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Sustainability and predictive accuracy evaluation of gel and embroidered electrodes for ECG monitoring

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A R T I C L E   I N F O

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A B S T R A C T

Despite standards on electrocardiogram (ECG) monitoring in medical diagnostics, signal acquisition is prone to noisy artifacts and relies greatly on the quality of skin contact and signal transducing interference. Electrodes, serving as indispensable conduits in ECG signal acquisition, act as the crucial interface between the human body and recording instrumentation. The usage of traditional gel electrodes may provoke skin irritation, by contrast, the advent of embroidered electrodes, a contemporary innovation, holds the promise of more comfort monitoring. However, the sustainability quotient and predictive precision of these novel electrodes require more in-depth investigation.

This paper endeavours a comprehensive evaluation of both gel and embroidered electrodes concerning ECG signal acquisition. Simultaneously, the study aims to construct a polynomial regression model leveraging advanced machine learning (ML) tools. The inferred model predicts embroidered signals based on experimental data obtained from gel electrodes. The methodology encompasses systematic data collection, preprocessing, insightful analysis, and the application of data-driven techniques.

The findings of this study highlight the viability of embroidered electrodes as a compelling alternative, transcending traditional paradigms. Employing ML tools, the developed model achieves predictive accuracy, reflected in robust R2 values extending up to 94.9%.

1. Introduction

Electrocardiogram (ECG) monitoring is ubiquitous in modern medical diagnostics, enabling healthcare professionals to gain insights into the electrical activity of the heart [1], albeit noisy artifacts. By assessing the patterns and rhythms of the heart's electrical signals, ECGs provide critical information about cardiac health, arrhythmia, and various cardiovascular conditions [2,3]. The continuous advancements in ECG monitoring techniques have significantly enhanced patient care by enabling timely intervention and improving overall health outcomes [4,5]. A fundamental component of ECG monitoring is the selection of appropriate electrodes for signal acquisition [6]. Electrodes act as the interface between the human body and the recording equipment, capturing the intricate electrical signals generated by the heart [7]. Various electrodes have been developed and employed for ECG recordings, each with unique characteristics, advantages, and limitations [8,9]. Among these, two prominent types are gel and embroidered electrodes, respectively [10,11].

Gel electrodes have been the cornerstone of ECG recordings for decades [12]. These electrodes use a conductive gel to establish a low-impedance interface between the skin and the recording apparatus.

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The gel facilitates optimal signal transmission, ensuring high-fidelity recordings even in challenging conditions [13]. The efficacy of gel electrodes has been widely acknowledged, owing to their proven track record in delivering reliable ECG data [14]. However, concerns have emerged regarding their prolonged use, as the gel can cause skin irritation and discomfort [15]. The use of traditional gel-based electrodes in medical applications often poses challenges due to their propensity to cause skin irritation and discomfort. This is particularly problematic in cases of long-term monitoring, as the conductive gels used tend to dry out and necessitate frequent replacement, typically every 2–3 days, affecting signal quality and patient comfort [16]. Furthermore, Shaikh et al. (2015) highlight that these issues become even more critical for ECG monitoring, where the use of wet electrodes can lead to skin irritation, dermal inflammation, and allergic reactions, ultimately reducing patient compliance [17]. Although our study did not specifically investigate skin irritation caused by embroidered electrodes, these concerns emphasize the importance of exploring alternative solutions like embroidered electrodes to enhance sustainability and patient comfort.

On the other hand, Embroidered electrodes represent a more recent innovation in ECG monitoring [18]. These electrodes are woven directly into fabrics, creating flexible, skin-friendly wearable devices. They offer the advantage of being non-invasive, eliminating the need for gels or adhesives that might cause skin sensitivity. Integrating these electrodes into clothing and accessories has opened doors to continuous, unobtrusive monitoring, enhancing patient comfort and compliance. The sustainability and reliability of embroidered electrodes are crucial, particularly for their integration into medical devices, as they must consistently endure the demands of repeated usage. Kannaian et al. (2013) examined the design and performance of embroidered textile electrodes, demonstrating their durability and efficiency in ECG signal acquisition over multiple washing cycles [19]. Meanwhile, Etana et al. (2023) showed the benefits of using embroidered electrodes and their sustainable impact for long-term electromyography monitoring [20]. Moreover, Etana et al. (2024) discussed the use of various textile fillings in embroidered electrodes, identifying that those utilizing 3D knitted fabric exhibited superior durability and moisture retention, thereby improving their sustainability for long-term use in electromyography applications [21]. Additionally, Zaman et al. (2020) investigated the washability issues of fabric-based electrodes, finding that certain materials like copper degrade more quickly while others can maintain integrity over multiple wash cycles [22]. These studies collectively highlight that, with careful material selection and design optimization, embroidered electrodes can offer durable, environmentally friendly solutions for long-term medical monitoring.

Gel and embroidered electrodes are key tools in ECG signal acquisition, each offering distinct advantages and drawbacks. Gel electrodes, widely used for decades, use conductive gel to establish a low-impedance interface between the electrode and skin, enabling reliable and high-quality ECG recordings. Their non-invasive nature and familiarity in clinical settings make them popular, but prolonged use can cause skin irritation and artifacts. In contrast, newer, embroidered electrodes are integrated into clothing for continuous monitoring without adhesive gels, reducing skin irritation [23]. While they enhance patient comfort and compliance, their stability and signal fidelity can be affected by their indirect placement on fabric rather than direct skin contact.

Advancements in artificial intelligence (AI) heralded a new era in medical applications. AI tools, with their ability to process vast amounts of data and discern intricate patterns, are showing promising results in various medical fields [24]. In anaesthesia, for instance, AI is revolutionizing dosage optimization, patient monitoring, and risk prediction, ultimately enhancing the safety and efficiency of surgical procedures [25,26]. This is just one facet of AI's transformative impact, with applications extending to radiology [27], pathology [28], and personalized medicine [29], revolutionizing the landscape of healthcare delivery. Incorporating machine learning (ML) into healthcare has revolutionized the analysis of complex physiological signals, particularly in the context of heart-related data [30–32]. ML techniques present an innovative avenue for advancing the precision and efficiency of electrocardiogram (ECG) monitoring [33].

In our study, we used a dataset of 11 patients, which can be considered small. However, it aligns with standard practices for preliminary investigations often structured as pilot studies. For instance, Okano et al. (2021) explored the effects of magnetic fields on cardiovascular function using only 12 subjects, underscoring the feasibility of pilot studies to investigate complex physiological phenomena [34]. Similarly, Zhu et al. (2019) demonstrated the efficacy of an ECG reconstruction approach using a small dataset, validating the method with only 42 recording sessions of subjects with varying combinations of age and weight [35]. Furthermore, Porumb et al. (2020) used a dataset of only 8 subjects to evaluate a personalized deep learning system for detecting hypoglycemic events based on ECG signals, establishing a new methodology despite the small cohort size [36]. Additionally, Briley and Lankappa (2021) assessed the use of handheld 6-lead ECGs in a pilot study involving only 6 patients, showing that meaningful cardiac data can be obtained even with a small patient cohort [37]. These examples highlight how small datasets can effectively derive meaningful insights, particularly when the research is exploratory and requires subsequent larger-scale investigations.

The objective of this research is twofold. First, to comprehensively evaluate the sustainability and effectiveness of both gel and embroidered electrodes in recording ECG signals. By analysing and comparing ECG data obtained from these two electrode types, we aim to elucidate their relative performance in signal quality and robustness. Second, develop a machine learning (ML) model to predict the embroidered Lead I ECG signal using data from gel electrode recordings as input. The main goal of the prediction approach is to maintain a balance between the accuracy of the measurement and the comfort of the patient. Indeed, gel electrodes provide an accurate and stable signal but could irritate the patient's skin. Conversely, embroidered electrodes are more comfortable and are not irritable to the skin, but they are often related to displacement and disconnection problems, which can affect the measured signal quality. This methodology ensures that we can leverage the benefits of both types, which is crucial for clinical applications. This predictive model explores the feasibility of accurately approximating embroidered ECG signals based on gel electrode recordings. This investigation will address the following critical questions:

- How do the ECG signals obtained from gel electrodes compare to those acquired using embroidered electrodes?
- Can the proposed ML model successfully predict embroidered ECG signals from gel electrode inputs?

The structure of this paper is organized as follows: The methodology section elaborates on the experimental design, data collection procedures, ML methodology, and analytical techniques employed in this study. The results section presents the empirical outcomes of the investigation, accompanied by a comprehensive analysis. Subsequently, the discussion section interprets the results in the context of existing literature, highlighting the implications and significance of the findings. Finally, the conclusion section summarizes the study's key takeaways and outlines potential avenues for future research.

2. Methodology

This section presents the proposed methodology to address the investigated hypothesis. A systematic framework encompassing distinct stages of data collection, preprocessing, analysis, and prediction is depicted in Fig. 1. Initial data acquisition involved the concurrent recording of ECG signals from 11 subjects using both gel and embroidered electrodes. To ensure robust analysis, a preprocessing phase was applied, including techniques such as noise reduction and baseline

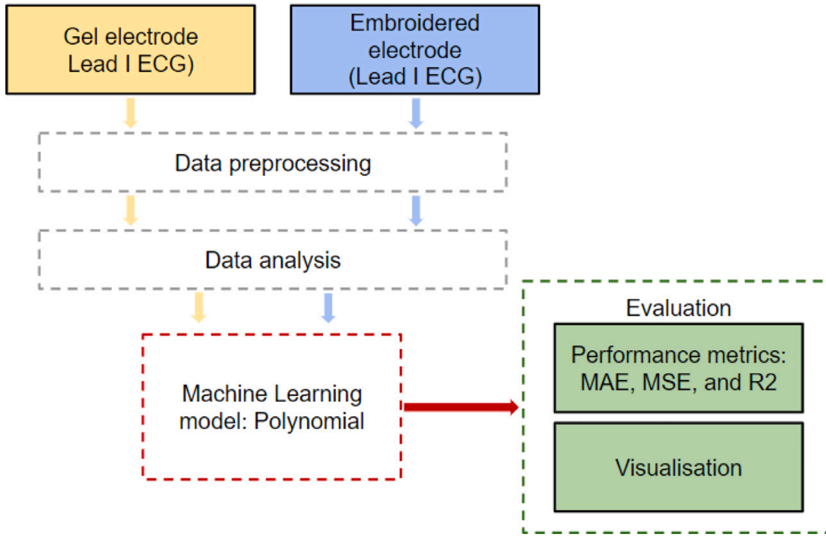


Fig. 1. Illustration of followed prediction architecture steps.

correction. Subsequent analyses incorporated Pearson correlation and cross-correlation methodologies to investigate the intricate relationship between gel and embroidered ECG signals. Central to our investigation was the development of a polynomial regression model aimed at predicting embroidered ECG patterns based on input data from gel electrodes; this model underwent training on an 80–20 train–test split. The progression of the methodology includes the prediction of ECG data collected by embroidered electrodes, shown with a red arrow.

An essential evaluation step occurs following the prediction of ECG data collected by embroidered electrodes. The predicted ECG data is rigorously compared and contrasted with the actual ECG signals obtained through the embroidered electrodes. This comparative analysis provides crucial insights into the predictive accuracy and performance of the developed polynomial regression model. The use of evaluation metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared statistics, further aids in quantifying the predictive capabilities and establishing a comprehensive understanding of the model's predictive accuracy.

2.1. Data collection protocol

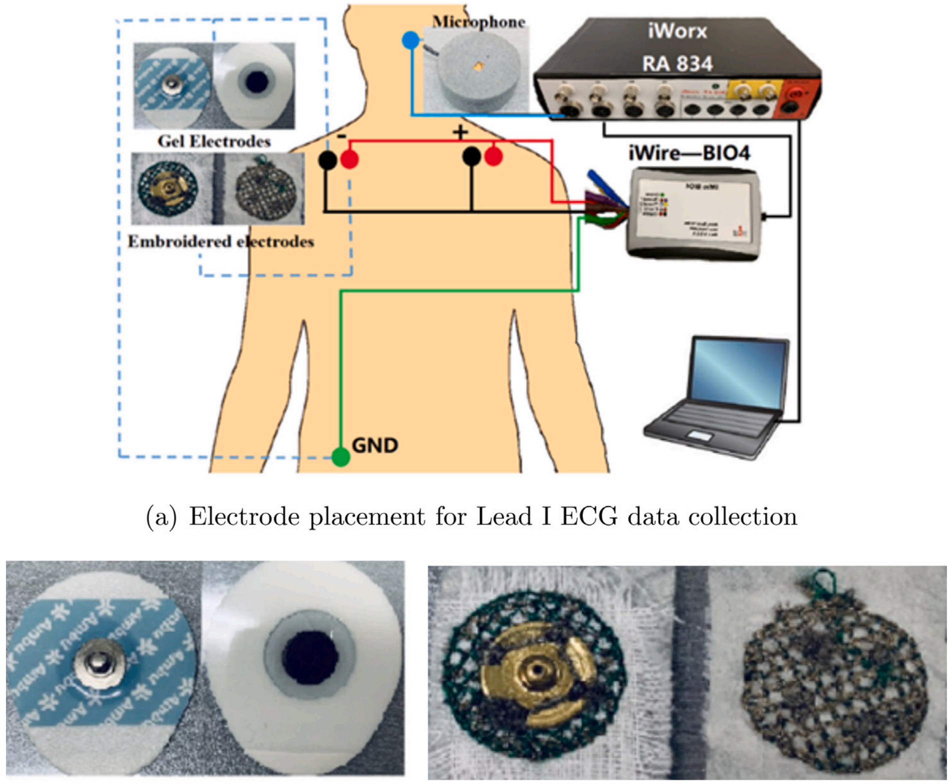
The study involved 11 individuals in good health (8 males and 3 females) aged between 21 and 29, with an average age of 25.9. None of the participants had a prior history of heart disease or respiratory problems. The research procedures obtained approval from the King's College Research Ethics Committee under Approval No.: LRS-18/19-10673. Before participating in the experiments, all subjects provided written informed consent. Data collection for the ECG analysis encompassed the acquisition of volunteer test subjects' ECG data. This involved recording the Lead I ECG signals three times for each subject. Recording sessions lasted three minutes each, separated by a two-minute break between trials. To refine the acquired data quality, the ECG signals underwent preliminary filtering to eliminate undesirable noise and artifacts [38,39]. The selection of sensors for ECG signal measurement is pivotal in attaining optimal outputs. Within the scope of this study, the data collection involved the use of gel and embroidered electrodes to gather ECG data at Lead I. The textile electrodes employed in the experiment were developed at the Centre for Robotics Research (CORE) at King's College London. They are constructed using silver-coated thread (Electro-Fashion Conductive Thread from Kitronik, with a resistance of 40 Ωm^{-1}) embroidered onto linen fabric, with a Vilene cut-away stabilizer. The embroidery pattern is a 20 mm diameter circle with a cross-hatched fill. The hatching has a 2 mm separation, and two iterations of embroidery are performed. The solid gel electrodes used in the experiment were Ambu WhiteSensor WS (36 × 40 in mm). The embroidered electrodes were fixed with medical tapes to enhance the adhesion. A microphone was placed under the subjects' nose to record the actual respiration as a reference. However, the recording from the microphone is not utilized in this study. The recording used the commercial acquisition system (iWorx, model RA 834) and ECG devices (iWire-BIO4) as recorder. The sampling frequency was 1 kHz, and the filter for the ECG was 0.05–40 Hz [40]. Additionally, Fig. 2 visually illustrates the placement of these electrodes for reference.

2.2. Data preprocessing

Data preprocessing is a crucial step in refining the collected dataset. After the data is gathered and stored, a series of steps are taken, i.e. Two filters are employed for this purpose: (1) 1st-order bidirectional Butterworth high-pass filter (set at 0.1 Hz) used to eliminate baseline oscillations caused by body movements like breathing [42]. (2) 1st-order low-pass filter designed to remove any noisy patches in the ECG signals. The cutoff frequency for both filters is adjusted based on the quality of each signal. Following this filtering process, the data is then normalized. This ensures that error metrics can be compared fairly with other datasets. The normalization process, involving the Min–Max method, renders the data scale-free. This means the fitting model can be evaluated without concern for scale differences between various datasets. This data preprocessing process serves two primary purposes: it enhances the quality of the dataset and establishes a strong foundation for the subsequent steps in the analysis and modelling work.

2.3. Data analysis

Data analysis guarantees that the data collected by gel and embroidered electrodes is suitable for further analysis and studies. This step also gives an insight into the correlation between gel and embroidered electrodes at the measurement points. The electrode data collected from each subject is analysed individually using the already available mathematical tools (mean, median, standard deviation, interquartile range, and correlation coefficient) to quantify the quality of the data collected. The data is then further used for the ML model. The plots and the correlation values are calculated using the Python programming language. The distribution of ECG signals was visualized using the Seaborn library version 0.11.1 in Python programming language version 3.9.1. The data was preprocessed by first normalizing it using the scikit-learn library version 0.24.0.



(a) Electrode placement for Lead I ECG data collection

(b) Gel electrode

(c) Embroidered electrode

Fig. 2. Electrode placement for Lead I ECG data collection using gel and embroidered electrode [41].

Comparative analysis: The comparison between gel and embroidered electrodes underscores the distinctive strengths and weaknesses of each approach. Gel electrodes offer reliable data collection but come with the drawback of potential skin sensitivity issues. In contrast, embroidered electrodes provide enhanced patient comfort. Still, they may demand attention to maintain consistent signal quality, especially in challenging scenarios such as signal stability on fabric and potential fidelity challenges.

Significance of the presented approach: The central objective of the work lies in evaluating the potential of ML, specifically polynomial regression, to predict ECG patterns at Lead I using embroidered electrodes. This approach taps into the inherent relationship between gel and embroidered electrode signals by leveraging ECG data collected from gel electrodes as input. This methodology has the potential to transform ECG monitoring, optimizing comfort while ensuring accurate predictions. It is especially relevant in the face of challenges that can compromise the quality of ECG data, such as damage to sensors or variations in signal fidelity. The exploration of this predictive model addresses the need for robust and sustainable electrode options, enhancing patient experience and diagnostic precision. The potential impact of this approach extends beyond traditional electrode concerns, encompassing data quality and reliability. By addressing challenges like sensor damage and signal variations, our research aims to provide an improved solution to ECG monitoring.

2.4. The regression model

Polynomial regression, a versatile modelling technique with roots predating the era of formal machine learning, extends linear regression by accommodating complex relationships between variables. Originating from classical statistical methods, polynomial regression has applications across various fields where linear models fall short in capturing intricate relationships.

In its essence, polynomial regression approximates the data using a polynomial function of the form:

$$f(x) = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n, \tag{1}$$

where n is the degree of the polynomial, and b is a set of coefficients.

Polynomial regression employs higher-degree polynomial equations to capture nonlinear patterns, making it suitable for addressing situations where linear models may be inadequate. This technique is known for its flexibility, higher fit accuracy, and interpretability, including benefits such as modelling diverse functions and capturing nonlinear trends [43,44].

In this paper, polynomial regression is chosen for its capacity to capture the potentially nonlinear relationship between gel and embroidered ECG signals. The technique's polynomial terms enable it to adapt to complex patterns, reflecting the physiological nature of ECG signals, which often exhibit nonlinear behaviours that simple linear models may overlook.

Performance metrics: A set of established performance metrics is employed to evaluate the effectiveness of the ML models in predicting ECG signals. These metrics are chosen to comprehensively evaluate various facets of the model's accuracy in approximating the observed ECG signal y_i and the predicted signal $\hat{y}_i$. The root mean squared error (RMSE):

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(\hat{y}_i - y_i)^2}{N}}, \tag{2}$$

the mean absolute errors (MAE):

$$MAE = \frac{1}{N} \sum_{i=1}^{N} \| y_i - \hat{y}_i \|, \tag{3}$$

and the coefficient of determination R^2:

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}, \tag{4}$$

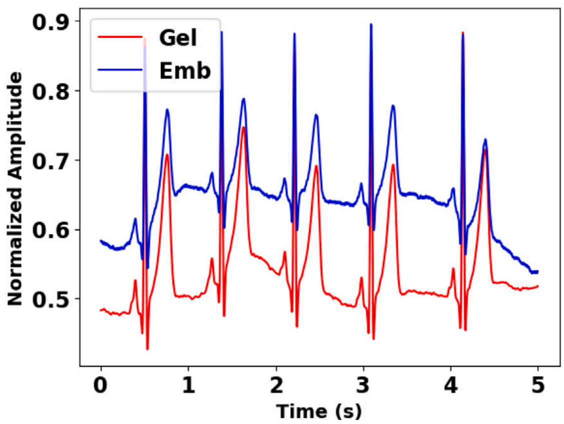


Fig. 3. A representative segment of the ECG signals captured by gel and embroidered electrodes.

Table 1
Heart rate variation of 11 subjects.

Subject no.	Heart rate range (bpm)
1	60.58–71.21
2	68.69–74.07
3	72.37–82.34
4	59.98–71.40
5	71.46–78.48
6	61.49–73.04
7	64.75–80.94
8	71.48–80.02
9	62.87–74.63
10	62.32–76.29
11	58.86–77.18

where $\bar{y}$ is the mean of the observed data.

The selection of these specific metrics (MSE, MAE, and R^2) is rooted in established literature and widely accepted within the domain of regression model evaluation [45,46]. Together, they provide a holistic appraisal of the model's performance, considering accuracy, resilience to outliers, and the extent to which the model accounts for variance.

3. Results

The results of data analysis and the proposed ML model are presented in this section.

3.1. Data analysis

All subjects used in this study were healthy individuals who were required to remain calm and supine throughout data collection. This protocol ensured that the sounds captured were solely from respiration without interference from other movements or noises. The heart rate variability of each subject, which is detailed in Table 1, was calculated to assess their health status.

As presented in Table 1, the heart rate variability for all 11 subjects falls within the normal resting range of 50–90 bpm, which is considered healthy for adults at rest [47,48]. This consistency across the patient data further supports the conclusion that the subjects were healthy and resting during the monitoring, aligning with established cardiovascular health standards and contributing to the reliability of the experimental findings.

The comparative statistical analysis of ECG signals recorded by gel and embroidered electrodes is presented. As mentioned in the methodology section, the data was collected three times for each subject. Hence, it is essential to analyse the signals for all three measurements (measurement 1 (M1), measurement 2 (M2), and measurement 3 (M3)). Mean, median, and standard deviation values are shown for each case, along with the correlation study.

Fig. 3 shows a representative ECG visualization from gel and embroidered (Emb) electrode for one study subject (subject 2).

Fig. 4 presents the superimposed density plot for the Lead I ECG signal measured using gel and embroidered electrode for measurement 1 (M1) for subject 2 and measurement 3 (M3) for subject 12. The shape of the density plot of the embroidered electrode almost follows the shape obtained using the gel electrode. The maximum density value is around 5.5 for the gel electrode and around 3.2–3.3 for the embroidered electrode for subject 2, while for subject 12, the maximum density value reaches around 3.5. The overlap between gel and embroidered electrodes in the superimposed density plot strongly indicates the potential for using embroidered electrodes for ECG signal collection.

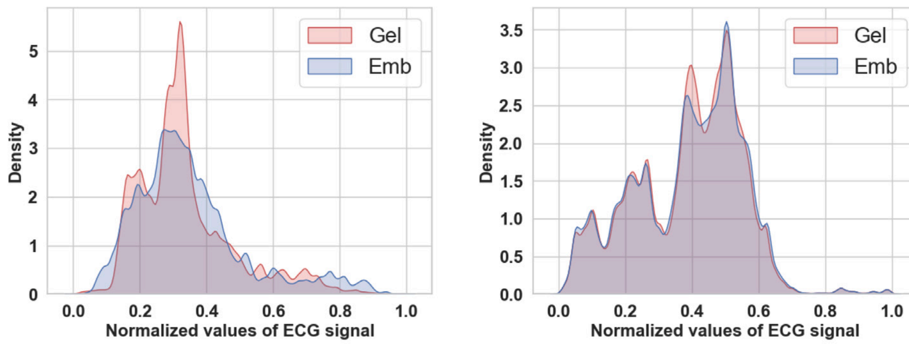
The superimposed density plot of ECG signals measured by gel and embroidered electrodes for the three measurements for subject 2 is shown in Fig. 5.

From Fig. 5(a), it can be seen that for subject 2, the superimposed density plots for the gel electrode show similar behaviour for all three trials. A maximum density value of about 6.5 was observed during the second trial, whereas it was almost the same for M2 and M3 (around 5.5). For subject 12 (Fig. 5(c)), the peak normalized values occur almost in the same zone for all three measurements. The maximum density value was observed during the first trial (about 4.3), while for M1 and M3, the maximum density values were almost the same. The superimposed density plots for the embroidered electrode (Fig. 5(b)) show considerable variation for the three measurements. The maximum density value observed during M3 was around 4.8, while for M1 and M2, it was around 3.3 and 3, respectively. Variations are also seen in the shape of the density plots, which indicates significant differences in the data collected using embroidered electrodes for the same subject. For subject 12 (Fig. 5(d)), The density plot is spread across the normalized values for the three trials. The peak for M1 is around 5.2, while for M2 and M3, it is about 3. It is also observed that the peak for M2 and M3 occurs at almost the same normalized values, whereas for M1, it occurs at a normalized value of 0.3.

To further understand the signals, the boxplot comparing the gel and embroidered electrode signals for the three measurements is presented in Fig. 6. For subject 2, it is seen that for all the three measurements, there are outliers on the top of the box plot, which could be due to the external environment and needs to be investigated further. The median values for M1 and M3 are close. In contrast, for M2, there is a considerable difference. The IQR values for gel electrodes were 0.15, 0.14, and 0.16 for M1, M2, and M3, respectively. The IQR values for embroidered electrodes were 0.18, 0.19, and 0.17 for M1, M2 and M3 respectively. For all measurements, the IQR values for embroidered electrodes are higher than those for gel electrodes, suggesting that embroidered electrodes have, on average, a more extensive spread or variability in measurements than gel electrodes. For subject 12 (Fig. 6(b), the outliers are seen mainly during M1, while for M2 and M3, they are minimal. This is also reflected in the difference between the median values for gel and embroidered electrodes in M1. For M2 and M3, the median values are very close. The IQR values for gel electrodes were 0.16, 0.22, and 0.24 for M1, M2, and M3, respectively, while for embroidered electrodes, they were 0.16, 0.23, and 0.25. The higher IQR for embroidered and gel electrodes suggest that for subject 12, the data collected during M2 and M3 are more spread out around the median.

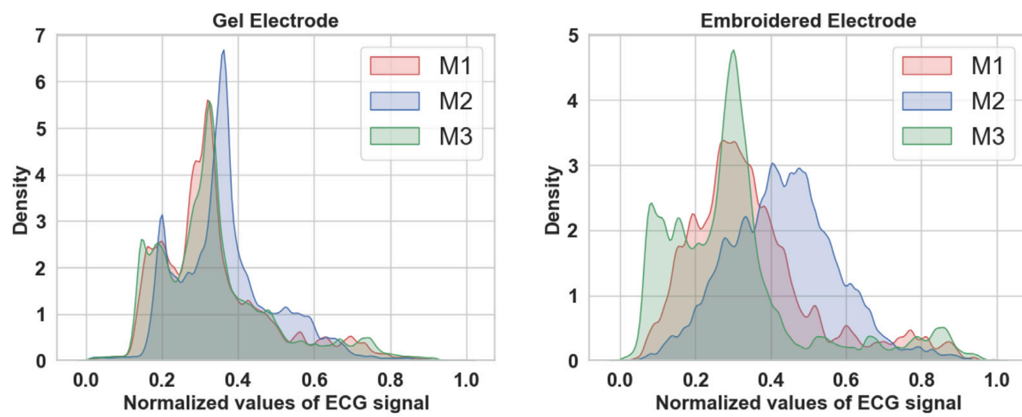
The mean, median, and standard deviation values calculated for the signals collected using gel and embroidered electrodes for the 11 subjects across the three measurements are shown in Figs. 7–9, respectively. Fig. 10 presents the boxplot of the mean, median, and standard deviation values to analyse the central tendency and variability of the data.

From Figs. 7(a), 7(b) and 10(a), for M1, the mean values for embroidered electrodes (in particular, subject 5 with 0.70) are notably higher compared to gel electrodes. For M2, the gel electrodes display

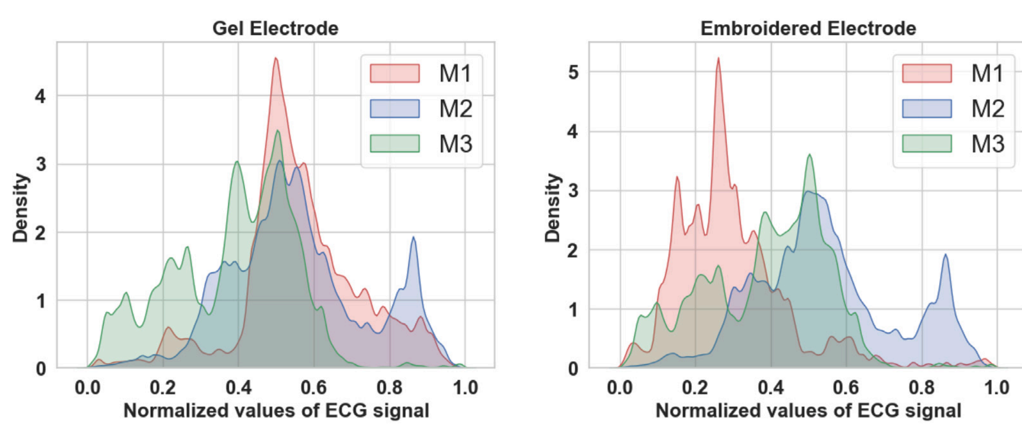


(a) Subject 2 (b) Subject 12

Fig. 4. Superimposed density plot for the signal Lead I ECG measured by gel and embroidered electrodes during three measurements for subject 2 and 12.



(a) Lead I ECG gel electrode subject 2 (b) Lead I ECG embroidered electrode subject 2

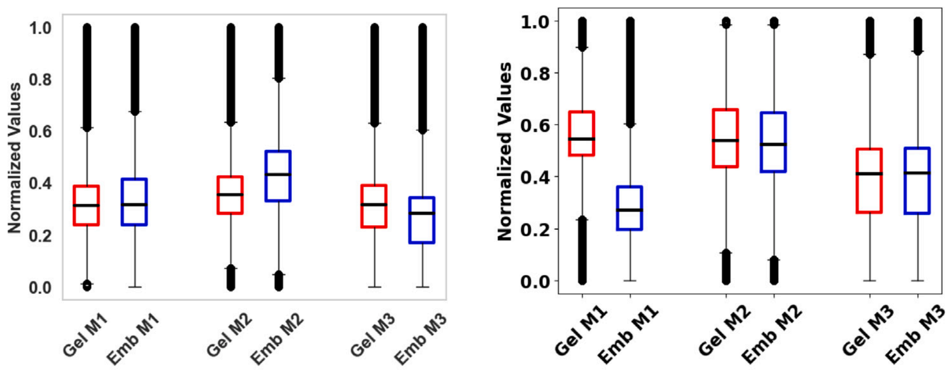


(c) Lead I ECG gel electrode subject 12 (d) Lead I ECG embroidered electrode subject 12

Fig. 5. Superimposed density plot for the signal Lead I ECG measured by gel and embroidered electrodes during three measurements for subject 2 and subject 12.

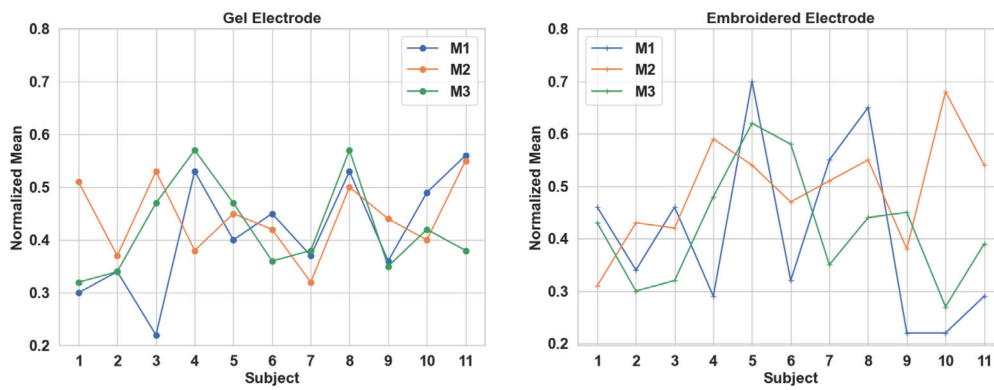
a significant increase in mean values compared to M1; meanwhile, embroidered electrodes continue to show higher mean values. A similar trend is observed for M3.

From Figs. 8(a), 8(b) and 10(b), we observe that, for M1, the median values for embroidered electrodes (in particular, for subject 5 with 0.77) are generally higher, with a broader spread (0.11 to 0.77) compared to gel electrodes (0.18 to 0.58); for M2, gel electrodes show a noticeable increase in median values compared to M1, with the highest median value at 0.53, embroidered electrodes maintain higher median values, with subject 4, 5, and 10 having relatively higher values; for M3, the gel electrodes exhibit a decrease in median values compared to M2, whereas, embroidered electrodes maintain higher median values with subject 5, again showing a higher value (0.66). It is also observed that subjects 4 and 5 consistently show higher median values across multiple measurements, particularly with embroidered electrodes. The gel electrodes generally display more stable median values across sessions than embroidered electrodes, which show more variability.



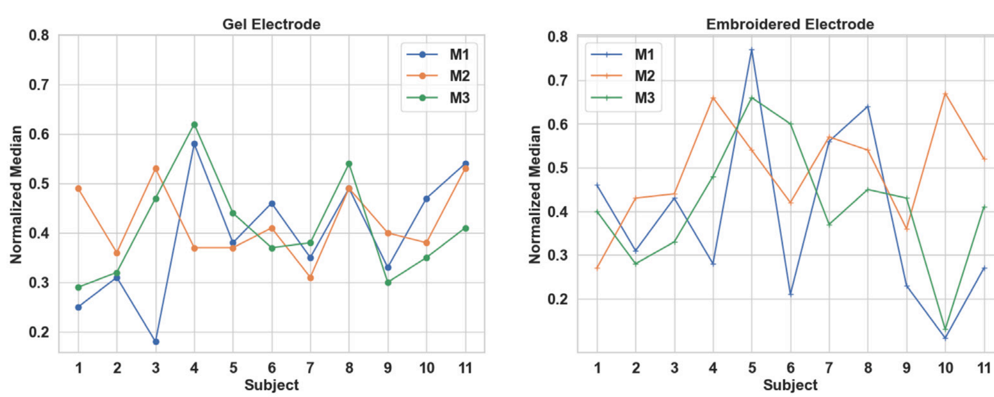
(a) Subject 2 (b) Subject 12

Fig. 6. Boxplot showing the normalized values obtained using gel and embroidered electrode for subject 2 and 12 for the three measurements.



(a) Mean for Lead I ECG gel electrode (b) Mean for Lead I ECG embroidered electrode

Fig. 7. Plots showing the mean values obtained for 11 subjects using gel and embroidered electrodes during the three measurements.

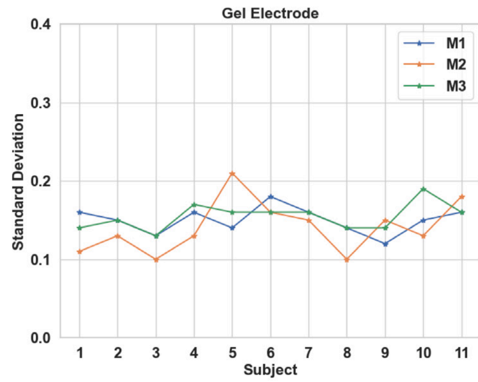


(a) Median for Lead I ECG gel electrode (b) Median for Lead I ECG embroidered electrode

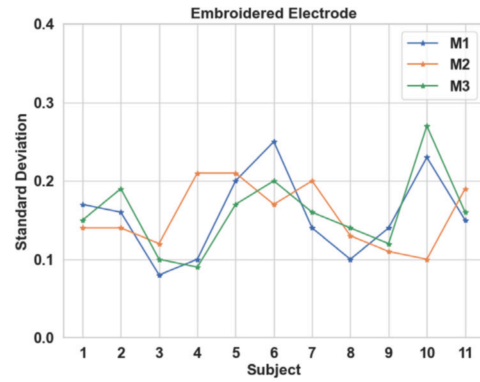
Fig. 8. Plots showing the median values obtained for 11 subjects using gel and embroidered electrodes during the three measurements.

From Figs. 9(a) and 10(c), it can be seen that for the gel electrode, moderate variation is seen in the std values for M1 (0.12 to 0.18) and M3 (0.13 to 0.19). In contrast, a higher variability is seen in the std values for M2 (0.10 to 0.21). This means that for M1 and M3, there is consistent dispersion in the collected signal while, for M2, potential variations in the quality or stability of signals are observed. From Figs. 9(b) and 10(c), high variability is observed in the std values for all three measurements (0.08 to 0.25 for M1, 0.10 to 0.21 for M2, and 0.09 to 0.27 for M3). This indicates that the signals collected using embroidered electrodes were not stable during the tests, and further investigation is needed about the electrode placement and electrode–skin interface.

Based on the boxplots in Fig. 10, we performed repeated measures ANOVA test on the ECG signals collected using gel and embroidered electrodes. To do this, we used the mean and median values of the three measurements for the 11 study subjects. For the mean values (Fig. 10(a), we obtained a p-value of 0.740 for the gel electrodes and a p-value of 0.282 for the embroidered electrodes. For the median values

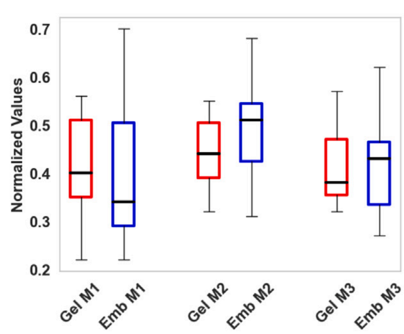


(a) Std for Lead I ECG gel electrode

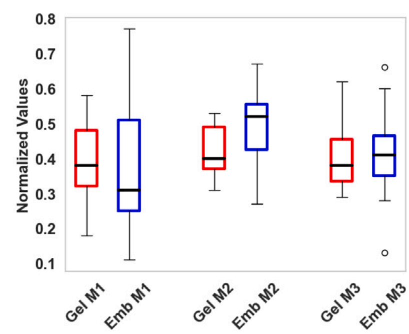


(b) Std for Lead I ECG embroidered electrode

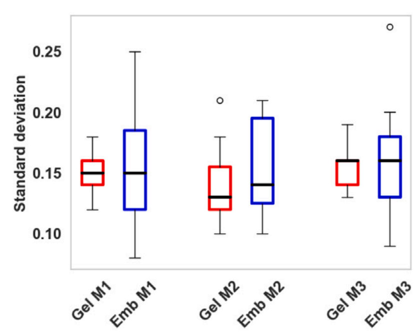
Fig. 9. Plots showing the standard deviation (std) values obtained for 11 subjects using gel and embroidered electrodes during the three measurements.



(a) Mean for all subjects across three measurements



(b) Median for all subjects across three measurements



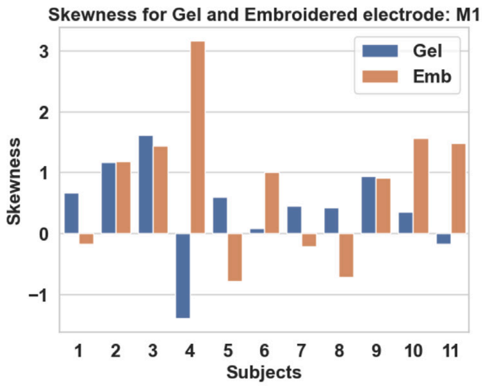
(c) Std for all subjects across three measurements

Fig. 10. Mean, median, and standard deviation values for all the study subjects during the three measurements.

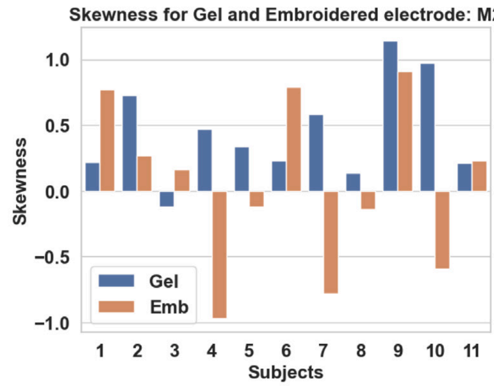
(Fig. 10(b)), we obtained a p-value of 0.825 for gel electrodes and a p-value of 0.292 for embroidered electrodes. The high p-value for gel and embroidered electrodes for the mean and median values suggests no significant difference in the respective values across different conditions or time points for the selected electrodes. The p-value of the paired t-test between gel and embroidered electrodes was 0.596, more significant than the commonly used significance level of 0.05. This high value again indicates no significant difference between signals measured using gel and embroidered electrodes.

To further understand the nature of the data, the skewness and kurtosis values are calculated for the ECG signals. Skewness is a measure of symmetry, or more precisely, the lack of symmetry in a data set, while kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution. Skewness and kurtosis are independent measures; one does not directly determine the other; however, they can provide complementary information about the data set.

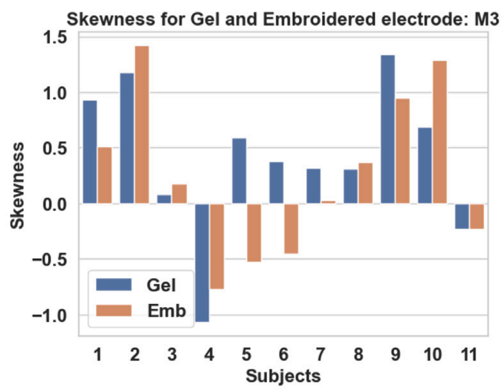
The skewness value of the ECG signal measured using gel and embroidered electrodes for the three measurements is shown in Fig. 11. A symmetrical data set distribution is preferred as it helps make accurate inferences and interpret data effectively. Generally, when the skewness values are close to zero, the data is distributed symmetrically; a positive skewness value indicates that the right tail of the distribution is longer than the left tail (a case where the mean is greater than the median). A negative value indicates the converse (the mean is lesser than the median). From Fig. 11, it can be seen that more values from embroidered electrodes are negatively skewed in comparison to gel electrodes. It is also observed that for the gel electrode, except for



(a) Measurement I



(b) Measurement II



(c) Measurement III

Fig. 11. Barplot of skewness values calculated for the ECG signals collected for the 11 study subjects during the three measurements.

subject 4, most values are positively skewed or closer to zero (which is desirable).

The kurtosis value of the ECG signal measured using gel and embroidered electrodes for the three measurements is shown in Fig. 12. Kurtosis measures the presence of extreme values in the tails of a distribution. High kurtosis indicates that data points are more concentrated in the tails than in a normal distribution, making the tails appear to pull towards the mean. Conversely, low kurtosis signifies fewer data points in the tails, causing the tails to spread out away from the mean. The kurtosis value of normally distributed data is 3, whereas a value greater than 3 indicates heavy tails and potential outliers, and a value less than 3 indicates light tails and fewer outliers. From Fig. 12, we see that for embroidered electrodes, higher kurtosis values (greater than 3) are obtained for subject 4 during two measurements. We also observe that values obtained using gel electrodes are closer to zero in most cases, indicating that the data is more evenly distributed across the range of values rather than clustering tightly around the mean or in the tails.

Following the individual analysis, we also present the mean, median, and standard deviation values were calculated by combining the values of the 11 subjects from the three measurements. The comparison between gel and embroidered electrodes is presented in Fig. 13. Based on the boxplots, we observe that the range of values for mean, median, and std for embroidered electrodes are higher than the range of values obtained for gel electrodes.

The correlation values between gel and embroidered electrodes for 11 study subjects for the three measurements are shown in Fig. 14. For M1, strong positive correlations are obtained for subjects 1, 2, 3, and 10, whereas negative correlations are obtained for subjects 5, 6, and 7, respectively. We have positive correlations for the rest of the subjects; however, the values are lower when compared to the other positively correlated subjects. Similarly, for M2, strong positive correlations are obtained for subjects 1, 2, 9, 10, and 11, and negative values are observed for subjects 3, 4, 5, 6 and 8. Lastly, for M3, strong positive correlations are obtained again for subjects 1, 2, 9, 10, and 11, and negative values are obtained for subjects 5 and 7. Across all three measurements, subjects 1, 2, 10, and 11 exhibit strong positive correlations, suggesting a robust positive association between gel and embroidered electrodes for these individuals. Also, for subjects 5, 6, and 7, the correlation values are either negative or close to zero, indicating a weak or inverse correlation between gel and embroidered electrodes.

In summary, the statistical analysis of combined data from all study subjects reveals that embroidered electrodes exhibit higher mean, median, and standard deviation values than gel electrodes, as depicted in Fig. 13. The correlation analysis across three measurements indicates strong positive correlations for some measurements and weak or inverse correlations for others. Notably, certain individuals consistently exhibit strong positive associations across all measurements. Considering the statistical analysis and the quality of the results, the study strategically reduced the number of subjects from 11 to 8 for the next phase, aiming to enhance the focus and precision of the investigation. The observed variations in correlation values suggest potential trial-specific effects on the relationship between gel and embroidered electrodes, emphasizing the need for further experiments to explore contributing factors to this variability.

The reduction from 11 to 8 subjects was necessary due to technical issues encountered during data collection, such as electrode disconnection and significant patient movement, which are common challenges with dry electrodes. These issues can introduce substantial motion artifacts, impacting the signal quality and integrity. The decision to exclude this data was made to ensure the reliability of the analysis, focusing on data where high-quality signal integrity was maintained.

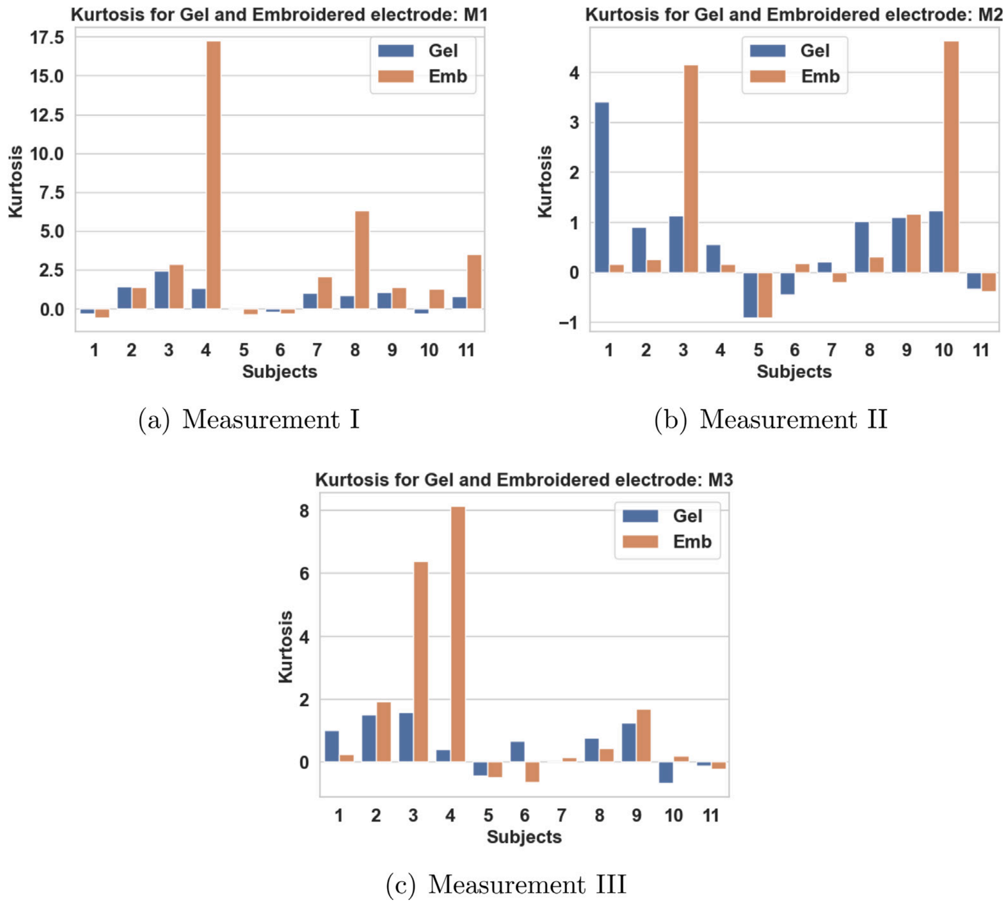


Fig. 12. Barplot of kurtosis values calculated for the ECG signals collected for the 11 study subjects at using gel and embroidered electrodes.

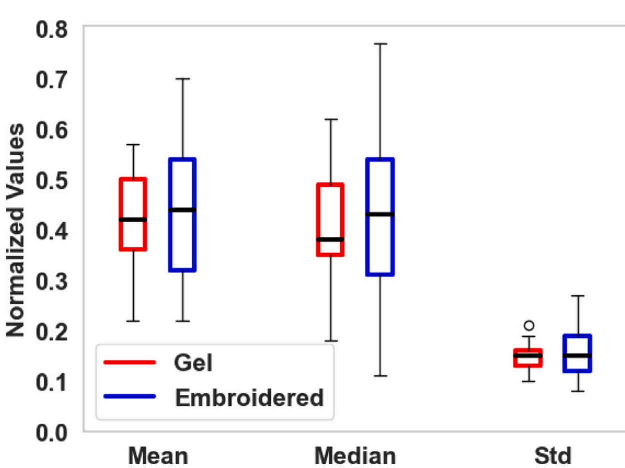


Fig. 13. Boxplot showing the statistical comparison between gel and embroidered electrode when the data from all the study subjects are combined together.

Additionally, the prediction of ECG signals from embroidered electrodes is designed to address these challenges, while also mitigating data loss due to the inherent limitations associated with dry electrodes. This approach helps in validating embroidered electrodes as a feasible alternative to gel electrodes by ensuring the accuracy and reliability of the data obtained, which is crucial for clinical settings. To achieve this, we computed a correlation matrix to examine the relationship between gel and embroidered electrodes for the 11 patients. In this study, we specifically chose patients whose ECG signals collected by gel and embroidered electrodes showed a correlation above 0.5 in at least one trial. Consequently, patients 4, 6, and 8 were eliminated from the study proposed in this paper.

Table 2
Mean prediction results based on Poly model: predicting embroidered electrode Lead I signal.

Subject	MAE	MSE	R2
SUB 1	0.00795	0.01286	94.583%
SUB 2	0.00887	0.01502	92.607%
SUB 3	0.01208	0.01685	94.898%
SUB 4	0.02325	0.03708	85.761%
SUB 5	0.00798	0.01314	94.344%
SUB 6	0.00886	0.01502	92.609%
SUB 7	0.00760	0.01208	94.710%
SUB 8	0.02357	0.03893	84.311%

3.2. Prediction results

The primary objective was to evaluate the predictive performance of the embroidered electrode-acquired Lead I ECG signal, using the gel electrode-acquired signal as a reference. The polynomial regression (Poly) model was adopted for this analysis. As summarized in Table 2, the mean prediction results based on the Poly model are presented, and MAE, MSE, and R2 were used as evaluation metrics.

The Table shows that the R^2 values span from a commendable 84.31%

In accordance with the sustainability objective, the results suggest that embroidered electrodes offer a promising alternative to gel electrodes for ECG data acquisition. The success in achieving high $R2$ values across subjects affirms the viability of embroidered electrodes in accurately recording Lead I ECG signals. This technology maintains

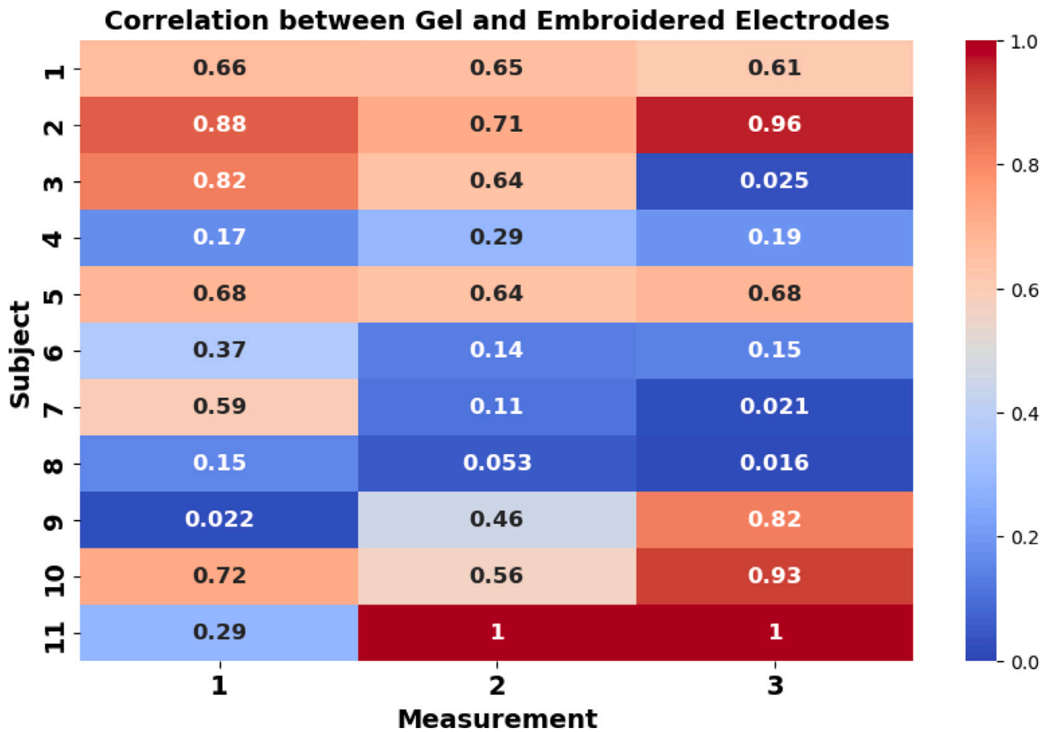


Fig. 14. Correlation between Gel and Embroidered electrodes for different subjects during the three trials.

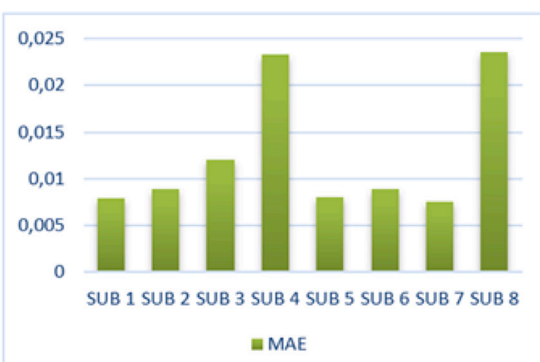


Fig. 15. MAE results with sensor signal prediction.

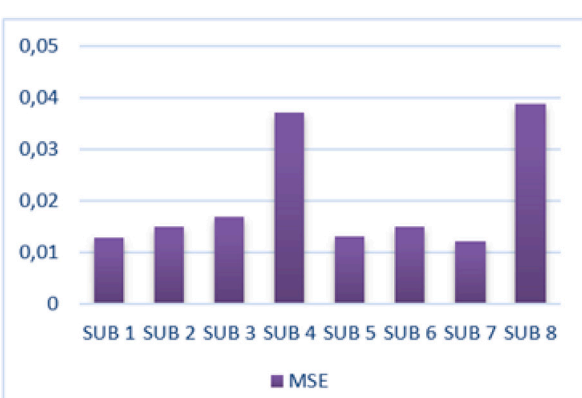


Fig. 16. MSE results with sensors signal prediction.

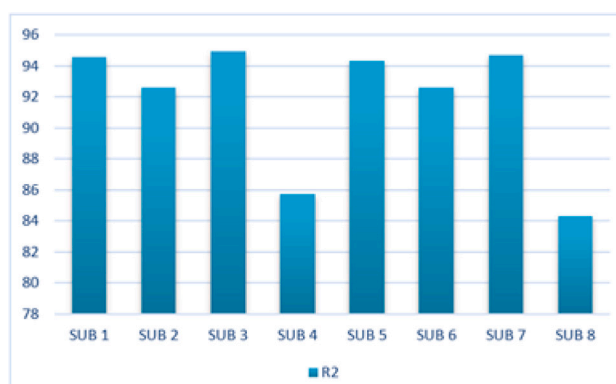


Fig. 17. R2 results with sensors signal prediction.

signal quality and ensures patient comfort, contributing to an enhanced user experience in long-term monitoring scenarios.

Additionally, Figs. 15, 16, and 17 provide visual insights into the prediction outcomes. These figures substantiate the R^2 values derived from Table 2. Fig. 15 (MAE results), Fig. 16 (MSE results), and Fig. 17 (R2 results) mirror the model's predictive accuracy and the efficacy of the embroidered electrode-acquired signals.

In conclusion, The R^2 values serve as a clear indicator of the success achieved in our endeavour to establish sustainable and effective ECG signal acquisition. The promising results underscore the potential of embroidered electrodes as a reliable and comfortable alternative to gel electrodes, aligning seamlessly with our primary aim of enhancing ECG monitoring techniques.

4. Discussion

The comprehensive data analysis conducted in this study sheds light on the intricate dynamics between gel and embroidered electrodes in the context of ECG signal acquisition. Exploring various statistical parameters and the subsequent machine learning predictions provides a nuanced understanding of the sustainability, accuracy, and potential applications of these two electrode types. The statistical analysis of individual subjects and the combined data from all study subjects reveal insights into the performance of gel and embroidered electrodes. The superimposed density plots for Lead I ECG signals during three measurements for subject 2 exemplify the potential of embroidered electrodes, demonstrating an overlap with gel electrodes. However, the analysis also uncovers variations in the shape and density of the plots, particularly for embroidered electrodes, hinting at potential challenges or differences in signal stability during different measurements.

The boxplot analysis further emphasizes the differences between gel and embroidered electrodes, showing that embroidered electrodes tend to have a wider spread or variability in measurements compared to gel electrodes. This variability is consistent across the three measurements, indicating that embroidered electrodes may introduce more signal instability or fluctuations than their gel counterparts. These findings raise questions about the electrode placement and the electrode–skin interface, highlighting areas for further investigation and optimization.

In addition to the statistical analysis and machine learning predictions conducted in this study, the repeated measures ANOVA test results offer valuable insights into the comparison between gel and embroidered electrodes. The ANOVA test, applied to the mean and median values across the three measurements for the 11 study subjects, revealed high p-values for both gel and embroidered electrodes. Specifically, the p-values were 0.740 for gel electrodes, 0.282 for embroidered electrodes when considering mean values, 0.825 for gel electrodes, and 0.292 for embroidered electrodes when considering median values. These high p-values suggest no significant difference in mean and median values across different conditions or time points for both types of electrodes. The paired t-test between gel and embroidered electrodes yielded a p-value of 0.596, indicating a lack of significant difference between signals measured using the two electrode types. This statistical analysis reinforces the notion that, on average, the performance of gel and embroidered electrodes is comparable across the evaluated conditions.

Adopting a polynomial regression model for predicting embroidered electrode-acquired Lead I ECG signals showcases promising results. The high R^2 values, ranging from 84.31%

While prior literature has primarily focused on comparing the performance of different electrodes based on experimental data [23,49], our study contributes a novel dimension by evaluating the predictive ability of one electrode using the other as input. This approach expands the scope of electrode assessment beyond traditional comparisons, providing a comprehensive analysis that includes predictive modelling. By adopting a polynomial regression model, we successfully demonstrated the predictive performance of embroidered electrodes in capturing Lead I ECG signals, showcasing strong agreement with gel electrode-acquired signals. This aspect of our study opens avenues for exploring electrode functionalities beyond their direct experimental performance, offering a more holistic understanding of their potential applications in real-world scenarios. The combination of experimental analysis and predictive modelling advances the understanding of electrode performance and aligns with the evolving landscape of healthcare technology. To benchmark the proposed methods, comparing their performance with state-of-the-art alternatives is essential. Shuvo et al. (2022) review the advancements in electronic textile sensors, highlighting that while embroidered electrodes offer enhanced comfort and sustainability, they still present challenges in signal stability compared to gel electrodes [50]. Pitou et al. (2018) specifically compare embroidered and gel electrodes, finding that the accuracy of signal capture using embroidered electrodes is comparable to gel electrodes. However, gel electrodes adhere more reliably to the skin, providing more consistent signal quality [51]. Nigusse et al. (2021) emphasize that embroidered electrodes have significant potential for long-term ECG monitoring, especially considering their benefits in reducing skin irritation compared to traditional gel electrodes [52]. However, embroidered electrodes are more prone to disconnections. Our study leverages a polynomial model to predict ECG signals from embroidered electrodes based on data from gel electrodes to address these limitations. This approach ensures we maintain a balance between the comfort of embroidered electrodes and the reliability of gel electrodes, thereby enhancing data integrity for clinical applications.

However, it is crucial to acknowledge the limitations of this study. The relatively small sample size and the exclusive focus on Lead I ECG signals may limit the generalizability of the findings to broader ECG patterns or electrode placements. While essential for analysis, applying noise reduction techniques during data preprocessing may have influenced specific signal characteristics.

5. Conclusion

In conclusion, the detailed data analysis and machine learning predictions presented in this study contribute significantly to the discourse on ECG monitoring technologies. The results suggest that embroidered electrodes hold promise as a comfortable and reliable alternative to traditional gel electrodes. The identified variations and challenges open avenues for future research to optimize embroidered electrode design, placement, and signal stability. The successful use of a polynomial regression model to predict embroidered ECG signals based on gel electrode data underscores the potential of this innovative approach. This research showcases how technological advancements can empower patient-centric healthcare solutions. Future work will include implementing more advanced algorithms and methodologies to further enhance healthcare outcomes in ECG monitoring.

CRediT authorship contribution statement

Ghada Ben Othman: Writing – review & editing, Conceptualization. **Atal Anil Kumar:** Writing – original draft. **Faten Ben Hassine:** Visualization. **Dana Copot:** Writing – original draft. **Lilia Sidhom:** Investigation. **Ernest N. Kamavuako:** Investigation. **Mohamed Trabelsi:** Investigation. **Clara Mihaela Ionescu:** Supervision. **Inès Chihi:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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