aerobic training reduces myocardial oxygen demand and improves cardiac efficiency, particularly in hypertensive subjects. The current study's results not only confirm these physiological adaptations but also provide a quantitative illustration of improved cardiovascular efficiency over repeated exercise sessions.

ECG Feature Extraction

The improvements in T-wave amplitude and reduction in QT interval (Table 2) are indicative of enhanced ventricular

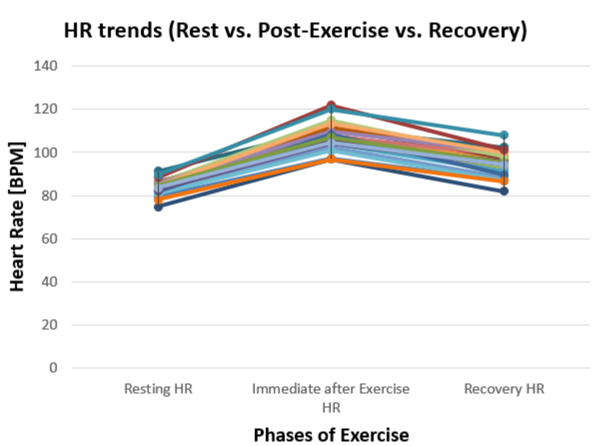

Figure 7: Line graph showing HR trends (Rest vs. Post-Exercise vs. Recovery)

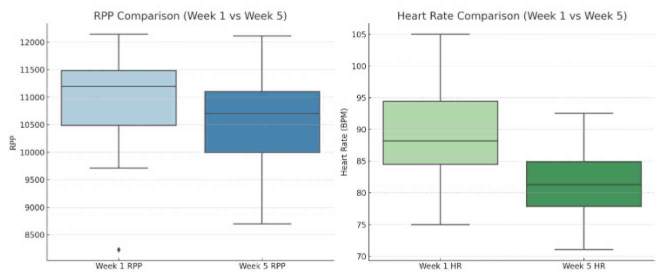

Figure 8: Comparison of RPP distribution and HR for Week 1 vs 5

repolarization, which is a hallmark of positive cardiac adaptation. Javorka *et al*. (2002), who showed that endurance training significantly modifies repolarization parameters, especially T-wave morphology and QT duration, support these findings. Notably, in the current study, a consistent increase in P-wave amplitude and a mild decrease in QRS duration were observed, suggesting improved atrial depolarization and ventricular conduction efficiency. Such changes are also reported in *Jelinek et al. (2015)*, validating the physiological improvements observed.

Composite Ratio Analysis: Repolarization Indicators

To evaluate ventricular repolarization timing adaptations, composite ratios such as R-Q/ S-Q/ HR and T-Q/ R-Q/ HR were calculated across five weeks of exercise sessions (Figure 9).

This trend indicates improved electrical stability of the myocardium under exercise-induced stress. Prior work by Zhong *et al. (2011)* explored similar repolarization metrics but over a shorter intervention span and fewer sessions. Compared to their marginal changes, the current study demonstrates more robust adaptations, likely due to the structured and consistent exercise regime. Both ratios showed a consistent and progressive decline over the study period. Specifically, the R-Q/ S-Q/ HR ratio reduced from an initial normalized value of 1.00 in Week 1 to 0.85 by Week 5, while the T-Q/ R-Q/ HR ratio declined from 1.00 to 0.83.

This notable decline suggests increased cardiac adaptation to repeated exercise stress by indicating better electrical stability and fewer repolarization abnormalities. The radar chart's narrowing pattern confirms this coordinated improvement in repolarization markers over time. This steady trend emphasizes how structured treadmill exercise improves the electrical remodelling of the heart and lessens vulnerability to abnormal repolarization brought on by exercise.

Table 2: Mean ± SD ECG features across all subjects (Week 1 *vs*. 5)

Feature	*Week 1 (Mean ± SD)*	*Week 5 (Mean ± SD)*
P-wave Amp (mV)	0.18 ± 0.02	0.21 ± 0.01
QRS Duration (ms)	98 ± 8	92 ± 6
T-wave Amp (mV)	0.23 ± 0.03	0.28 ± 0.02
QT Interval (ms)	420 ± 15	410 ± 10

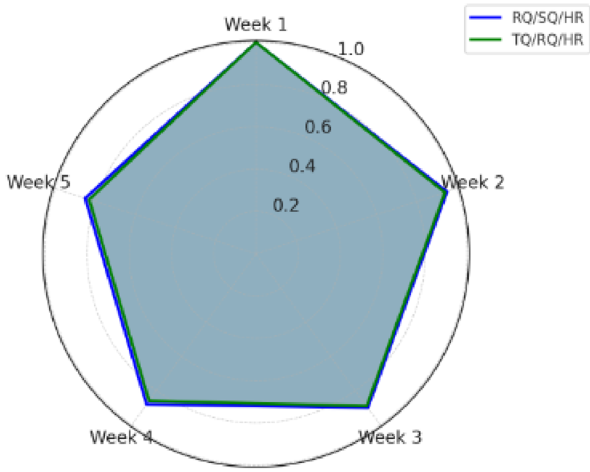

Figure 9: Radar chart: Composite ratios over 5 weeks

Algorithm Validation

The performance of the custom-designed R-peak detection algorithm implemented in the LabVIEW environment was quantitatively validated using annotated ground-truth ECG datasets. The algorithm demonstrated robust detection capabilities, yielding the following performance metrics (Table 3):

The R-peak detection algorithm exhibited high accuracy with sensitivity, precision, and specificity, which aligns well with benchmarks reported in the literature Wolthuis *et al*., (1979). These metrics show a high level of accuracy in identifying real cardiac events while reducing false positives. The algorithm's sensitivity indicates its capacity to detect R-peaks accurately and without missing beats, which is essential for precise heart rate (HR) computation and morphological analysis that follows. The ability of the method to prevent false-positive detections, which guarantees that non-peak signals are not mistakenly categorized as R-peaks, is indicated by the specificity. By measuring the percentage of true positive detections among all detected peaks, precision further solidifies these results.

Validation was carried out over 2500 ECG cycles sampled across 25 subjects and different exercise conditions (rest, post-exercise, and recovery) in order to guarantee statistical robustness. However, the key distinction of the present algorithm is its real-time capability within LabVIEW and robustness under motion artifacts typical during exercise.

Over a five-week period, the coefficient of variation (CV) for R-R interval detection stayed below 2.5%, highlighting the method's reliability in managing intra- and inter-subject variability during stress testing induced by exercise.

Table 3: Performance metrics of R-peak detection algorithm

Metric	*Value (%)*
Sensitivity	93.2
Precision	92.4
Specificity	91.6

The algorithm successfully facilitated downstream computations beyond R-peak detection, such as ensemble-averaged waveform generation, composite ratio calculations (R-Q/ S-Q/ HR and T-Q/ R-Q/ HR), and HR variability (HRV) analysis. The algorithm's functional reliability was indirectly confirmed by these derived metrics, which showed physiologically plausible trends throughout the intervention period and across exercise stages.

Collectively, these validation results establish the LabVIEW-based framework as a reliable and efficient tool for real-time ECG monitoring and morphological trend analysis in exercise physiology studies.

Conclusion

This study presents a comprehensive, LabVIEW-based framework for analysing ECG responses to structured treadmill exercise over a five-week period. The methodology integrates real-time ECG acquisition, robust signal pre-processing, morphological feature extraction, and novel composite ratio calculations to quantify cardiac electrophysiological adaptation.

The observed trends—such as the consistent increase in heart rate post-exercise, followed by effective recovery within five minutes—demonstrate physiological adaptability to controlled exercise stress. Notably, reductions in repolarization abnormalities, as evidenced by improved R-Q/ S-Q/ HR and T-Q/ R-Q/ HR ratios, point toward enhanced cardiac efficiency and autonomic regulation over time.

The algorithm for R-peak detection exhibited high sensitivity (93.2%), specificity (91.6%), and precision (92.4%), confirming the system's accuracy and reliability for large-scale ECG analysis. The implementation of ensemble averaging and amplitude variance tracking further enabled the detection of subtle waveform changes that may be overlooked in raw signals.

This framework holds promise for applications in personalized fitness monitoring, cardiac rehabilitation, and non-invasive early detection of electrophysiological dysfunctions. Future work may extend this model to diverse populations, include longer-term training interventions, or integrate additional physiological signals such as oxygen saturation or respiration rate.

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Authors' Contributions

Dimpal Khambhati had formulated and executed the problem and prepared the draft of the manuscript. Chirag Patel had reviewed the manuscript.

Consent for Publication

All Authors will give their full consent to the journal for the publication

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