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ECG in Real World Scenario: Time Variability in Biometric Using Wearable Smart Textile Shirts

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ABSTRACT

Biomedical signals, such as an electrocardiogram (ECG), have been included in wearable platforms for biometric reasons due to the rapid expansion of apps and technology capable of gathering this physiological data. Most studies using ECG biometrics are conducted in clinical settings, which is impractical for wearable ECG-based biometric applications. Therefore, this study aims to determine the reliability of ECG signals obtained from the commercially available Hexoskin Proshirt and HeartIn Fit shirt, which may be worn for biometric verification in real-world scenarios. ECG data from 22 participants were collected over a span period of more than 30 days. The raw ECG signal is first pre-processed in the time domain using noise-removal Butterworth filters, and then a successful QRS segmented feature extraction method is used. Not to mention, 300 datasets were used to test the recommended recognition method using a Quadratic Support Vector Machine (QSVM). In comparison, around 854 datasets were prepared for training and validation of the classifier. The findings showed that the proposed method provided a considerable accuracy above 99.63 % with a FAR of 0.14 %, an FRR of 2.86 %, and a TPR of 97.14 %. Thus, the study supports using ECG biometrics for verification in real-world settings by employing a smart textile shirt with varying temporal variability.

Keywords:
ECG; Biometric; Authentication; Smart Shirt; Wearable; Time Variability

1. Introduction

From the first cry of a newborn child until the end of their life, humans and textile are two distinct elements that coexist. Nearly every single human being on the planet wears a protective layer of material to cover their body. The human demand for textiles has caused the wearable textile sector to expand from a fundamental human requirement to the human desire for fashion, sports, health care, medical support apparel, first responder protection, and advanced safety and security purposes. Wearable textile technology advancements have now reached the point of smart capabilities that can effortlessly capture the bio signal of its wearer [1-3].

Moreover, breathing rate [4], heart rate [4], blood pressure, oxygen saturation [5], bioimpedance, electromyogram (EMG), and electrocardiogram (ECG) [6-8]. are some of the bio-signal traits that are

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often acquired utilising wearable and smart textile sensors. Furthermore, wearable devices that do not require invasive procedures to record human ECG over a long time and do not disrupt the user's routine have ignited consumer market demand for a shirt-like wearable ECG device with embedded measuring electrodes and lead [6,9]. Furthermore, the wearability of a smart textile shirt for a more extended period to obtain physiological parameters without significant discomfort or mobility restrictions has outweighed all of the disadvantages of portable and wearable devices [9], making it an essential component for biometric recognition.

In addition, the need to remember their passcodes makes some people uncomfortable with standard identifying methods like ID cards, passwords, and token-based authentication [10]. Theft, squinting, and loss make them also vulnerable to forgeries. Biometrics, on the other hand, provide foolproof security by allowing the identification of a person based on physiological or behavioural characteristics. Additionally, due to the advancement of real-time measuring technology and the expansion of research into the security of authentication information in electronic devices, ECG, as one of the biometrics modalities, is becoming more and more appropriate for various applications [11,12].

Furthermore, ECG signals are unique and can only be captured by direct physical contact, impenetrable from the outside and includes a liveness indication at the detection location [13]. As a result, in the future of biometric recognition, ECG-based biometrics have the potential to partially or entirely replace other existing biometrics such as vein [14-16], gait [17], face [18-22], fingerprint [23,24], and iris [25-27].

While an efficient and resilient biometric recognition system anticipates the influence of time variability and capacity in its discriminative capabilities to maintain a stable biometric recognition performance over time. In addition, Lehmann *et al.,* [28] advised that biometric evaluations be conducted in a less controlled, real-world scenario. Their findings also suggest that it was feasible to train ECG data from numerous days for improved biometric verification performance, despite researchers in Pinto *et al.,* [29] quoting time variability as a drawback of ECG biometric recognition. However, their work in [29,30] demonstrates that the ECG biometric is one of the most promising in contrast to other biometric modalities.

Therefore, this study aims to analyse the ECG signals obtained from commercially available wearable shirts, such as the Hexoskin Proshirt and the HeartIn Fit shirt, for biometric verification in various temporal variations. The focus of this study is to get a deeper understanding of the influence that the template's ageing and the different enrolment days have on the consistency of ECG-based authentication in a wearable smart textile shirt.

Whereas for that reason, the rest of this paper is organised as follows. Section 2 provides an overview of the present state of the art in ECG-based wearable biometric identification. Section 3 of this article addresses the technique utilised to acquire ECG in a real-world scenario while wearing wearable smart textile shirts and the methods necessary to assess and extract the raw ECG. Section 4 discusses the study's performance evaluation and biometric authentication achieved. Finally, Section 5 concludes this analysis with recommendations and directions for future work.

2. Related Works

Due to several drawbacks, many present approaches for wearable ECG devices and algorithms are still in their infancy and far from practical implementations. For instance, many contemporary ECG signal recognition algorithms were developed using public ECG datasets. Furthermore, most of these ECG datasets are collected in clinical settings using medical-grade sensors in a controlled environment [31]. Therefore, it is inappropriate for wearable gadgets [32]. In addition, wearable systems using time variability for ECG biometric detection have only been the focus of a small number of studies in [28,31,33,34]. Besides, only work in [33,34] have developed a wearable ECG biometric model incorporating smart textile shirts in their study.

Despite this, VitalJacket's wearable smart textiles shirts were used in groundbreaking biometric research by Ye *at al.,* [33]. Using a Support Vector Machine (SVM) with a radius basis function, the study collected data from five firefighters over the course of six months to reach a biometric recognition rate between 70 to 100 % with a six heartbeats method. The work demonstrated that obtaining an ECG signal from a smart textile may be a reliable biometric, and it validated the idea of fiducial point data from ECG signals.

Meanwhile, work by Alonso *et al.,* [35] proposed a similar use of SVM to the previous researcher in this related work for biometric identification. This study datasets are generated from 25 subjects using a built prototype to acquire several biometric traits such EMG, PPG and ECG for 1 minute in each trait. The acquisition for each subject was done twice at different times and achieved a 92% of correct recognition rate.

In addition, research by Martinho *et al.,* [36] demonstrated the viability of multimodal blood volume pulse (BVP) and ECG biometrics for biometric identification utilising prototype wearable devices. Fifty-three participants were recruited for the study, and data were gathered from them over the course of two separate eight-week periods. Using a five-heartbeat ECG approach, the study utilised k-Nearest Neighbors and Nave-Bayes decision for its classifier and obtained a 13 % error rate.

According to Pourbabaee *et al.,* [34], they conducted research using wearable smart textiles from OMSignal for biometric identification. As a result, their research demonstrates that noise, artefacts, and other disturbances make the fiducial point identification technique ineffective. This study employed ECG data from 33 female volunteers collected six times over the course of a week and put into a convolutional neural network (CNN) classifier to achieve a biometric identification rate of 95% with a 10-heartbeat technique.

Subsequently, Chen *et al.,* [37] combined data acquisition of ECG signals from 68 healthy and unhealthy subjects to perform biometric identification across a month. The study developed a self-prototype wearable device that acquired two sets of 45-second ECG data from each subject to feed in a Random Forest (RF) classifier under resting conditions. The work also indicates a better identification accuracy of 98.14% for a healthy person.

Similarly, research work by Lehmann *et al.,* [28] focuses on authentication using ECG collected from 20 subjects. Their subject was wearing a chest belt tracking wearable device of EcgMove3 and EcgMove4. The work found the best EER of 9.15% based on the 15 heartbeats approach with the training duration across a week. This study fulfilled its classification stage by using RF classifier and highlighted that wearable ECG biometric could be deployed in a real-world scenario; however, the robustness is less in contrast to under controlled conditions environments.

It should be highlighted that only [28,33,34] studied real-world scenarios with time variability in wearable devices. In the actual world, ECG-based authentication would likely be performed spanning several days. To fill in the gap, this project intends to employ wearable smart textile shirts to assess the efficacy of ECG authentication in different time variations. This study created an ECG dataset from 22 subjects who wore wearable Hexoskin Proshirts and HeartIn Fit Shirts from two distinct commercial brands for biometric verification in a real-world scenario on different acquisition times.

3. Methodology

Figure 1 is a block diagram of the approach framework chosen and redeveloped from research in [29,38-45]. Data acquisition, followed by baseline correction and denoising in pre-processing, fiducials detection in feature extraction, and parameter assessment in the classification block stage, provides the foundation for identity authentication in this study.

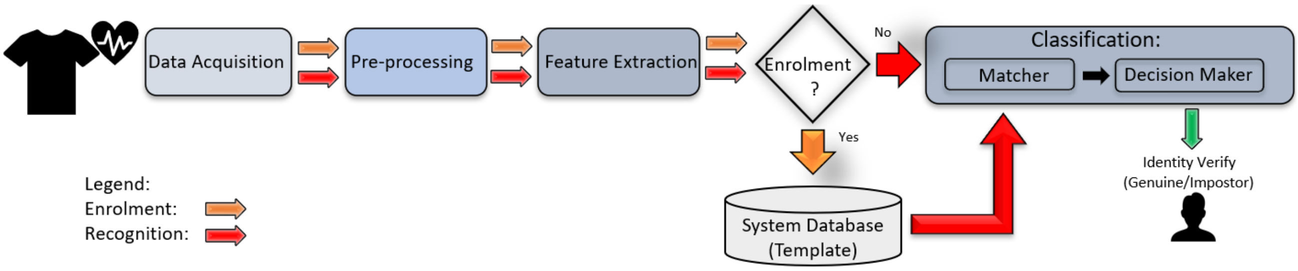
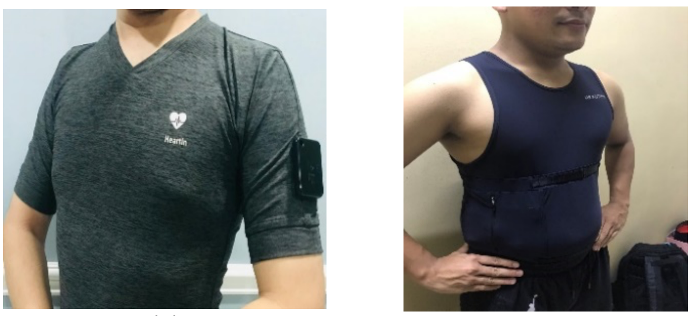


Fig. 1. Biometric Operation framework

The biometric system has two modes of operation: recognition and enrolment [46]. Following the completion of feature extraction in the recognition mode, the data will proceed directly to the classification step. After the feature extraction step, the enrolment mode input data will be saved as a template in the system's database and subsequently utilised in recognition mode. The matcher will next compare the ECG data to the template data in the database to anticipate the verification decision. In the next part, this article will explore the proposed structure.

3.1 Data Acquisition

The International Islamic University Malaysia Research Ethics Committee approved this study (IREC 2021-058), and 22 subjects (18 men and 4 women) in good health shape agreed to participate in this work. Before granting their consent, all participants were fully briefed about the nature of the study and the risks that may be incurred. Figure 2(a) portrays one of the individuals in this study wearing a Hexoskin Proshirt smart textile shirt, while Figure 2(b) represents another subject wearing a HeartIn Fit smart textile shirt. A minimum of 15 minutes was required while wearing the high-tech shirt.



(a) (b)

Fig. 2. Two Types of Smart Shirts Used in This Study (a) HeartIn, (b) Hexoskin

Meanwhile, three textile electrodes, two on the chest and one on the lower right side in the rib cages, were sewn into the Hexoskin Proshirt smart textile shirt to capture the ECG signal at 256 Hz. At the same time, the signal's average over the preceding 16 beats of ECG points was saved to a data file at a rate of 1 Hz. The Hexoskin smart textile captured ECG is visualised in real-time and sends real-time data over a secure Bluetooth wireless connection during data collection. Additionally, the raw data were locally saved on the Hexoskin device and uploaded to a cloud service when connected to the internet, enabling later access and analysis of the data.

On the other hand, the HeartIn Fit smart textile shirt records the ECG data from two textile electrodes at 512 Hz. In the HeartIn wearable smart textile, the two textile electrodes were located on the right and left sides of the chest. During data collection, the HeartIn smart textile delivered secure Bluetooth wireless data to the smartphone so that the data could be seen in real-time. The HeartIn smart textile device does not save any data on the device itself; instead, all data is stored locally on the phones by a dedicated application. Besides, In the mobile application for the latest version of the dedicated application for the HeartIn wearable smart textile device, only the ten most recent data acquisitions will be stored. However, the ten most recent data sets that this smart textile has acquired may always be sent and stored somewhere to be accessed and analysed again.

In addition, as illustrated in the data acquisition framework in Figure 3, the study separates the 22 participants into two equal groups of 11 subjects in group A and another 11 subjects in group B. Group A participants wear the smart textile shirt of their choice and perform their daily routine activity in their own environment for at least 15 minutes. The same procedure was repeated for each group A participant in the second data acquisition with a spanning period of 30 days.

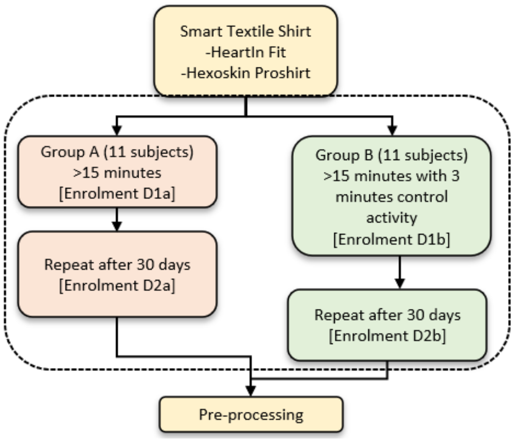


Fig. 3. Data Acquisition Framework

In contrast, the 11 participants in group B were asked to wear the smart textile shirt and perform 3 minutes lite and easy walking activities. After finishing the walking activities, the participants were given the complete freedom of their desired normal routine activities to complete the minimum 15-minute procedures. The same measures were repeated during the second data acquisition for participants of group B with a minimum separation of 30 days from the first data acquisition for each subject. After completing all activities in both groups, the raw ECG data were extracted to perform the pre-processing outlined in the subsequent section.

3.2 Pre-Processing

The raw ECG signal lacked a smooth waveform due to the presence of noise caused by the wearer's movement when the data was being collected. This is because the motion of the body causes motion artefacts, which are often in high-frequency vibrations form [42]. In the next section, several data pre-processing approaches were employed to treat the raw ECG signal to fulfil the least acceptable feature criterion before feature extraction.

Figure 4 pre-processing structure is used to derive the entire study framework on pre-processing stages. Which the raw ECG data from participants wearing the HeartIn smart textile shirt were resampled from the original sampling frequency of 512Hz to the new sampling frequency of 256Hz to maintain sampling parity with Hexoskin user data. This data was inverted across the isoelectric line and rescaled to match the size of all datasets from both brands.

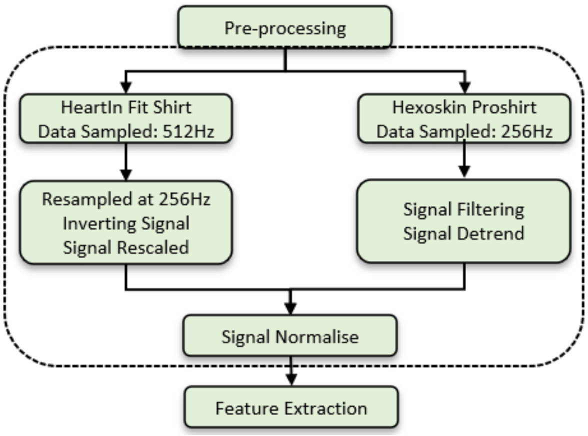


Fig. 4. Pre-processing framework

Meanwhile, the raw ECG data from the Hexoskin smart textile shirt was initially sampled at 256Hz. is subjected to some data pre-processing by adding a lowpass Butterworth Filter with a cut-off frequency of 30Hz to remove undesired noise, which subsequently aids in the reduction of high-frequency noise and interference noise from power lines. In addition to eliminating baseline drift during the detrending procedure, the filter returned the ECG data to the isoelectric line through a straightforward Fast Fourier Transform (FFT). Then, the inverse FFT returns the ECG signal to its original state in the time domain, allowing for a more precise data analysis during the feature extraction stage.

3.3 Feature Extraction

After the first two steps, i.e., the acquisition and pre-processing phases, are completed, feature extraction begins. These processes enhance signal representation and decision-making by minimising residual noise and within-subject variability. By removing certain transitional gaps, the PQRST morphology of the electrocardiogram (ECG) facilitates the observation of wave variations in each individual's response from the overall ECG signal. This has led to its widespread application, and most of the leading studies in literature implemented extracted biometric features in ECG centred on the QRS complex signal itself [28,30,47]. Similarly, classification in this study also relies on the QRS complex characteristic, as illustrated in the feature extraction framework in Figure 5.

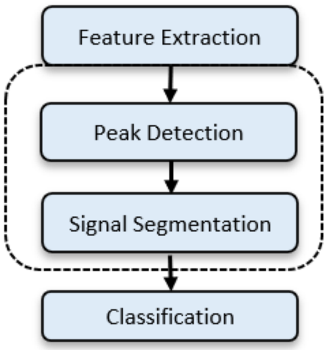


Fig. 5. Feature extraction framework

The study segmented the QRS complex using the concept of local maxima and a windowed filter to identify the R-peaks. This filter disregards all other values and only displays the window's maximum value. The work also made use of a window of default proportions. Then, a threshold is employed to eliminate the values of minor peaks while preserving the values of significant peaks. Later, in order to improve the filtration quality, the window size was altered, and the filtering method was done many times to guarantee that all R-peaks were present and accurately recognised. After successfully identifying the R-peaks of the ECG signal, 20 points were segmented around the peaks and saved in the database for classification purposes.

3.4 Classification

Finally, the training and testing datasets for each of the 22 participants in this study were split 80/20 in the construction of the classification technique. Furthermore, the ECG data was trained and evaluated with five principles from a predetermined scenario under different time-varying settings in scenarios A, B, C, D, and E, as summarised in Figure 6.

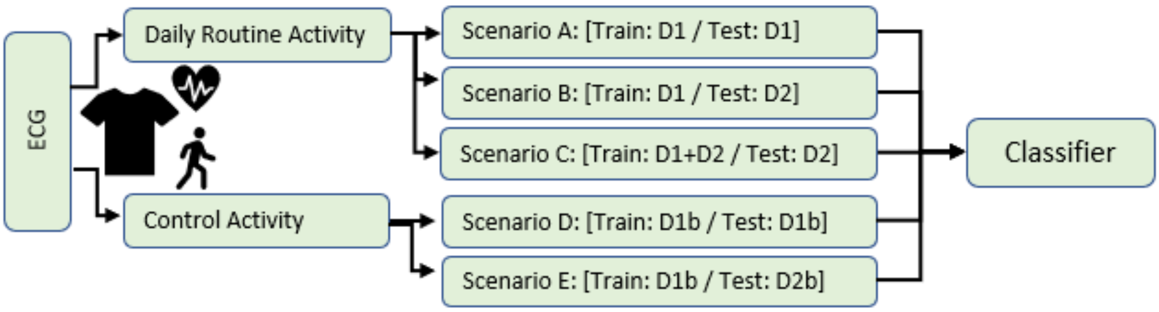


Fig. 6. Training and testing scenario

In principle, this study investigates whether a system can distinguish between distinct people based on recorded ECG data using conventional biometric assessments. Intuitively, the study trains classifiers to discriminate between one real user and everyone else and then evaluates this system using data from that legitimate user in scenarios A, B, C, D, or E and the rest of the subject data in the same scenario as the attacker or impostor to the model.

Figure 7 shows how this evaluation strategy was used in the authentication process. The main ideas were the same as those in Lehmann *at al.,* [28]. For each pair of two subjects, the study officially names participant "u" as the actual user and participant "I" as the counterfeit user (u, i). A classifier that the study trained separates the real user u, who is given the label 1, from all the other users r, who are given the label -1. All other participants, which are r ∈ U\{u, i}, I represent the "rest of the subject," such as all the other people in an enrolment database. It should be noted that the study-designated participant "u" is trained based on the study scenario set against the other subjects in the same scenario. The study then put the classifier to the test by giving it two sets of data: Set 1 (the test part of u's data), which it should ideally accept, and Set 2 (the imposter part of i's data), which it should ideally reject (output -1).

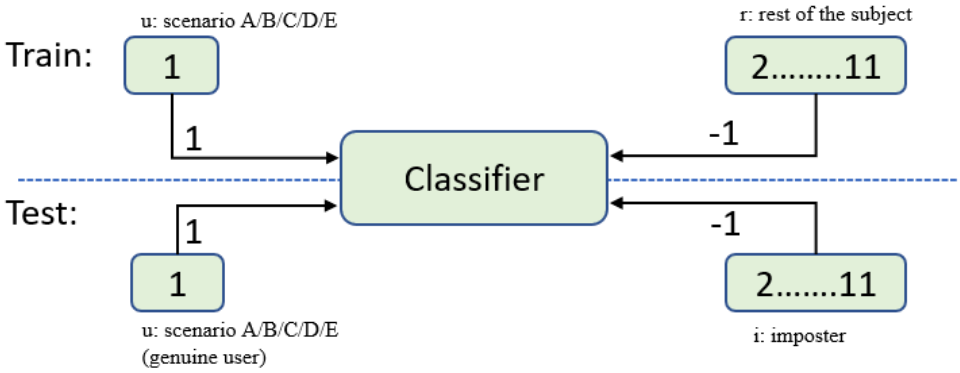


Fig. 7. Classification study framework

Classifiers based on the Quadratic Support Vector Machine (QSVM) model are used to evaluate the performance of a classification scheme based on a collection of predetermined characteristics. 10-fold cross-validation was used to train and assess the classifiers; in this approach, the complete dataset is partitioned into ten halves, each serving as a test set. The remaining nine elements are used to assemble a training set. As will be seen and expounded upon in the next section, this procedure is repeated ten times, and the average result is determined.

During the matcher stage of the classification process, the QSVM classifier implemented in the classification learner app on the MATLAB program is based on the QSVM equation, which can be expressed as Eq. (1).

$$(1/2) \times \| w \|^2 + C \times \sum i = 1 \; to \; n \; \mathcal{E}i \tag{1}$$

This is subject to the following conditions:

$$yi \times (w^T xi + b) \geq 1 - \varepsilon i \tag{2}$$

And

$$\varepsilon i \geq 0 \; for \; i = 1,2, \dots, n \tag{3}$$

Where “w” is the weight vector to be trained by the algorithm, “b” is the bias term, and “C” is a regularisation parameter that controls the trade-off between low training error and low norm of the weight vector. “xi” is the *i*-th training instance of the vector features, and “yi” is the associated class label (+1 or -1). Similarly, “Ɛi” is a slack variable that allows for some misclassification in the training set.

Meanwhile, the following section offers the assessment results and analyses the implementation of different time variability conditions for wearable biometric authentication. In addition, to evaluate the performance of the classifier, several biometric authentication statistical performance metrics, such as accuracy, hit rate or true positive rate (TPR), miss rate or false rejection rate (FRR), and false match or false acceptance rate (FAR), were generated with a confusion matrix and illustrated in the following section.

4. Results and Discussion

This study's performance evaluation was supported by 2.90 GHz Intel(R) Core (TM) i5-10400F processors combined with 32 GB of RAM utilised for signal processing and data analysis. In addition, NVIDIA GeForce GTX 1050Ti 4GB graphics cards were equipped to support the suggested procedures. Using MATLAB R2021a software, the dataset was analysed. It contained information from 22 volunteers wearing smart textile shirts while performing everyday activities.

Meanwhile, in order to eliminate undesirable noise, the raw ECG signal Figure 8(a) undergoes some data pre-processing by adding a lowpass Butterworth filter. Consequently, Figure 8(b) demonstrates how filtering helps minimise high-frequency noise as well as interference noise from power lines. In addition, the filter minimises baseline drift throughout the detrending procedure, ensuring that the ECG signal returns to the isoelectric line, as seen in Figure 8(c), prior to segmentation.

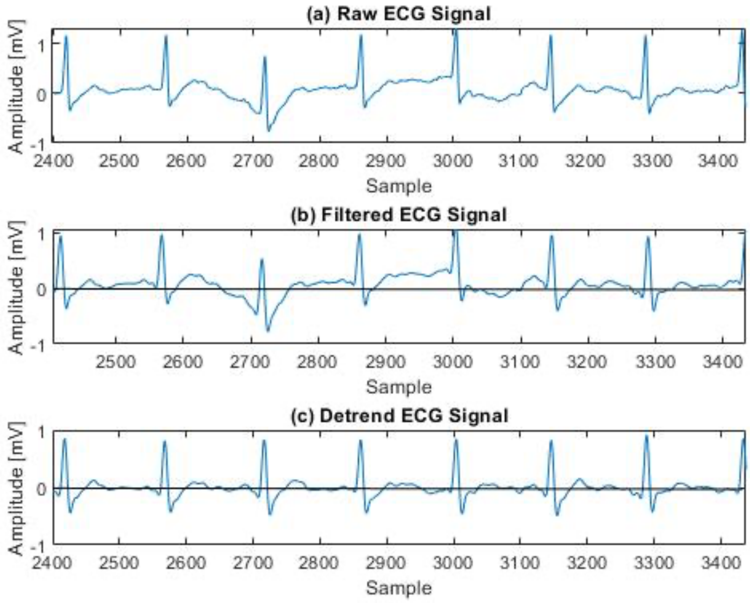
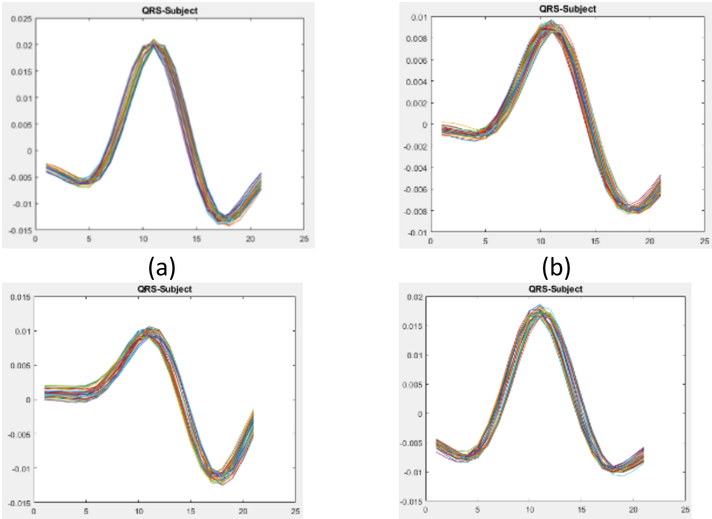


Fig. 8. ECG Signal Through Pre-processing Process

Figure 9 demonstrates segmentation findings by displaying the QRS of the ECG signal for several of the participants in this research. From these figures, it can be deduced that there were substantial differences in the patterns of each QRS data point for each participant in this investigation. These patterns were effectively captured on a smart textile shirt from a textile electrode.



(a) (b) (c) (d)

Fig. 9. Segmented ECG from different subjects (a) subject 1, (b) subject 8, (c) subject 21, (d) subject 22

Each test was conducted using the MATLAB 2021a software's built-in classification learner app toolbox. The Classification Learner App utilised the Quadratic Support Vector Machine (QSVM) techniques, as these machine learning algorithms are recognised as effective pattern analysis instruments [48]. Besides that, the training and testing part of the model was constructed using 10-fold cross-validation with an 80/20 split between training and testing data. Meanwhile, Table 1 displays the classification performance using QSVM machine learning algorithms.

Table 1
Summary of classification performance

Scenarios	Accuracy (%)	TPR (%)	FRR (%)	FAR (%)
Scenario A	99.27	92.77	7.23	0.40
Scenario B	93.59	30.81	69.19	2.84
Scenario C	99.20	90.32	9.68	0.27
Scenario D	99.63	97.14	2.86	0.14
Scenario E	88.86	44.56	55.44	6.05

Classification performance is a crucial aspect of evaluating the proposed models employing a variety of matrices, such as the biometric performance illustrated in Table 1. In the meanwhile, results derive from Scenario A, which exposes the classifier to the same enrolment session for both training and testing, prove to be outstanding in terms of the performance as biometric recognition purpose in terms of its accuracy, true positive rate (TPR), false rejection rate (FRR) and false acceptance rate (FAR). The study further discovered that in real-world scenarios, when implemented the biometric on human regular daily life activity captured by ECG textile sensor on smart textile shirts, it showed a bit of decreasing performance when tested with data a month apart, as demonstrated in Scenario B. However, if the original template data were updated with the new data within the different spanning time of this study, showing a fantastic performance of verification in biometric, this result would be in line with [49], [50] that conclude almost the same stand in the area of time variability and its significant role on biometric.

In Scenario D, surprisingly, the study achieves outstanding performance in all tested parameters of the current scenario. The data were tested within the boundaries of known activity of those wearer subject ECG. Meanwhile, even in Scenario E, the findings were not very encouraging; this result has drawn attention to the importance of continuously updating template data in maintaining reliability in biometric verification performance. This, study performance was outstanding and on par with the current state-of-the-art approaches, as demonstrated in Table 2.

Table 2
Summary of state-of-the-art approaches on wearable ECG biometric anticipate time variability

Paper	Variability	Wearable	Subjects	Scenarios	Classifier	Performance
[28]	1 week	Commercial	20	Real World	RF	EER=9.15%
[33]	24 weeks	Commercial	5	Real World	SVM	Acc=70-100%
[34]	1 week	Commercial	33	Real World	CNN	Acc=95%
[35]	Different days	Prototype	25	Resting	SVM	Acc=92%
[36]	8 weeks	Prototype	53	Resting	k-NN	EER=13%
[37]	4 weeks	Prototype	68	Resting	RF	Acc=98.14%
Proposed	4 weeks	Commercial	22	Real World	QSVM	Acc=99.63%

Notes: Acc=Accuracy, EER=Equal Error Rate, RF= Random Forest, CNN=Convolution Neural Network, QSVM=Qudratic Support Vector Machine

It is also important to note that, with respect to ECG-based biometric recognition systems that rely on wearable devices, only a small number of studies have investigated the reliability of the employed classifier by executing tests on a database of diverse time spans. Moreover, only the intended work and study in [33] and [34] address their research pertaining to real-world scenarios and employ smart textile shirts as a data acquisition method. One thing worth noting is that although work in Ye *et al.,* [33] claim their work has up to 100% recognition performance, unfortunately, their number of subjects is significantly smaller than the others. Another thing worth noting is that even the research in Pourbabaee *et al.,* [34] has a more significant number of subjects and a contradictory stance on the fiducial point technique adopted from Ye *et al.,* [33] and proposed work. However, the assessment performance of their work is inferior to that of the suggested work.

Meanwhile, the restricted number of individuals in this study is acknowledged as a possible restriction that may impact the generalisability of the findings. Moreover, the limited sample size may reduce the statistical power of the study's analysis. Nevertheless, despite these constraints, this work gives valuable insights into the Real-World Scenario by including the influence of temporal variability on ECG Biometric utilising two distinct brands of wearable smart textile shirts. While additional research with bigger sample sizes may be required to validate and extend the research findings, this work illustrates the feasibility of using ECG capture with textile electrodes for biometric recognition in the real world. In addition, this research contributes to the current literature on wearable biometric recognition and lays the groundwork for future research in this field. By identifying the limits of the work and recognising the possible influence of these constraints on the findings, this study also wants to motivate more research into wearable ECG biometric recognition.

5. Conclusions and Future Work

Most ECG biometrics investigations have been conducted in a controlled setting using high-quality medical sensors to ensure accurate results. For this reason, the findings may not be applicable to all real-world circumstances. Similarly, wearable ECG biometrics lacked a comprehensive understanding of how temporal variability affects them. Therefore, empirical fieldwork was compelled by the available literature. In addition, this research aimed to satisfy this need by offering in-depth analyses of ECG biometrics using a non-medical textile sensor integrated into both smart shirts for different time courses in a real-world context.

The key contributions of this work are the implementation of a smart shirt with textile electrodes as a biometric recording medium and the performance evaluation of different time variability circumstances for biometric authentication in a real-world setting. Furthermore, this study shows that it is possible to distinguish between people using the ECG data recorded by the textile sensor on both smart shirts, regardless of humans' activities as part of everyday routines.

Positive results revealed that smart textile shirts could be used for accurate ECG-based biometric verification. The study raises several intriguing follow-up questions, such as whether adding a second classifier to the one used in the study can improve its accuracy under various time variability conditions and whether deep learning can improve the classifier's performance in real-world biometric recognition for the wearable ECG smart shirt over a more extended period.

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