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Biometric Analysis on Smart Textile Garment in Real Life Scenario

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ABSTRACT

The rapid proliferation of wearable applications and technologies capable of acquiring biomedical signals has prompted the incorporation of biomedical signals, such as the electrocardiogram (ECG), for biometric purposes in wearable platforms. Most ECG biometric research utilises medical-grade sensors in clinical settings, which is unrealistic for wearable ECG-based biometric applications in the real world. Therefore, this research aims to examine the ECG biometric on smart textile garments in real life, collected from commercially available wearable Hexoskin Proshirt and HeartIn Fit shirts. ECG data were obtained from 22 participants who took part in this study. The raw ECG signal is initially pre-processed using noise-removal Butterworth filters in the time domain, followed by an effective QRS segmented feature extraction technique. Finally, around 2076 datasets were created for training and validation, while the remaining 501 datasets were employed to test the suggested recognition approach with 29 Machine Learning Classifiers. Subsequently, Quadratic SVM has the highest accuracy at 96.8% for ECG biometrics, followed by Narrow Neural Network with 95.8% and Wide Neural Network with 95.4%. Further improvement to the QSVM parameter improved the accuracy to 97.4% with an error rate of 2.6%, followed by a sensitivity of 97.4% with a precision of 97.7% and a false rejection rate of 2.6%. Thus, the results of this study further validate the feasibility of applying ECG biometrics for recognition in real-life scenarios utilising a smart textile shirt with different configurations and brand is possible.

1. Introduction

Almost every human being in this world uses some sort of protective layer of textile to cover their body. Since babies are born till the end of their time, humans and textile are two different elements that co-exist together. The human need for textiles has made the wearable textile industry evolve from a basic human necessity to human fashion desire, sports, health care, medical support attire, first responder protection and advanced safety and security purpose. Nowadays, the advances of wearable textile technology growth have reached the stage of a smart capability that can acquire the biosignal of its wearer seamlessly [1-3].

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Some of the bio-signal traits that typically acquire using wearable and smart textile sensors are breathing rate, heart rate, blood pressure, oxygen saturation, bioimpedance, electromyogram (EMG), and electrocardiogram (ECG) [4-8]. In addition, wearable devices that do not require any invasive procedures to record human ECG over an extended period and do not interfere with the user's routine have garnered interest and sparked a consumer market demand for a shirt-like wearable ECG device with embedded measuring electrodes and lead [6,9]. Moreover, the wearability of a smart textile shirt for a longer period of time to obtain physiological parameters without experiencing significant discomfort or mobility restrictions has outweighed all of the drawbacks of portable and wearable devices, and it has become an essential component for biometric recognition [9].

Moreover, standard identification techniques, such as ID cards, passwords, and token-based authentication, may make people feel uneasy since they must remember their passcodes [10]. Additionally, they are prone to forgery due to theft, squinting, and loss. In contrast, biometrics enable foolproof security by identifying a person based on physiological or behavioural features. In addition, as one of the biometrics modalities, ECG is becoming increasingly suitable for various applications due to the development of real-time measurement equipment and the growth of research into safeguarding authentication information in electronic devices [11,12].

Furthermore, ECG signals are distinct from one another. They can only be collected by direct physical contact that is impenetrable from the outside and contains a liveness indicator at the detection site [13]. As a result, ECG-based biometrics have the potential to completely replace other traditional biometrics, such as vein, gait, face, fingerprint, and iris in the near future of biometric recognition [14-27].

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 determining the best machine learning classifier performance for biometric recognition in real-life scenarios. The best classifier performance will then select and undergo parameter tunning to achieve the highest possible biometric recognition performance in real-life scenarios. For that reason, the rest of this paper is ordered as follows. Section 2 of this article discusses the technique used to capture ECG in a real scenario while wearing wearable smart textile shirts and the processes required to evaluate and extract the raw ECG. This study's performance evaluation and conclusions for biometric authentication are then addressed in Section 3. Finally, Section 4 closes this study with various recommendations and directions for potential future initiatives.

2. Proposed Biometric Frameworks

Figure 1 is a block diagram illustrating the approach framework selected and reconstructed from researches in Toulni *et al.,* [28], Althabhawee *et al.,* [29], Ashwini and Nagaraj [30], Uwaechia and Ramli [31], and Ugi *et al.,* [32]. The framework for identity authentication consists of four phases: data gathering, baseline correction and denoising in pre-processing, fiducials detection in feature extraction, and parameter evaluation in the classification block stage.

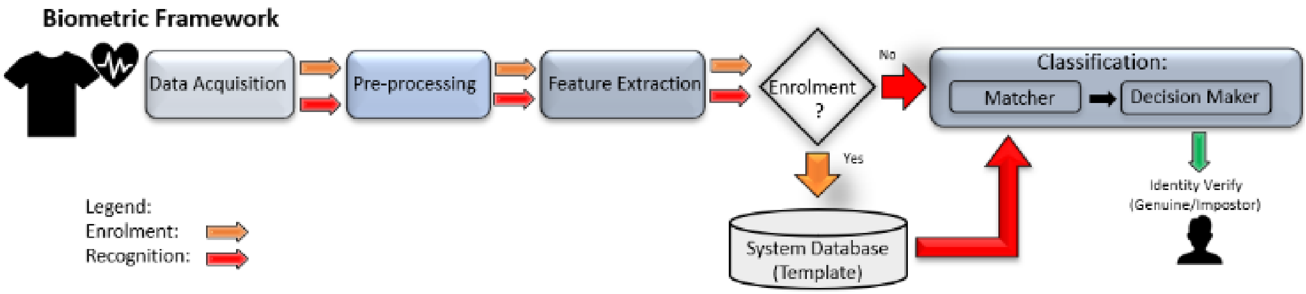


Fig. 1. Biometric Operation framework

There are two operating modes for the biometric system: recognition and enrolment [33]. After feature extraction is completed in the recognition mode, the data will go right on to the classification stage. The input data from enrolment mode will be kept as a template in the system's database after the feature extraction stage so that it may be used later in recognition mode. In order to forecast the verification decision, the matcher will compare the ECG data to the template data in the database. This paper will go deeper into the suggested structure in the next sub-section.

2.1 Data Acquisition

A total of 22 healthy participants (18 male and four female) took part in this study under the International Islamic University Malaysia Research Ethics Committee identification number IREC 2021-058. (IREC). All participants were informed and told of any potential risks before providing their consent. They had to put on the smart textile shirt for at least 15 minutes. Figure 2(a) displays a HeartIn Fit smart textile shirt worn by one of the subjects in this study, and Figure 2(b) demonstrates a Hexoskin Proshirt smart textile shirt worn by another subject.

(a) (b)

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

The Hexoskin Proshirt smart textile shirt recorded the ECG signal at 256 Hz from three textile electrodes sewn into the shirt, two on the chest and one on the right side of the rib cages. The average signal over the last 16 beats was written to a data file at a rate of 1 Hz. During data acquisition, the Hexoskin smart textile sends real-time data through a safe Bluetooth wireless connection and can see in real-time. Furthermore, the raw data were stored locally on the Hexoskin device before being sent to a cloud server. This made it possible to access and analyse the data later.

Meanwhile, the HeartIn Fit smart textile shirt record the ECG signal at 512 Hz from two textile electrodes installed into the shirt. The two textile electrodes were on the right and left sides of the body in the HeartIn wearable smart textile at the chest level. During data collection, the HeartIn smart textile also sent real-time data to the smartphone through secure Bluetooth wireless communication so that the data could be seen in real-time. Besides, HeartIn smart textile device does not store any data in the machine. All the information is saved locally in the smartphone's wearable app. Furthermore, Only the ten most recent data acquisitions will be saved in the mobile application for the unsubscribe version of the dedicated application in the HeartIn wearable smart textile device. But the ten most recent pieces of data that this smart textile has collected can always be sent by email and saved elsewhere so that the data can be accessed and analysed in the pre-processing stage as described in the following sub-section.

2.2 Pre-processing

Derive from the pre-processing framework of Figure 3. 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 the same sampling ground with data from Hexoskin wearer. This data latter was inverted through the isoelectric line and rescaled to match the scale of entire datasets from both brands.

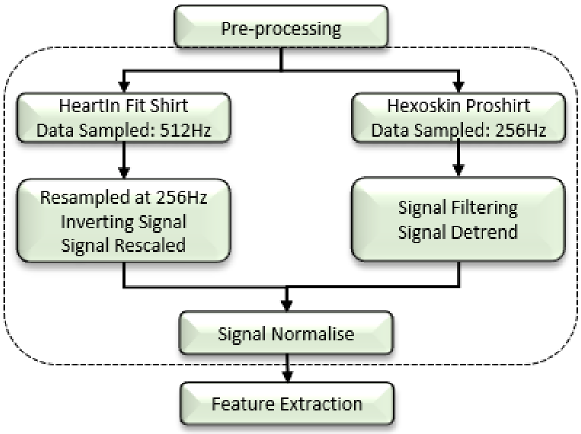


Fig. 3. Pre-processing framework

Meanwhile, the raw ECG data from Hexoskin smart textile shirt was originally sampled at 256Hz. It is subjected to some data pre-processing by adding a lowpass Butterworth Filter with a cut-off frequency of 30Hz to remove unwanted noise, which then helps to reduce high-frequency noise and interference noise from power lines. In addition to eliminating baseline drift during the detrending operation, the filter returned the ECG data to the isoelectric line through a direct Fast Fourier Transform (FFT). Then, the inverse FFT restores the ECG signal to its original condition in the time domain, enabling a more accurate examination of the data during the feature extraction step.

2.3 Feature Extraction

After the first two steps, i.e., the acquisition and pre-processing phases, have been completed, feature extraction commences. These steps are designed to improve the signal’s representation and decision-making by minimising residual noise and within-subject variability. The PQRST morphology of the ECG has been utilised widely because it permits the detection of wave variances in each individual’s response from the overall ECG signal by eliminating particular transitional intervals. The QRS complex signal is the most often extracted biometric characteristic in ECG [34-36]. Similarly, this study depends on the QRS complex feature for classification purposes.

2.4 Classification

Finally, the classification method in this study was constructed with an 80/20 split between training and testing datasets for each of the 22 individuals. Subsequently, in this stage, various classifiers and their variants are compared regarding their ability to conduct exhaustive classification based on specified attributes. A 10-fold cross-validation method was utilised for training and assessing 29 Machine Learning classifiers. In 10-fold cross-validation, the entire dataset is divided into ten subsets, each serving as the test set. The training set is comprised of the remaining nine subsets. The technique is done ten times, and the findings are averaged over all repeats, as demonstrated, and elaborated on in the next section.

3. 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 who wore smart textile shirts while performing typical everyday activities.

Since good biometric performance mainly comes from the best combination of filtering processes to overcome the noise challenges in the raw data, admittedly, that noise on the data due to motion artefacts is the biggest challenge in wearable biometric data. Several alternatives in handling this interesting obstacle by proper filtering process and segmentation. On the other hand, the raw ECG data also had to be ensured are not over-filtered as this will course in losing meaningful data point locations for biometric. Furthermore, the interesting part was finding the balance between acceptable noise that can be tolerated and smoothing the ECG signal to its original form. Therefore, to eliminate undesirable noise within the acceptance range, the raw ECG signal Figure 4(a) undergoes some data pre-processing by adding a lowpass Butterworth filter. Consequently, Figure 4(b) next demonstrates how filtering helps minimise high-frequency noise as well as interference noise from power lines. In addition, the filter also minimises baseline drift throughout the detrending procedure, ensuring that the ECG signal returns to the isoelectric line, as seen in Figure 4(c), prior to segmentation.

A total of 2076 data sets for training and 501 data sets for testing was generated in validating and testing all the classifier in the classification stages. Figure 5 demonstrates segmentation findings by displaying the QRS of the ECG signal for several 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 and that these repeating patterns were effectively captured from a textile electrode on a smart textile shirt. As a result of these recurring data point patterns, this study uses this segmented QRS points pattern as part of the classification data.

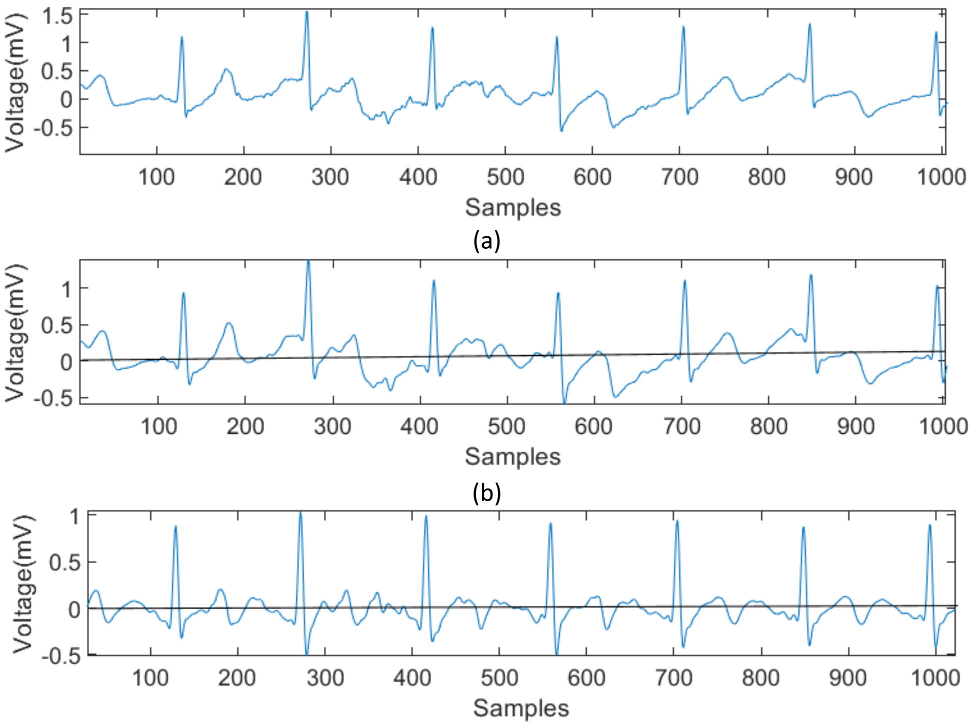
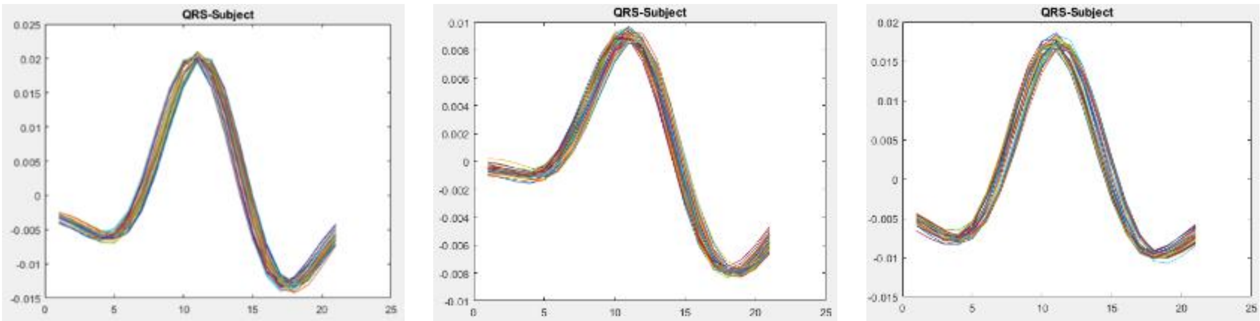


Fig. 4. ECG Signal Through Pre-processing Process (a) Raw ECG, (b) Filtered ECG, (c) Detrend ECG



(a) (b) (c)

Fig. 5. Segmented ECG from different subjects (a) subject 1, (b) subject 8, (c) subject 22

In addition, various standard statistical performance criteria, such as training and validation accuracy, as well as test accuracy, were developed to assess the classifier's efficacy. Admittedly, a good performance classifier characteristic should consist of clear boundaries between the different classes of subjects and can accurately recognise its subjects across classes. Similarly, among other criteria, as a good classifier, it should be robust and reliable to handle changes in the data and still produce consistent results in predictions of unseen data. For this reason, the classification learner app toolbox available in the MATLAB 2021a program was utilised to conduct classifier performance tests. All 29 machine learning algorithms of the Classification Learner App were selected, as these machine learning algorithms are known as reliable tools for pattern analysis [37]. Furthermore, the study model's training and testing data were generated using 10-fold cross-validation with an 80/20 split between training and testing data. Subsequently, the classification findings of the 29 machine-learning algorithms are displayed in Table 1.

Table 1
The performance of 29 classifiers

Classifier	Classifier Type	Validation Accuracy (%)	Test Accuracy (%)
Decision Tree	Fine Tree	85.6	81.8
	Medium Tree	57.7	55.3
	Coarse Tree	19.7	20.0
Discriminant Analysis	Linear Discriminant	95.3	95.4
	Quadratic Discriminant	failed	failed
Naïve Bayes	Gaussian	80.3	76.6
	Kernel	82.3	79.8
SVM	Linear	94.3	92.8
	Quadratic	97.1	96.8
	Cubic	96.8	94.2
	Fine Gaussian	87.3	75.4
	Medium Gaussian	94.7	92.8
	Coarse Gaussian	86.3	84.4
KNN	Fine	95.1	89.8
	Medium	91.7	85.4
	Coarse	70.8	64.9
	Cosine	86.7	83.4
	Cubic	91.7	85.8
	Weighted	93.2	87.4
Ensemble	Boosted Trees	78	77.4
	Bagged Trees	93	87.6
	Subspace Discriminant	94.7	95.4
	Subspace KNN	94.5	88.2
	RUSBoosted Trees	77.6	77.4
Neural Network	Narrow	97.2	95.8
	Medium	96.4	93.6
	Wide	96.8	95.4
	Bilayered	95.6	94.0
	Trilayered	95.1	92.0

Indeed, it is clear from the information shown in Table 1 that the SVM and Neural Network dominate the top performance of the 29 classifiers during training. A Narrow Neural Network led the accuracy performance, followed closely by Quadratic SVM. However quadratic support vector machine algorithm contributed to achieving the most significant classification accuracy of 96.80% during the testing process. Furthermore, the results also demonstrated that most classifiers could perform well in classifying a biometrics accuracy. Only several classifiers like Medium Tree, Coarse Tree, Quadratic Discriminant, coarse KNN, Boosted Trees, and RUSBoosted Trees are not very suitable as biometric classifiers in this study data, as they performed below 80%. Besides, the low-performance classifier can be understandable as each of these algorithms has its own strengths and weaknesses. Indeed, the choice of classifier algorithm depends on the data and the problem being solved.

Since Support Vector Machines (SVM) are a powerful classification technique that can be used when data is not linearly separable, SVM is also good for large datasets as they have good generalisation properties. Meanwhile, the K-Nearest Neighbors (KNN) is a non-parametric classification technique that can be used when the data is not linearly separable. KNN is good for large datasets, as it can adapt to new data points and classify them correctly. Subsequently, Decision Trees are another popular classification technique that can be used for both linear and non-linear data. Furthermore, Decision Trees are good for large datasets, as they can handle many features and missing data.

On the other hand, quadratic discriminant analysis (QDA) is a classification technique used when there is more than one class, and the data is normally distributed. QDA is a good choice for small datasets, but it can be prone to overfitting when the dataset is large. However, it can perform well if the data is linearly separable. Therefore, even though, Changing the parameter of the covariance structure for quadratic discriminant analysis (QDA) from a full structure to a diagonal structure overcame the obstacles posed by the initial implementation of QDA to the research data, which yielded unsatisfactory results in the early validation and testing phases. Modification to the classifier parameter using a diagonal setup resulted in the QDA achieving a validation accuracy of 80.1% and a testing accuracy of 76.66%. Figure 6 demonstrates that most of the top-performing classifiers previously remain superior despite this improvement.

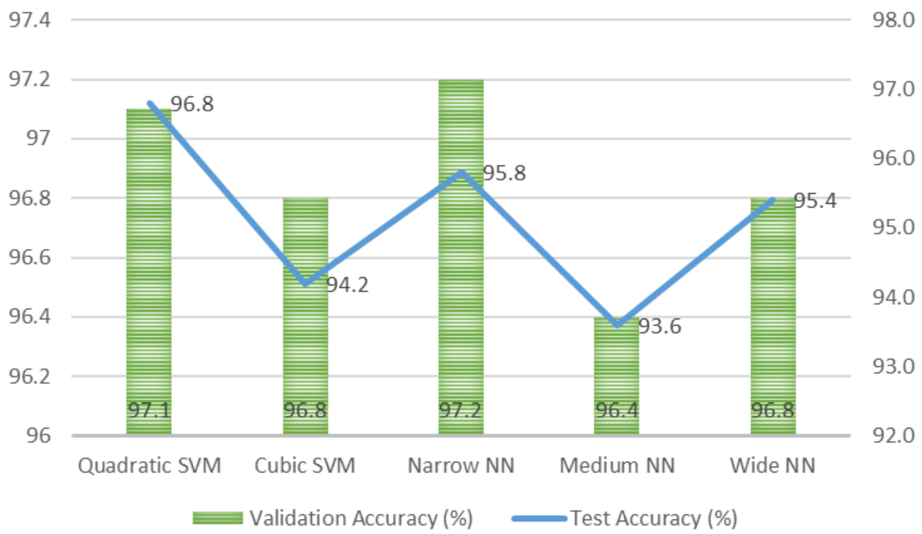


Fig. 6. Best Top Five Classifier Performance

Out of all 29 classifiers, Based on Figure 6, the Five topmost performed classifier was Quadratic SVM, Cubic SVM, Narrow Neural Network, Medium Neural Network and Wide Neural Network. At the same time, Narrow NN, followed by Quadratic SVM, outperforms the rest in the training performance of those classifiers. However, Quadratic SVM showed more accuracy during testing than the rest of the classifiers. Furthermore, due to the stability and outstanding performance of the Quadratic SVM with the in-house datasets, this classifier was further improvised and fine-tuned to produce better performance, as demonstrated in the following results of Figure 7.

Figure 7 shows the performance of selected QSVM across box constraints level used in training, validation, and testing accuracy for the in-house data sets. What stands out in this figure is the growth of validation accuracy when the level of box constraint increases up until the saturation accuracy values of 97.4% at level nine. Unfortunately, the training and validation accuracy trend decreased after box constraint level 10. However, testing performance across box constraint levels demonstrates a clear trend of fluctuations in accuracy parameters. Meanwhile, the most interesting aspect of this graph is that its peak performance value also stands out from box constraint level 10 with 97.4%. Therefore, the box constraint level 10 was set as parameter tuning in the model to access other's performance metrics through the confusion matrix, as illustrated in Figure 8(a) and (b).

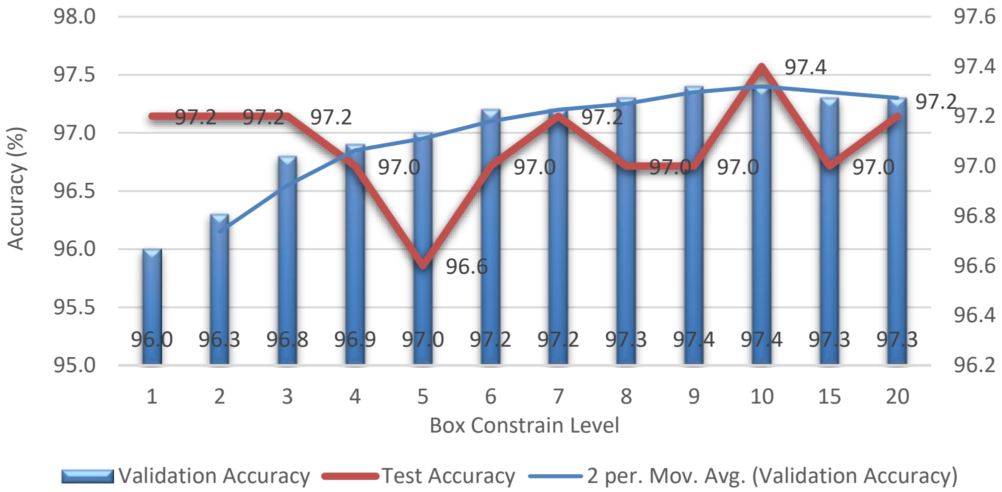
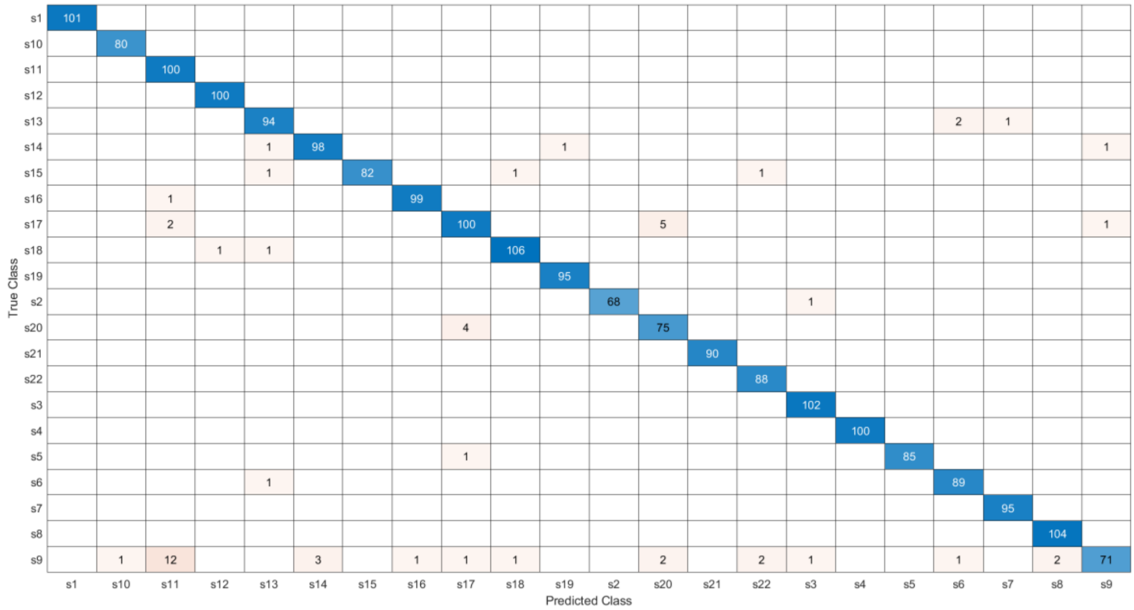


Fig. 7. Performance of QSVM across Box Constrain Level

Figure 8(a) displays the performance of the confusion matrix for 22 persons using the Quadratic Support Vector Machine, which was among the best-performing classifiers for validation and Testing datasets. Twenty-seven datasets from subject number 9 are misclassified as belonging to other individuals, which is a somewhat disappointing result for the training and validation data utilised for this subject. However, this miss-hits scenario is significantly small compared to the datasets used for training, consisting of 2076 datasets from all 22 study participants. At the same time, every other class of subject attained acceptable levels of accuracy. Besides, their also many subjects with a remarkable performance of 100% accuracy.

Meanwhile, the performance assessment for the same classifier for the test data sets is shown in Figure 8(b). According to this analysis, the proportion of subjects who were misclassified in relation to the actual classes of subjects was 2.6% of the entire research population. The 13 miss-hit data sets only included information on subjects' numbers 2, 4, 8, 9, 12, and 17. On the other hand, Other subject classes performed quite well. Subsequently, next Figure 9 shows an additional assessment of the performance parameter of the research model.

What is striking about Figure 9 is that the graph highlights four performance parameters across different box constraint levels. The parameter is sensitivity (TPR) which is the proportion of correctly classified observation over true class. Meanwhile, the precision (PPV) is the proportion of correctly classified observations over the predicted class in the confusion matrix generated. In addition, the rejection of valid subject data or incorrectly classified observation over true class is also known as the false rejection rate (FRR). Moreover, it is widely agreed that an excellent biometric verification classification model should have a high sensitivity value and the lowest FRR percentages.


(a)

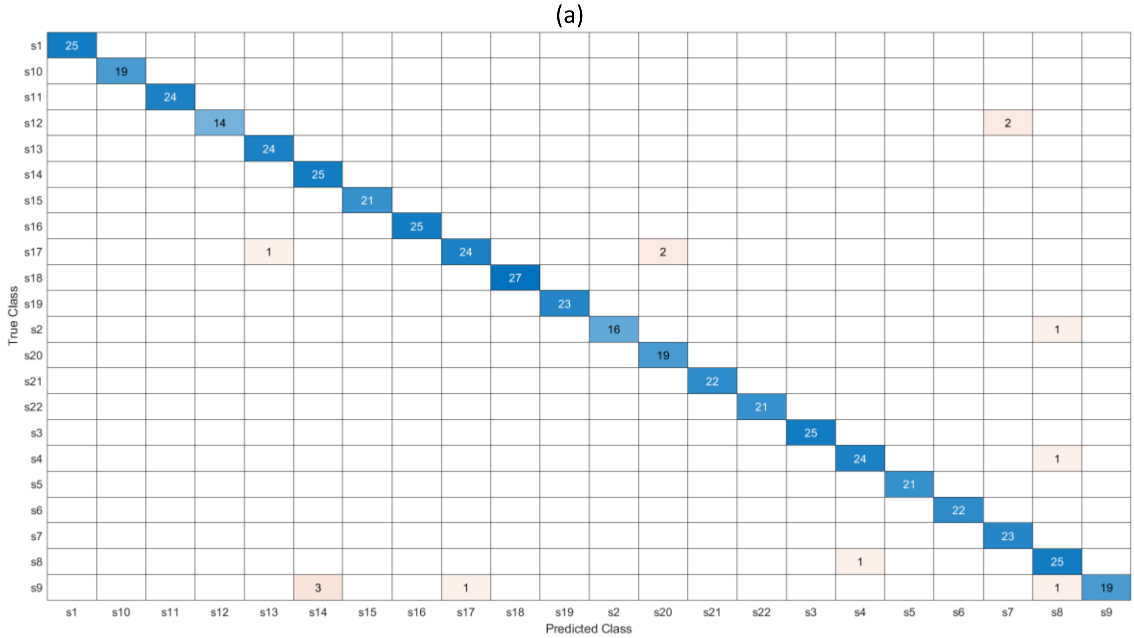

(b)

Fig. 8. (a) Confusion Matrix Performance Evaluation for Validation, (b) Confusion Matrix Performance for Testing using Quadratic SVM

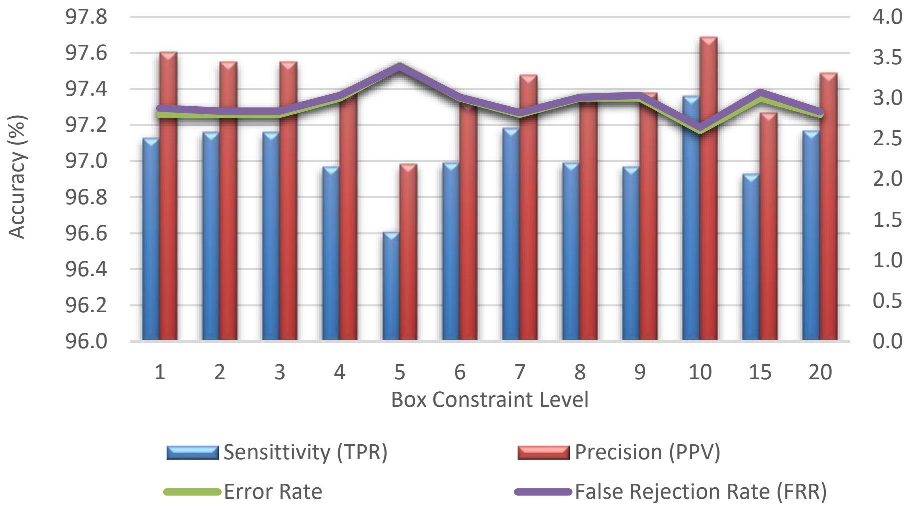


Fig. 9. Performance Across Different Box Constraint

Furthermore, from the chart, it can be seen that box constraint level 10 demonstrated the dominant values of PPV at 97.7% and the outstanding value of TPR at 97.4%. Subsequently, this high value of sensitivity resulting the lowest error rate and FRR of 2.6%. Additionally, this present study has laid the groundwork for strategies analysis in finding the best suit classifier and parameter tuning for the selected classifier to forecast the ECG biometric in real-life scenarios using smart garments. On the other hand, the performance of the suggested technique is summarised in Table 2 compared to existing state-of-the-art research.

Table 2
Summary of state-of-the-art performance in wearable and portable ECG biometric recognition

Paper	Device	Subjects	Classifier	Performance
Ye *et al.,* [38]	Commercial (Garment)	5	SVM	Acc = 70 – 100%
Alonso *et al.,* [39]	Prototype	25	SVM	Acc = 92%
Martinho *et al.,* [40]	Prototype	53	KNN	EER = 13%
Pourbabaee *et al.,* [41]	Commercial (Garment)	33	CNN	Acc = 95.95%
Chen *et al.,* [42]	Prototype	68	Random Forest	Acc = 98.14%
Lehmann and Buschek [34]	Commercial (Chest Belt)	20	Random Forest	EER = 9.15% AUC = 0.964
Proposed Method	Commercial (Garment)	22	QSVM	Acc = 97.4%

*Acc = accuracy, EER = equal error rate, AUC = area under the curve

Nevertheless, Table 2 shows the current state of the art in wearable ECG-based biometric recognition systems and compares them to the proposed approach. It can be observed that the suggested method's recognition performance is equivalent to, if not better than, that of several current methods. At the same time, only Lehmann and Buschek [34], Ye *et al.,* [38], Pourbabaee *et al.,* [41] and this study are performed in real-life scenarios without the restriction of a controlled clinical or laboratory environment. Usually, in real-life scenarios, the participant is enjoying the freedom of everyday routine activity of their own, which this study tries to highlight. Furthermore, only studies in Ye *et al.,* [38], Pourbabaee *et al.,* [41] and the proposed work consider textile-type biometric recognition. One prominent advantage of a shirt-type biometric is that the wearer does not need all the technical skills to place the ECG electrode in the body to acquire the ECG. The participant is free to wear it normally to perform the acquisition, and almost all the acquisitions perform seamlessly in the wearer's comfort. Besides, to the best of the author's knowledge, only this work considers acquiring ECG data from two different types of smart garments for biometric recognition. Finally, the next section will conclude the findings and suggest the future direction of this study.

4. Conclusion and Future Work

Most of the studies on ECG biometrics have been performed in a controlled environment, with high-quality medical sensors, to ensure reliable results. The findings may not be relevant to all real-life scenarios. For this reason, wearable ECG biometrics lacked a full picture of how real-life scenarios can influence ECG biometric performance. Therefore, the existing literature mandated that empirical fieldwork be conducted. In addition, our study attempted to meet this demand by providing in-depth studies of ECG biometrics utilising a non-medical textile sensor embedded in different smart garments brands that consist of several configurations of manufacturer settings. The study involved 22 subjects in normal real-life activities.

The primary contribution of this work is to determine which ECG morphology point has statistically significant values and patterns for biometric recognition purposes in wearable smart textile shirts and then to focus on this QRS morphology point for feature extraction and classification. Furthermore, during the classification phase, the dataset was compared to 29 machine learning algorithms to see which classifier would work best with the segmented ECG data for biometric verification. Moreover, the study results are quite positive and justify the use of ECG from smart textile shirts as a biometric authentication technique.

Examining all classifiers indicates that the Quadratic SVM has the greatest accuracy for ECG biometrics at 96.8 %, followed by the Narrow Neural Network at 95.8 % and the Wide Neural Network at 95.4 % for biometric recognition utilising a smart shirt ECG. The best classifier performance was then selected and went through the parameter tunning that, in the end, demonstrated the best parameter was from box constraint level 10, producing an accuracy of 97.4% with an error rate of 2.6%, followed by a sensitivity of 97.4% with a precision of 97.7% and a false rejection rate of 2.6%. Thus, these positive results indicated reliable biometric verification using ECG is possible with smart textile shirts. This research also demonstrates that biometric recognition can operate successfully on both brands despite their different ECG smart shirt materials. The study raises several interesting questions for further investigation, including whether machine learning or deep learning can enhance the classifier’s performance in real-life biometric recognition for the wearable ECG smart shirt in longer durations.

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