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# Improving Performance Classification in Wireless Body Area Sensor Networks Based on Machine Learning Techniques

Sabreen Waheed Kadhum*, Mohammed Ali Tawfeeq

Computer Engineering Department, College of Engineering, Mustansiriyah University, Baghdad, Iraq

*Email: sabreenwhd@uomustansiriyah.edu.iq

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**Abstract**

Wireless Body Area Sensor Networks (WBASNs) have garnered significant attention due to the implementation of self-automaton and modern technologies. Within the healthcare WBASN, certain sensed data hold greater significance than others in light of their critical aspect. Such vital data must be given within a specified time frame. Data loss and delay could not be tolerated in such types of systems. Intelligent algorithms are distinguished by their superior ability to interact with various data systems. Machine learning methods can analyze the gathered data and uncover previously unknown patterns and information. These approaches can also diagnose and notify critical conditions in patients under monitoring. This study implements two supervised machine learning classification techniques, Learning Vector Quantization (LVQ) and Support Vector Machine (SVM) classifiers, to achieve better search performance and high classification accuracy in a heterogeneous WBASN. These classification techniques are responsible for categorizing each incoming packet into normal, critical, or very critical, depending on the patient's condition, so that any problem affecting him can be addressed promptly. Comparative analyses reveal that LVQ outperforms SVM in terms of accuracy at 91.45% and 80%, respectively.

**Keywords:** Data analytics, Learning Vector Quantization, Machine Learning, Support Vector Machine, Wireless Body Area Network

## 1. Introduction

Nowadays, Smart healthcare is a highly dynamic and demanding field. Wireless Body Area Sensor Networks (WBASNs) play an essential role in healthcare monitoring since they utilize wireless sensors to monitor physiological data and anticipate the beginning of illnesses. [1],[2]. The most common applications of machine learning (ML) techniques play an important role in various fields, such as healthcare, childcare, and detecting emergencies [3]. Over the last decade, a large number of studies have utilized machine learning (ML) algorithms, as they are one of the main methodologies that clinical researchers are interested in. These techniques implement various markers to detect and categorize physiological information. Each of these researches has involved a different technique of ML and a special set of medical features to identify illnesses and conditions. Researchers have also identified and classified diseases using deep learning as a supervised learning technique in ML. Classification involves gathering provided physiological information and creating a system that categorizes vital data into several distinct cases. [4]. WBASN is a cutting-edge medical system that helps monitor patients' vital signs. The aggregated physiological data is transmitted to the healthcare center for further processing [5]. Constructing an effective system for identifying huge vital data using ML on WBASNs is essential. This profoundly impacts the comprehensive examination of evaluating the generated physiological data of patients. through the implementation of WBASNs[6].

Data categorization is essential in mitigating network delay but also results in higher consumption power for a sensor when delivering many packets across the network [7]. The primary goal of this project is to develop a mechanism for segregating and classifying data in WBASNs to improve the overall performance of the network and to ensure a rapid response to critical and very critical situations. This will make the network more efficient, dependable, and able to support various healthcare applications. Previous research has extensively employed supervised learning techniques to analyze medical signals. Optimizing the balance between classification accuracy and computational complexity is crucial in studying vital signs. To accomplish quick classification of medical information with a high level of accuracy in predicting outcomes, hence the immediate applicability of decision-making processes is enabled. Learning vector quantization (LVQ) algorithms are considered interpretable machine learning methods. LVQ, introduced by Kohonen in 1990, has emerged as a significant group of supervised learning algorithms. During training, the algorithms establish prototypes that accurately represent the classes in the provided data. Novel samples are predicted by analyzing the receptive fields of the prototypes. Put, a novel sample is categorized by calculating the distance between the sample and all prototypes and then assigning it the label of the closest prototype[8].

This study utilizes medical records from 10 physiological sensors capable of encompassing a wide range of human body analysis techniques, such as electroencephalography (EEG), electrocardiogram (ECG), oxygen saturation (SO2), respiration (BRTH), blood pressure (BP), glaucous (Gloc), temperature (Temp), pulse rate (PR), electrooculography (EOG), and heart failure (HF). Reducing the number of resources needed to describe enormous data quantities is one aspect of feature extraction. One of the significant challenges for successful machine learning applications was selecting the optimal feature from specific data types [9], [10]. In this work, four features are involved (gender, age, vital data, and sensor ID). The proposed algorithm classifies human cases into three categories based on their health status: Very Critical Data (VCD), Critical Data (CD), and Normal Data (ND). These cases are classified based on the sensor data using the LVQ classifier. LVQ learns from labeled instances to categorize new, unseen cases.

The following is the structure of the research: Section 2 demonstrates the previous studies, Section 3 discusses the proposed methodology, Section 4 demonstrates the performance metrics, and Section 5 reports and analyzes the simulation findings, along with a comparison among two different ML classification algorithms, wherein the conclusions are presented in Section 6.

## 2. Literature Review

A substantial study on ML and its applications in healthcare has been conducted in the past several years. Here are some of the most cutting-edge methods for quickly and precisely diagnosing medical conditions by evaluating clinical and paraclinical data:

Jung [11] presented a novel hybrid awareness model for tailored aged healthcare service that organizes health state as either positive or negative inside a smart home setting. The model additionally suggested a hybrid inspection service system to ensure the safety of older individuals by categorizing their condition as either safe or emergency. The middleware service evaluates the health risk by considering the activities and whereabouts of older patients. Primary and contextual data are acquired using wearable and motion sensors, which are subsequently evaluated using various machine-learning algorithms to help healthcare practitioners make clinical decisions using CDSS (Clinical Decision Support System) sensors. Additionally, situation-awareness technology can help proactively identify aberrant health conditions to prevent medical emergencies. In an interesting article by Chen et al.[12] acknowledged that physiological indicators like nutrition and activity are essential for diabetes prevention and post-hospitalization management. Thus, they proposed a "5G-Smart Diabetes" system with individualized data analytics to improve diabetes care. The system was evaluated using SVM, artificial neural networks (ANN), and decision trees (DT). The system's social networking service (SNS) improves diabetic patient care. The experimental results reveal that the suggested approach can give patients individualized diagnosis and therapy. Roy et al.[13] proposed a methodology to assist in identifying vital signals in IoT and WBASN-based ECG monitoring equipment using machine learning. The identified signals are then transmitted while operating at low power levels. Bilandi et al.[14] suggested a new coronavirus-body area networks (CoV-BANs) model that utilizes Internet of Things (IoT) technology. This model would serve as a real-time health monitoring system that would use many wearable biosensors to assess the patient's health state and detect the early stages of coronavirus infection. Optimal diagnostic performance is achieved by putting the model through its paces using five machine learning-based classification methods: logistic regression, support vector machine, random forest, Naive Bayes, and multi-layer perceptron classifiers. According to the testing findings, the suggested model employing the random forest classifier achieves an average accuracy of 88.6%, higher than models utilizing the other classifiers. Lopez-Martin et al.[15] presented unique architectures and loss functions for supervised contrastive learning by embedding labels and features in the same space and comparing their distances. This approach enables contrastive learning-based supervised classification. Each embedded label was a class prototype in the embedding space, with sample features flocking to it. The suggested method dramatically decreases pair-wise comparisons, boosting model performance. The presented models perform well in all experiments, have low execution times, and are suitable for noisy and imbalanced multi-class classification tasks like intrusion detection. Nilashi et al. [16] suggested a novel approach. Their work employed a bagged tree technique in conjunction with the Learning Vector Quantization (LVQ) technique to enhance the accuracy of EEG classification while simultaneously improving the time complexity. Compared to other classifiers, the combination of the bagged tree with the LVQ technique yielded optimal results, showcasing the efficacy of integrating ensemble learning and clustering schemes in analyzing EEG vital signals. Yıldırım et al. [17] introduced an Internet of Medical Things (IoMT) architecture that includes a novel scenario for predicting chronic diseases (diabetes). By utilizing cloud computing and machine learning algorithms, including support vector machine (SVM), random forest (RF), and artificial neural network (ANN), the diabetes prediction process makes use of fog computing for fuzzy logic decision-making. Regarding diabetes prediction in cloud computing, SVM achieved an accuracy performance of 89.5%, RF of 88.4%, and ANN of 87.2%; in fog computing, fuzzy logic only reached a 64% performance accuracy. Bhattarai et al.[3]

offered three separate methods: support vector machine (SVM), kernel neural network (KNN), and logistic regression to investigate human activity recognition, including walking, sitting, standing, and lying down. What was the level of classification accuracy across three distinct ML classifiers? The performance of SVM classification was superior to that of Logistic Regression and KNN about classification.

Kaleema et al.[1] presented a method for identifying interference in a signal between bio nodes in a WBASN network using a support vector machine (SVM) classifier. They achieved a classification rate of 96.66%, a packet delivery ratio (PDR) of 97.2%, and a delay of 9.65 ms.

### 3. Materials and Methods

The measurements of the physiological sensors need to be classified according to the patient's condition into three cases: VCD, CD, and ND. This requires the use of an efficient and accurate classifier to determine the nature of the vital information that needs to be delivered within a particular time-bound from these sensors for timely transmission and real-time responses in anticipation of any health emergency that the patient may be exposed to, which requires remediation by giving priority to very critical cases.

Analyzing vital signs requires careful consideration of the trade-off between computational complexity and classification accuracy. The proposed model aims to build an accurate and high-precision classifier that quickly classifies vital data while maintaining high prediction accuracy. This will allow us to make decisions in real-time. LVQ algorithms can be practically implemented in medical emergencies to meet these requirements.

The proposed WBASN model comprises ten physiological sensors. These sensors detect vital information from the human body and transmit it to a personal device, i.e., sink node (CC), that collects and classifies the aggregated medical data into one of three cases: average data (ND), critical data (CD), and very critical data (VCD). VCD is forwarded to the emergency center to dispatch an ambulance, CD is sent to a doctor, and ND is transmitted to a medical center. The modules for the system are shown in Fig.1.

Initially, features are extracted from the vital data sensed by the WBASN network's physiological sensors. Then, some of the extracted vital data is used to train and test the LVQ neural network, which represents one of the sophisticated regression and classification networks used in various domains. Fig. 2 illustrates the detailed steps of the proposed technique.

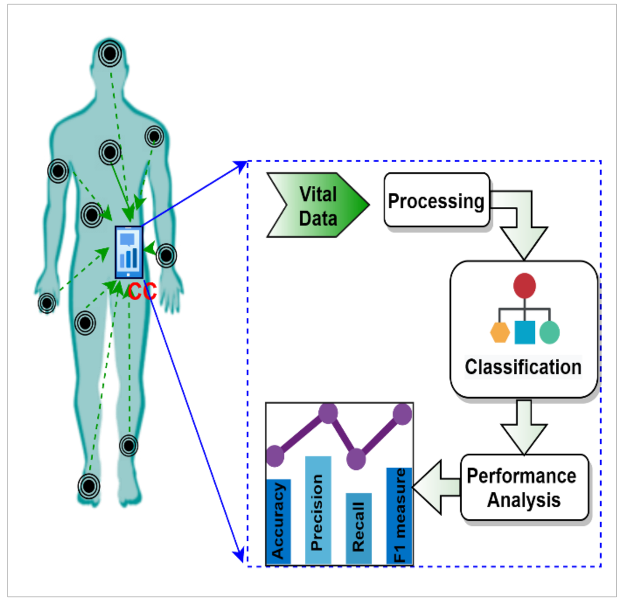



**Figure 1.** Module for The System

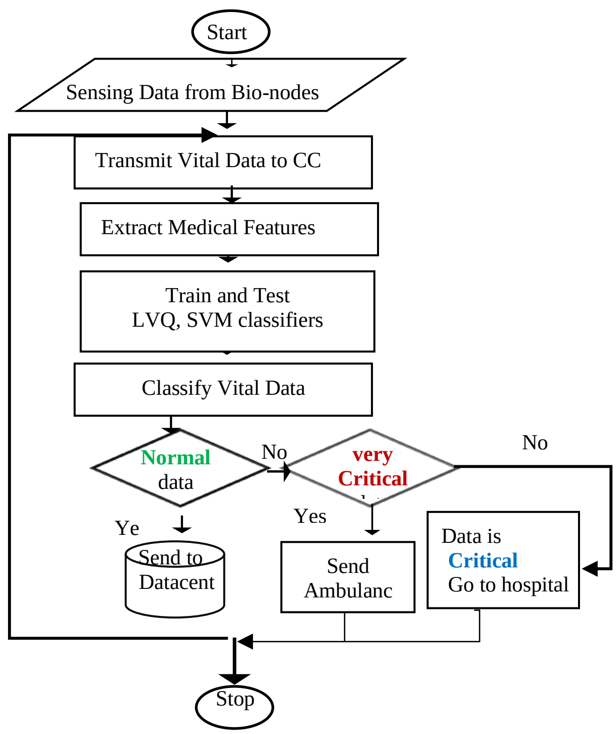



**Figure 2.** Flowchart of the proposed System

### 2.1. Data Selection and Loading

Physiological sensors gather individual data and significant disease symptoms and forward them to a personal device for further processing. A dataset of ten bio-sensors (EEG, ECG, SO2, BRTH, BP, Gloc, Temp, PR, EOG, and HF) was used to train and assess the suggested model's efficiency. One thousand records were obtained from the Kaggle site[18]. These data were classified into three states (VCD, CD, ND) utilizing the physiological nodes' thresholds, as shown in Table 1.

**Table 1.** Thresholds of the Employed Physiological Nodes.[19]

| No | Abbreviation | Normal | Critical | Very Critical |
|---|---|---|---|---|
| 1 | EEG | Upper than 8Hz | 7-8 Hz | Lower than 7 H z |
| 2 | ECG | 60-100 bpm | Less than 60 bpm | greater than 100 bpm |
| 3 | SO2 | 94-99% | 60-80% | Below 60% |
| 4 | BRTH | 12-20 breaths/minute | Less than 15 or greater than 25 breaths/minute | Under 5 breaths/minute |
| 5 | BP | Less than 120/80 mmg | 120-139 nnHg | 140 mmHg and greater |
| 6 | Gloc | Less than 100 mg/dl | Between the range of 101-126 mg/dl | Greater than 126 mg/dl |
| 7 | Temp | 37 C | 38 C | 39 C |
| 8 | PR | 40-100 bpm | 101-109 bpm | 130 BPM or more |
| 9 | EOG | 1.80 or greater | 1.65 to 1.80 | Lower than 1.65 |
| 10 | HF | (BNP) below 100 pg/mL | (BNP) range from 101-400 pg/mL | (BNP) greater than 400pg/mL |

### 2.2. Partitioning Dataset into Training and Testing Data (Preprocessing)

In data splitting, the observed data is divided into two parts for re-examination. The larger data, which accounts for 80% of the total, is utilized for training, while 20% of the remaining amount is allocated for testing. Table 2 includes samples of data sets used for training and testing.

**Table 2.** Samples of The Used Medical Dataset

| Gender | Age | Vital data | Sensor ID | Target |
|---|---|---|---|---|
| 0 | 58 | 169 | HR | Very Critical |
| 1 | 30 | 151 | HR | Critical |
| 1 | 45 | 77 | BP | Normal |
| 0 | 44 | 36.6388 | Temp | Normal |
| 0 | 22 | 39 | Temp | Critical |
| 0 | 31 | 55 | ECG | Critical |
| 1 | 23 | 115 | ECG | Very Critical |
| 1 | 39 | 125 | ECG | Very Critical |
| 1 | 48 | 4.676844 | EEG | Very Critical |
| 0 | 37 | 90 | Gloc | Normal |
| 0 | 56 | 95.44174 | SO2 | Normal |
| 0 | 41 | 120 | BP | Critical |
| 1 | 44 | 62.44174 | SO2 | Very Critical |
| 0 | 23 | 81 | BP | Normal |

### 2.3 Classification

Data has been classified using two machine learning algorithms, LVQ and SVM. These algorithms are utilized to train and test the patient's dataset. Additionally, the Kaggle library is used to implement classification algorithms. In this context, the training data is used to train the models, while the test data is employed to assess the performance of the models.

The LVQ classifier implemented in the present study comprises four inputs representing the patient's (age, gender, vital signs, and sensor ID) and an output layer of three neurons (one neuron for each output case: VCD, CD, and ND). The LVQ net's training process aims to locate the output unit that closely matches the input vector. When the input pattern x and the weight $w_j$ of neuron j are in the same category, the training algorithm adjusts the weights towards the new input vector to achieve this objective. Conversely, if x and $w_j$ belong to different categories, the weights are adjusted to move away from this input vector. as shown in equations 1 and 2, respectively [20]:

$$wJ(new) = wJ(old) + \alpha\,[x - wJ(old)] \quad (1)$$
$$wJ(new) = wJ(old) - \alpha\,[x - wJ(old)] \quad (2)$$

Where α represents the learning rate.

On the other hand, when it comes to supervised learning algorithms, one of the most popular choices is a Support Vector Machine or SVM. Its applications include classification and regression analysis. The SVM algorithm aims to create an ideal linear or decision boundary that may successfully divide the one-dimensional space into discrete classes, allowing for the correct classification of fresh data points in the future. The hyperplane is the decision boundary that ideally separates the data points. SVM detects the most influential points/vectors essential in constructing the hyperplane. The technique is called a support vector machine because it focuses on extreme instances known as support vectors.

## 3. Performance Metrics

In general, methods aiming to classify data use the following parameters: true positive (TP), false positive (FP), true negative (TN), and false negative (FN).

In this work, these parameters are used to calculate the following metrics [21]:

- **Precision:** The number of positive classes that are accurately anticipated out of all the anticipated positive classes. The calculation of precision is as follows:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (3)$$

- **Recall:** All the favorable classes are precisely anticipated. It should be maximized to the greatest extent possible. The calculation of recall is as follows:

$$\text{Recall} = \frac{TP}{TP+FN} \quad (4)$$

- **Accuracy:** All the classes are accurately expected. It should be maximized to the greatest possible extent.
- **Specificity (True Negative Rate):** The measure, known as the true negative rate, quantifies the proportion of real negative cases correctly anticipated as negative. The calculation of Specificity is as follows:

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (5)$$

- **F-measure:** When comparing multiple classifiers, it becomes problematic when one has low precision and the other has high recall. So, the F-score is used to make them comparable. F-score simultaneously evaluates precision and recall. It employs the Harmonic Mean by penalizing excessive values. The calculation of the F-measure is as follows:

$$\text{F} - \text{measure} = \frac{2*Recall*Precision}{Recall+Precision} \quad (6)$$

- **Matthews Correlation Coefficient (MCC)**
  This formula easily yields some useful MCC properties: when the classifier achieves perfection (FP=FN=0), the MCC result is 1, indicating an ideal correlation that is positive. If the classifier incorrectly classifies (TP=TN=0), it returns a value of -1, indicating a perfect negative correlation. To obtain the ideal classifier, reverse the classifier's output. MCC considers all four values in the confusion matrix, and a high value (around 1) indicates that both classes are well predicted, even if one class is disproportionately underrepresented (or overrepresented). The calculation of MCC is:
  $$MCC = \frac{TP*TN-FP*FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (7)$$
- **Receiver Operating Characteristic (ROC) Curve**
  Curve refers to a metric used to evaluate the performance of a classification issue at various threshold values. The ROC curve is a graphical representation of the likelihood of a binary classifier, while the AUC (Area Under the Curve) quantifies the level of separability between the classes. It quantifies the model's ability to distinguish across different classes.

- **Error Rate (ERR)**
  The error rate is determined by dividing the total number of incorrect estimations by the total dataset size. The optimal error rate is 0.0, whereas the maximum error rate is 1.0. The error rate is determined by dividing the sum of false negative and false positive predictions (FN+FP) by the total number of instances in the dataset (P+N). The calculation of ERR is as follows:

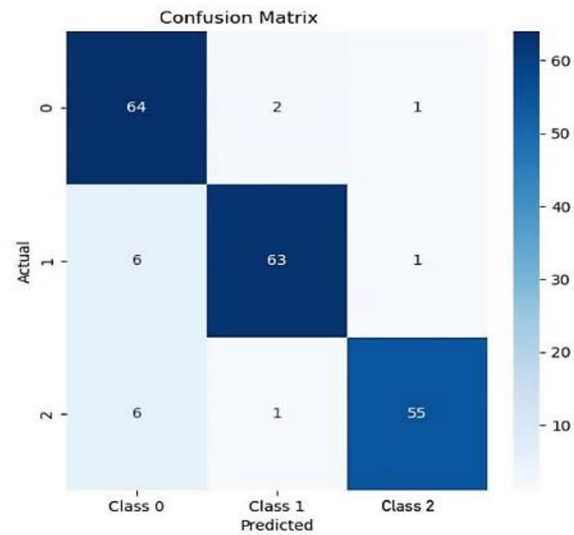
  $$\text{ERR} = 1 - \frac{TP+TN}{TP+FN+TN+FP} \quad (8)$$

## 4. Performance Analysis and Simulation Results

The performance evaluation of the two distinct classifiers was assessed by implementing the PYTHON tool. The efficacy of the suggested methodology is evaluated by assessing multiple characteristics, including accuracy, precision-recall, and specificity. The performance matrix (confusion matrix) displays the count of accurate and inaccurate estimates (referred to as hits and misses) generated by the classification algorithms using the real results obtained from the data. The confusion matrix is the predominant statistic utilized for evaluating models' performance metrics. In Fig.3a and b, the confusion matrix of multiple classes was represented as follows: VCD (class 0), CD (class 1), and ND (class 2) obtained from LVQ and SVM classification methods, respectively. The performance values (accuracy, recall, precision, F1-score) of the LVQ and SVM classification algorithms are calculated using the TP, TN, FN, and FP values provided in the confusion matrix. The time required to classify medical data using SVM is about 0.54 sec; meanwhile, using LVQ, the time has decreased drastically to about 0.28 sec, which is around half the recorded time of LVQ. The results demonstrate that the LVQ algorithm yields superior overall performance compared to SVM.

### 4.1 Accuracy

A set of extensive experiments was carried out to evaluate the efficacy of each LVQ and SVM as machine-learning classification techniques for segregating medical data. The results indicate that LVQ outperforms SVM in terms of accuracy, with LVQ achieving 91.45% accuracy compared to SVM's 80%, as shown in Fig.4.




**(a)**

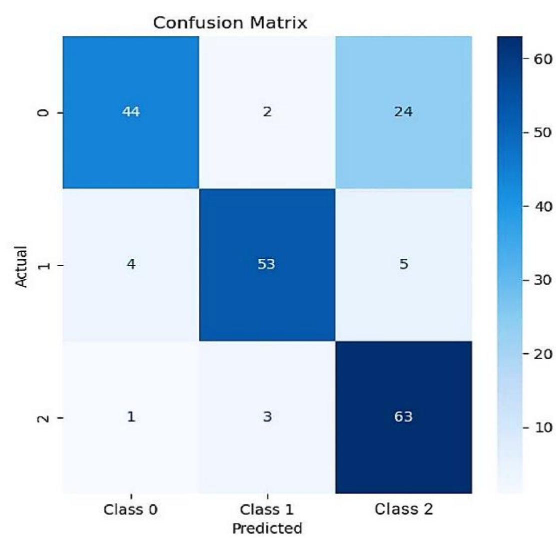



**Figure 3**: **(a)** Confusion Matrix of LVQ
**(b)** Confusion Matrix of SVM.

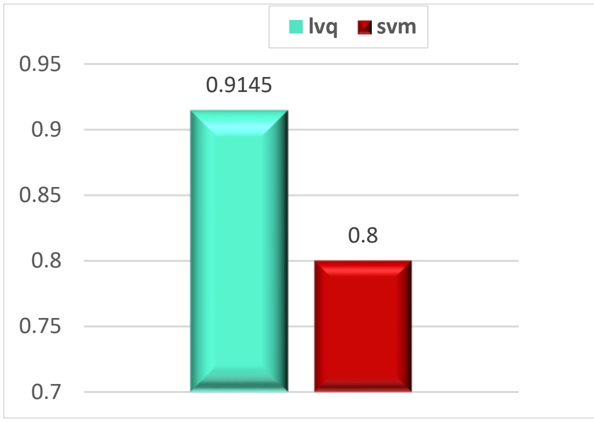



**Figure 4:** Classification Accuracy

### 4.2 Performance

The two parameters, recall and precision, evaluate the results' significance. As demonstrated in Fig.5, the LVQ classification algorithm achieves a precision rate of 0.96, an F-score of 0.949, and a high recall rate of 0.94. This reveals that it outperforms SVM algorithms in terms of medical diagnostic validity, with a 0.83 precision rate, F1-score, and recall of 0.80 for each.

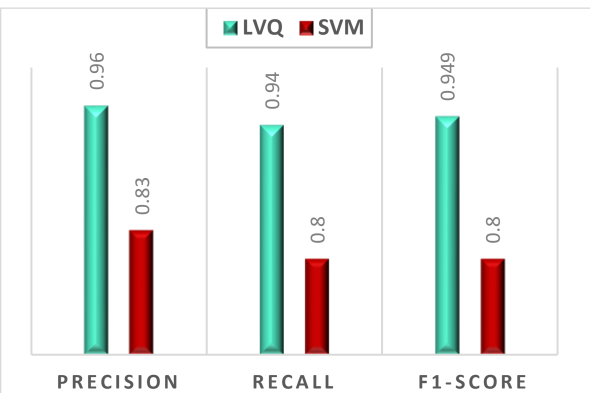
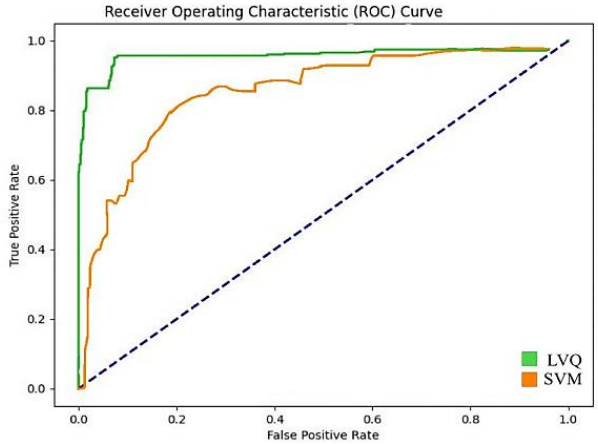



**Figure 5**: LVQ and SVM Performance Graph

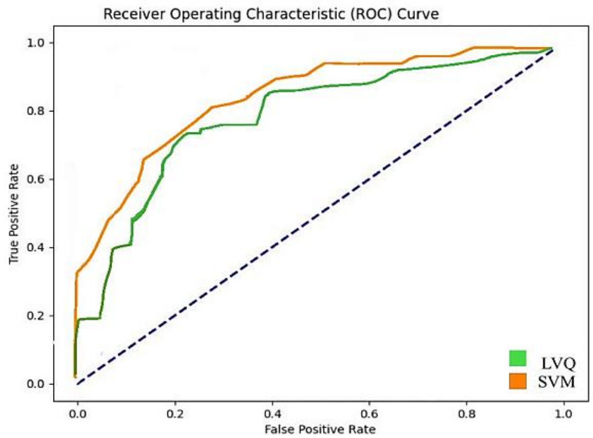
The results demonstrate that the LVQ algorithm yields superior performance compared to SVM in terms of precision rate by 13%, recall rate by 14%, and F1-score by 15%.

### 4.3 Receiver Operating Characteristic (ROC)

A perfect classifier would have a curve that hugs the upper left corner, indicating a high true positive rate (TPR) and a low false positive rate (FPR). Fig.6(a, b, and c) demonstrates the ROC curve for three classes where the LVQ algorithm outperforms SVM in both very critical and normal classes. In t
he critical class SVM advanced LVQ.




**(a)**

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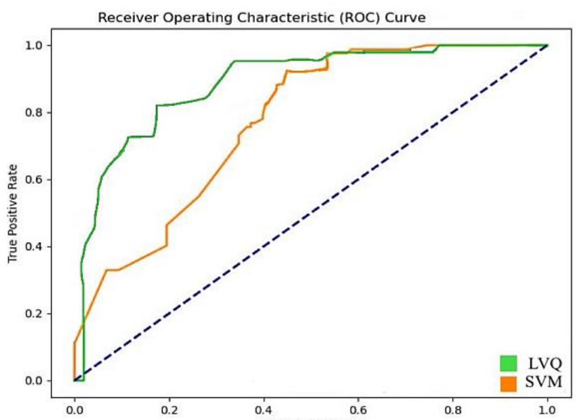


**(c)**

**Figure 6 (a)** Receiver Operating Characteristic (ROC) for class Very Critical **(b)** Receiver Operating Characteristic (ROC) for class Critical **(c)** Receiver Operating Characteristic (ROC) for class Normal

Table 3 presents the comparison results between LVQ and SVM for each precision, recall, accuracy, specificity, F-measure, MCC, and ERR. Table 4 compares the proposed techniques with the state of the artworks.

**Table 3.** Comparison Results Between LVQ and SVM.

| Metrics | LVQ | SVM |
|---|---|---|
| Precision | 0.96 | 0.83 |
| Recall | 0.94 | 0.80 |
| Accuracy | 0.9145 | 0.80 |
| F-measure | 0.949 | 0.80 |
| Specificity | 0.806 | 0.902 |
| MCC | 0.873 | 0.705 |
| ERR | 0.085 | 0.2 |

**Table 4.** Comparison of medical data classification techniques.

| Ref. | Classification Method | Accuracy |
|---|---|---|
| [16] | Combined LVQ with other classification techniques | 83.1% |
| [22] | Support Vector Machine | 88.02% |
| Proposed technique | Learning Vector Quantization | 91.45% |

## 5. Conclusion

The WBASN is attached to the human body to provide uninterrupted monitoring. Ensuring prompt transfer of data packets from the several physiological sensors to the medical center poses a substantial problem. The classification technique facilitated effective and dependable communication within the network, guaranteeing quick and precise transmission of essential data and enhancing the system's reliability. This study implements packet classification for dynamic physiological-sensors criticalities using machine learning-based classification techniques: learning vector machine (LVQ) and support vector machine (SVM). When working with big and unbalanced datasets, SVM is not commonly utilized because some SVM implementations require extensive training time. The major objective of this work was to decrease the intricacy of WBASN while improving its accuracy using the LVQ classification model. Upon analyzing the experiment findings on a dataset accessible to the public, it is evident that LVQ achieves the highest performance with an accuracy value of 91.45%. The performance of SVM is relatively modest, with an accuracy of 80% and an error rate of 11.5% higher than that of the LVQ.

Applying the LVQ technique significantly reduces the classification time needed to approximately half the time required for the SVM technique.


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## Conflict of Interest

'The authors confirm that the publication of this article causes no conflict of interest.

## Author Contribution Statement

Authors Sabreen Waheed Kadhum, Mohammed Ali Tawfeeq proposed the research problem and developed the theory and performed the computations. They both verified the analytical methods and investigation and supervised the findings of this work. Both authors discussed the results and contributed to the final manuscript.

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