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An Optimized Support Vector Machine-Based Embedded Framework for Real-Time Personalized Health

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Abstract:

Continuous monitoring of physiological parameters is essential for early detection of health risks. This paper proposes an optimized embedded health monitoring system using Particle Swarm Optimization-based Support Vector Machine (PSO-SVM). The system collects real-time data such as heart rate, blood pressure, glucose level, and temperature using multiple sensors. A dataset of 300 samples is used for training and evaluation. The data is preprocessed using noise filtering and normalization techniques. Statistical features are extracted to represent physiological behavior. PSO is used to optimize SVM parameters for improved classification. The proposed model achieves an accuracy of 97.1% with high precision and recall. It outperforms conventional SVM (94.5%) and Random Forest (96.2%). The system effectively detects abnormal health conditions and is suitable for real-time healthcare applications.

Keywords: Support Vector Machine (SVM), Particle Swarm Optimization (PSO), Feature Extraction, Smart Healthcare Systems.

1. Introduction

The increasing demand for continuous and real-time healthcare monitoring has led to significant advancements in smart health systems that integrate embedded devices with machine learning techniques. Early detection of abnormal physiological conditions plays a crucial role in preventing severe health complications and improving patient outcomes. Traditional healthcare systems primarily rely on periodic clinical assessments and hospital-based monitoring, which are often insufficient to capture sudden or dynamic changes in a patient's health status. Therefore, there is a growing need for intelligent, low-cost, and real-time monitoring solutions capable of continuously analyzing physiological parameters [1-4]. Recent developments in wearable sensors and embedded systems have enabled the acquisition of vital health data such as heart rate, blood pressure, body temperature, and glucose levels. In addition to physiological parameters, environmental factors such as ambient temperature and humidity significantly influence human health and can contribute to conditions like heat stress and

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dehydration. Integrating both physiological and environmental data enhances the reliability and accuracy of health monitoring systems[5-7]. However, the large volume and complexity of such multi-parameter data require efficient data processing and intelligent decision-making techniques [8-10].

Machine learning (ML) algorithms have emerged as powerful tools for analyzing complex biomedical data and identifying patterns associated with various health conditions. Among these, Support Vector Machine (SVM) is widely recognized for its strong classification capability, especially in high-dimensional and nonlinear datasets. SVM constructs an optimal decision boundary that maximizes the margin between different classes, thereby improving classification accuracy. Despite its advantages, the performance of SVM largely depends on the proper selection of kernel parameters such as the penalty factor and kernel coefficient. Improper parameter selection can lead to reduced accuracy and poor generalization [11-15]. To overcome this limitation, optimization techniques such as Particle Swarm Optimization (PSO) have been employed to enhance the performance of machine learning models. PSO is a population-based optimization algorithm inspired by the social behavior of bird flocking, which efficiently searches for optimal solutions by updating candidate solutions iteratively. By integrating PSO with SVM, the model parameters can be automatically optimized, resulting in improved classification accuracy and robustness. Motivated by these advancements, this paper proposes an optimized embedded machine learning framework for personalized health monitoring using a PSO-SVM model. The system integrates multiple physiological and environmental sensors to collect real-time data, which is then preprocessed and transformed into meaningful features. The optimized SVM classifier is employed to accurately predict health conditions and detect abnormalities at an early stage. Compared to conventional machine learning approaches, the proposed PSO-SVM model offers enhanced prediction performance, reduced classification error, and better generalization capability. The proposed system aims to provide a reliable, efficient, and cost-effective solution for continuous health monitoring, making it suitable for applications in wearable healthcare devices, remote patient monitoring, and smart healthcare systems.

2. Methodology

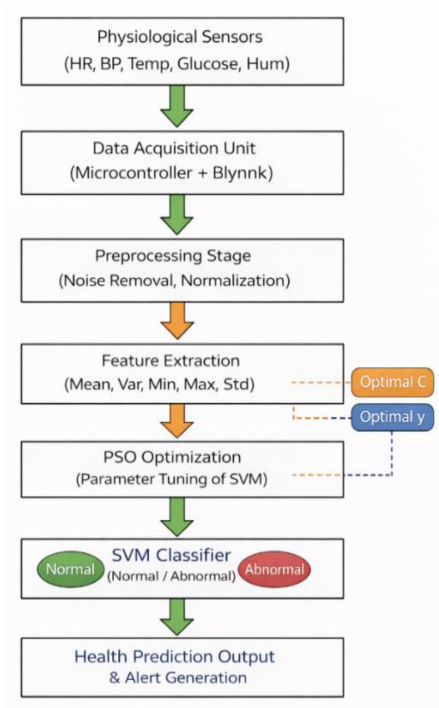

Figure 1. Architecture Of The Proposed Methodology

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The proposed system implements an optimized embedded health monitoring framework using Particle Swarm Optimization-based Support Vector Machine (PSO-SVM). The methodology consists of multiple stages including data acquisition, preprocessing, feature extraction, optimization, and classification as shown in Figure 1.

2.1 Data Acquisition

Physiological and environmental data are collected using embedded sensors such as heart rate sensors, blood pressure monitors, temperature sensors, glucose sensors, and humidity sensors. These sensors are interfaced with a microcontroller to continuously acquire real-time data.

2.2 Data preprocessing

Figure 2. Preprocessing Steps

Data preprocessing is an essential process to ensure that the physiological sensor data obtained is reliable and high-quality prior to its utilization in the machine learning model. The data acquired from the physiological sensors could be noisy, with gaps, and inconsistencies owing to interference with the environment and the limits of the sensors. The first process entails noise reduction through smoothing. This is followed by the management of the gaps through interpolation or imputation. The third process involves outlier elimination to remove any abnormal results that would have a negative impact on the model's performance. Normalization processes such as Min-Max scaling are employed to ensure that all variables fall within the same scale. Figure 2 depicts the preprocessing steps adopted in this work.

2.3 Feature Extraction

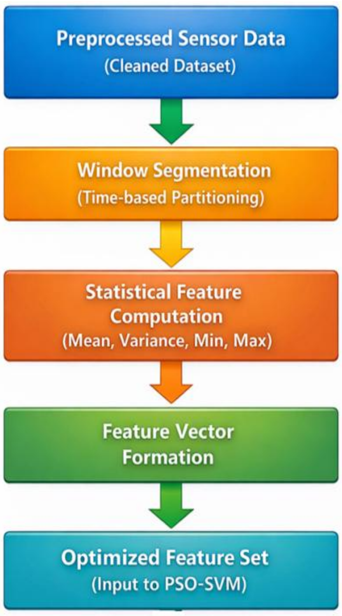

Figure 3. Feature Extraction

Feature extraction shown in Figure3 is a key process which involves the transformation of pre-processed physiological data into relevant feature vectors to classify the data effectively. Rather than relying on direct use of sensor values, features based on descriptive and

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statistical analysis are extracted, providing a clearer understanding of the behavior of the physiological variables involved. Statistical features such as the mean, variance, maximum, minimum, and standard deviation from each physiological variable like heart rate, blood pressure, glucose concentration, and temperature are extracted within a particular time interval. Moreover, feature extraction helps increase efficiency through dimensional reduction of data without sacrificing important information. The extracted features are used for input in the PSO-SVM classifier in order to predict health conditions effectively and accurately.

2.3 PSO-SVM classifier

In the suggested system, PSO is used for optimization of the support vector machine (SVM) algorithm to enhance classification efficiency. The SVM is a type of supervised machine learning method which is applied in classification because of its ability to solve high-dimensional and non-linear problems. Its functionality entails the development of the best possible hyperplane that creates maximum distance between the classes.

Nevertheless, the classification efficiency of SVM mainly relies on the value of some parameters such as penalty factor (C) and kernel factor (γ). When the inappropriate values of such parameters are used, it may result in low classification efficiency and over-fitting. For this reason, the combination of PSO and SVM techniques has been proposed.

The PSO is a population-based optimization algorithm which imitates the social behavior of flocking birds. Each particle in PSO acts as a possible solution and corresponds to a particular set of SVM parameters. Particles keep adjusting their position and velocity based on pbest (personal best) and gbest (global best) values. It will go on until the solution with minimum classification error is obtained. Figure 4 depicts the flowchart of PSO–SVM topology.

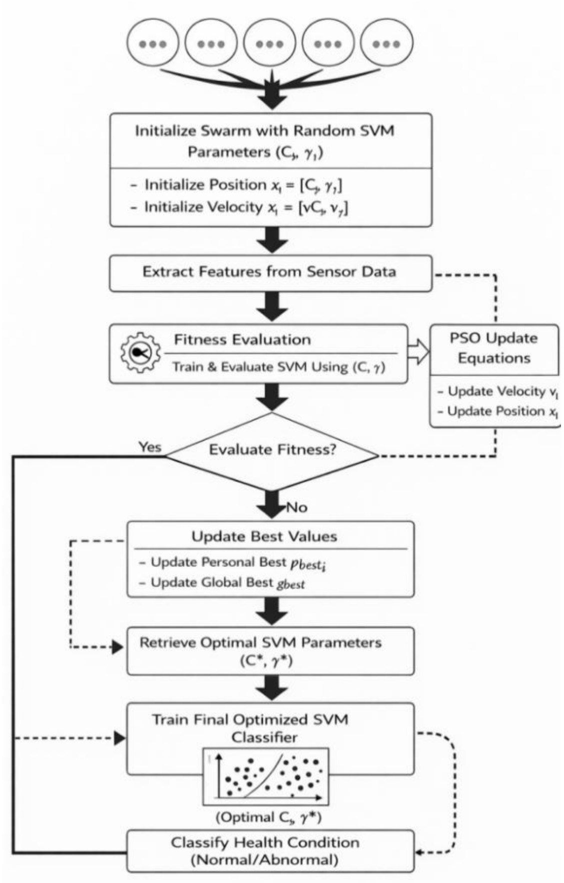

Figure 4. Flow chart- PSO–SVM

3. Results and Discussion

3.1 Hardware Setup

In this study, the developed health monitoring system was built based on the embedded microcontroller that had been combined with several kinds of sensors. These sensors were used to obtain live data about the body including temperature, humidity, heart rate, and blood pressure, among others. All of the acquired sensor data were sent to the Blynk app. Blynk is one of the platforms that give the user the opportunity to view real-time

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sensor readings. From the Blynk app dashboard, the following values, temperature, humidity and BP can be seen: Nonetheless, considering that the information on the Blynk dashboard is real-time, data is transformed into time series before any analysis takes place. Figure 5 represents the experimental setup.

Table 1: Extracted Statistical Features from Sensor data

Parameter	Mean	Variance	Minimum	Maximum	Std. Deviation
Temperature (°C)	27.0	0.18	26.5	27.6	0.42
Humidity (%)	62.0	1.25	60.0	65.0	1.12
Heart Rate (bpm)	78.5	15.2	70.0	95.0	3.89
Blood Pressure (mmHg)	122.5	22.4	110.0	140.0	4.73

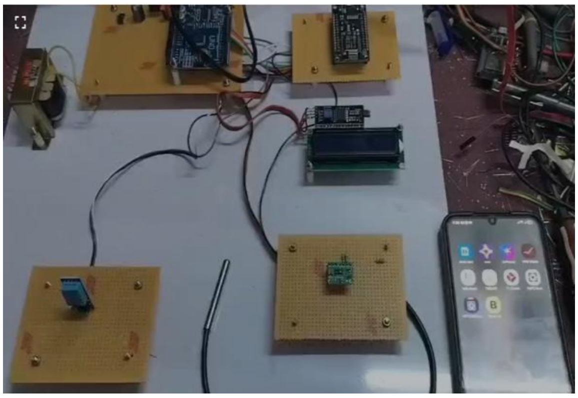

Figure 5. Hardware Setup

3.2 Feature Extraction and Representation

Statistical characteristics including mean, variance, maximum, minimum, and standard deviation are derived from the signal. Table 1 displays the values of the extracted features. These measures help summarize the pattern in the physiological signal and lower the dimension of the data. They provide information about static as well as dynamic characteristics of the signal.

3.3 PSO-SVM Classifier Performance

The obtained features are used for training the PSO-SVM classifier. Particle swarm optimization technique is utilized for parameter tuning of the SVM classifier, which yields better results. The proposed technique's performance is analyzed based on various evaluation criteria such as accuracy, precision, recall, and F1-score. Table 2 and Figure 6 represents the PSO-SVM Classifier Performance.

Table 2. PSO-SVM Performance Metrics

Metric	Value (%)
Accuracy	97.1
Precision	96.5
Recall	95.9
F1-Score	96.2

The suggested PSO-SVM model exhibits an outstanding accuracy rate of 97.1%, which signifies its remarkable capability in predicting health conditions. The model

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demonstrates a precision rate of 96.5%, which means that the model is effective in avoiding unnecessary false alarms. Its recall rate of 95.9% proves that the model successfully detects most of the abnormal health conditions. Finally, the model exhibits an F1-score of 96.2%

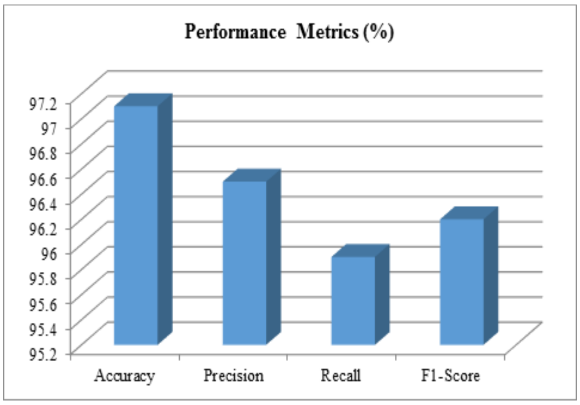

Figure 6. Performance Metrics

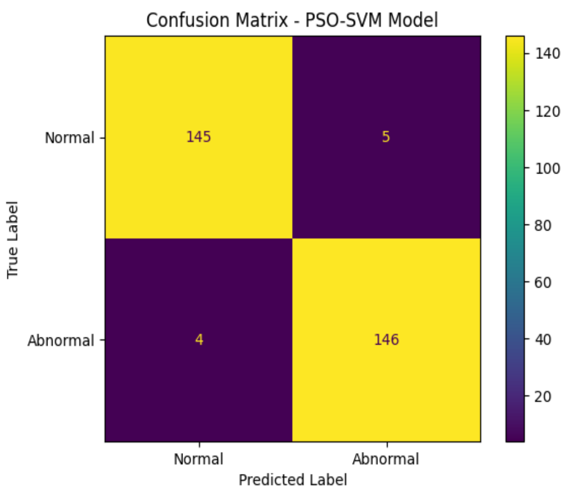

Figure 7. Confusion Matrix

From the confusion matrix (Figure 7), it can be noted that the PSO-SVM model offers excellent reliability when classifying samples as it makes a considerable number of correct classifications. A total of 145 samples were accurately classified as normal, and another total of 146 samples were classified as abnormal. These findings suggest that the model is highly accurate. It should be noted that there was a very low percentage of misclassification, where five samples were misclassified as normal, while four other samples were misclassified as abnormal. In general, the findings show that the PSO-SVM model is reliable and accurate.

3.4 Comparison with Existing Model

To validate the effectiveness of the proposed approach, a comparison is made with the SVM and Random Forest (RF) model as depicted in Table 3 and Figure 8.

Table 3. Comparison Analysis

Model	Accuracy (%)
SVM	94.5
Random Forest	96.2
PSO–SVM (Proposed)	97.1

The comparison results indicate that the proposed PSO–SVM model achieves the highest accuracy of 97.1%, outperforming both conventional SVM (94.5%) and Random Forest (96.2%) models. This improvement is due to the optimization of SVM parameters using Particle Swarm Optimization, which enhances classification performance and generalization capability. The results demonstrate that the PSO–SVM approach provides more accurate and reliable health condition prediction, making it suitable for real-time healthcare monitoring applications.

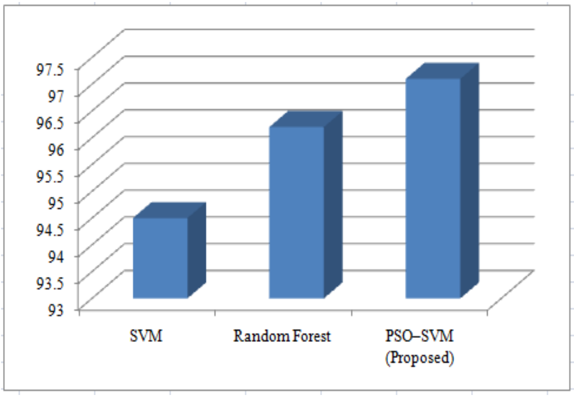

Figure 8. Comparison Analysis

4. Conclusion

In this paper, an embedded health monitoring system was developed using a PSO-SVM model that was found to give accurate health conditions. The system incorporates the use of different types of sensors that are used to capture different health parameters, including temperature, humidity, heart rate, and blood pressure. The obtained data from these sensors undergo different types of preprocessing, which involve noise filtering and normalization. This process ensures that the obtained data is more precise. Further data analysis involves feature extraction using statistical methods, which include mean, variance, and standard deviations. The use of time series waveforms enhances data comprehension and understanding. The PSO algorithm was used to optimize the SVM model, and this improved its accuracy and generalization capabilities. The model produced an accuracy of 97.1%, which was better than the conventional models.The use of the Blynk system in the project provides real-time visualization and analysis of the sensor data. This system will be useful in applying it in practice due to its efficiency and reduced cost. For the future development of this model, deep learning approaches such as CNN and LSTM may be considered. Moreover, the use of cloud and wearable sensors could be included.

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