RESEARCH PAPER

Embedded Machine Learning Framework For Personalized Health Monitoring

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ABSTRACT

Continuous monitoring of various physiological parameters is vital to detect various health risks early on. The recent developments in embedded systems and machine learning have made it possible to develop intelligent healthcare monitoring systems that can process various physiological signals. This paper aims to propose an embedded machine learning (ML) based framework for personal health monitoring. The proposed framework includes a set of physiological sensors to measure various vital parameters such as heart rate, blood pressure, body temperature, ambient temperature, humidity and blood glucose levels. The proposed embedded device is connected to a set of sensors to collect data on various vital parameters. The collected data are then analyzed using a Random Forest (RF) classifier. A dataset of 300 physiological sample data was used to train the model. The Random Forest classifier is able to deal effectively with multiple physiological features and nonlinear relationships between health parameters. From the experimental results, it is clear that the system is able to effectively identify health hazards such as heat stress, dehydration, hypertension and abnormal glucose levels, thereby sending timely alerts to the users. The use of embedded sensors along with the RF model is an effective and affordable solution for continuous health monitoring.

Keywords: Embedded machine learning, Personalized health monitoring, Random Forest algorithm.

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INTRODUCTION

The increasing demand for continuous healthcare monitoring has led to the development of intelligent health monitoring systems capable of analyzing physiological signals in real time. Early detection of abnormal health conditions plays a crucial role in preventing serious medical complications and improving the quality of life. Traditional healthcare monitoring methods mainly rely on periodic clinical examinations or hospital-based monitoring equipment. However, these approaches do not provide continuous monitoring and may fail to detect sudden physiological changes that occur outside clinical environments [2-5].

Recent advancements in wearable sensors, embedded systems and ML technologies have enabled the development of smart health monitoring solutions. These systems can continuously measure important physiological parameters such as heart rate, blood pressure, body temperature, and blood glucose levels. Monitoring these parameters helps identify potential health risks related to cardiovascular disorders, metabolic diseases, and environmental stress conditions.

In addition to physiological parameters, environmental factors such as ambient temperature and humidity can significantly influence human health. High environmental temperature combined with elevated body temperature and abnormal heart rate can lead to heat stress and dehydration. Therefore, integrating both physiological and environmental parameters can improve the reliability of health monitoring systems [9].

Among various ML algorithms, the Random Forest (RF) algorithm has gained considerable attention due to its robustness, high prediction accuracy, and ability to handle multiple health parameters simultaneously. By learning from historical physiological data, ML models can classify health conditions and provide early alerts for abnormal physiological patterns. Motivated by these developments, this work proposes an embedded machine learning framework for personalized health monitoring using physiological sensors and environmental parameters. The proposed system measures heart rate, blood pressure, body temperature, ambient temperature, humidity and blood glucose level using sensor modules connected to an embedded hardware platform. The collected data are analyzed using a RF model to predict potential health risks and provide early health alerts.

RELATED WORK

Several studies have explored the application of ML in healthcare prediction systems. Niu et al. [1] proposed a non-parametric clustering approach that combines attention

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*Author for Correspondence: parventhanac@rediffmail.com mechanisms with Dirichlet Process Mixture Models to predict illness risks from electronic health records (EHR), achieving strong predictive performance while improving model interpretability. Similarly, Pedro [6] applied an explainable XGBoost model for chronic kidney disease detection and identified important clinical variables such as hypertension and hemoglobin levels that significantly influence prediction outcomes. However, this study lacked validation across larger and more diverse populations.

Martino et al.[7] introduced an explainable model for malnutrition prediction using heterogeneous mobile-health data and emphasized the importance of incorporating longitudinal patient information for improving personalized healthcare assessment.

Giovanni et al. [8] utilized a deep neural network to predict postprandial glucose levels in individuals with Type-1 diabetes and incorporated SHAP analysis to identify key glycemic predictors. Although the model provided useful insights, further validation in real clinical environments is still required. Ooi et al. [10] conducted a comprehensive review highlighting that explainability methods such as SHAP and Grad-CAM are widely used to enhance the interpretability of healthcare prediction models, though limited research focuses on interpreting anomaly detection in biosignal data.

Yang et al.[11] developed a system that integrates wearable sensor data with interpretable machine learning models for stress detection using multimodal physiological and biomarker data. Senthilkumar et al.[12] proposed IoT-enabled healthcare monitoring systems incorporating explainable AI techniques for resource-constrained devices.

3. PROBLEM STATEMENT

Although several ML and AI models have been developed for healthcare prediction, many of them focus on specific diseases or limited physiological parameters [13-15]. Most existing studies rely on large clinical datasets and complex models that are not suitable for embedded health monitoring systems. In addition, many approaches lack real-time monitoring capabilities and do not integrate multiple physiological and environmental parameters simultaneously. Some models also lack proper validation in real-world healthcare settings. Therefore, there is a need for an efficient embedded machine learning framework that can analyze multiple health indicators and provide reliable personalized health monitoring.

4. NOVELTY

The proposed work develops an embedded machine learning framework for personalized health monitoring that integrates multiple physiological and environmental parameters. A Random Forest (RF) model is used to analyze vital signs such as heart rate, blood pressure, glucose level, body temperature, ambient temperature, and humidity.

5. KEY CONTRIBUTIONS

Development of an embedded machine learning framework for personalized health monitoring using physiological and environmental sensor data.

Integration of multiple health parameters including heart rate, blood pressure, glucose level, body temperature, ambient temperature, and humidity for comprehensive health assessment.

Application of the Random Forest (RF) algorithm to analyze physiological signals and accurately classify potential health risks.

Design of a low-cost embedded monitoring system capable of real-time health prediction suitable for wearable or remote healthcare applications.

6. METHODOLOGY

The proposed system shown in figure 1 implements an embedded machine learning framework for personalized health monitoring by integrating physiological sensors, an embedded microcontroller, and a RF model. The methodology consists of several stages including data acquisition, preprocessing, feature extraction, model training, and health condition prediction.

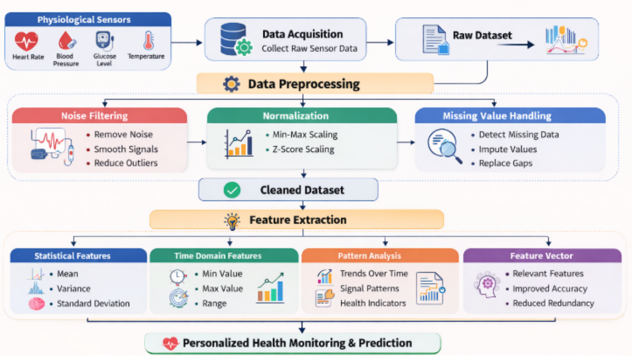

Figure 1. Proposed Architecture

6.1 Data Acquisition

The health monitoring system is implemented using an Arduino-based embedded hardware platform integrated with multiple physiological sensors. The sensors measure vital health parameters including heart rate, blood pressure, glucose level, body temperature, ambient temperature, and humidity. These sensors are connected to the microcontroller, which continuously collects real-time physiological data. The collected sensor readings are displayed on a 16×2 LCD display and transmitted for further analysis.

6.2 Data Preprocessing

As depicted in figure 2, the raw physiological sensor data may contain noise, missing values, and irregular measurements due to environmental disturbances or sensor inaccuracies. Therefore, a preprocessing stage is applied before feature extraction. Initially, the collected data is inspected to identify inconsistencies and unwanted variations. Noise filtering techniques are then used to smooth the sensor signals and remove disturbances. Outlier detection is performed to eliminate abnormal readings that may affect the learning process. Missing values are handled using interpolation or imputation methods to maintain dataset continuity. Finally, normalization techniques such as Min–Max scaling or Z-score standardization are applied to bring all features to a common scale. The resulting cleaned dataset becomes suitable for feature extraction and subsequent machine learning analysis.

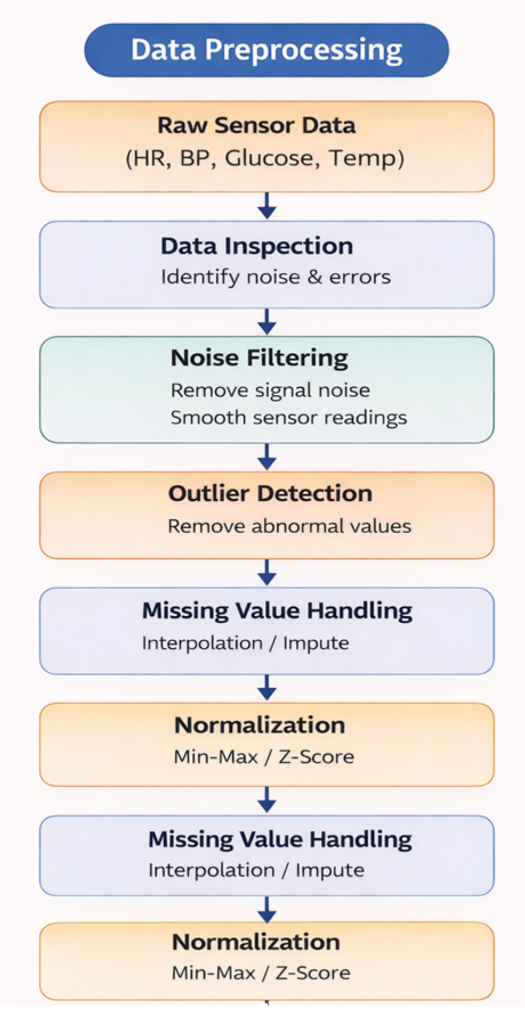

Figure 2. Pre-Processing

6.3 Feature Extraction

Feature extraction (Figure 3) is used to convert the preprocessed sensor data into more meaningful and informative variables that can improve the performance of the machine learning model. Even after preprocessing, the raw physiological readings such as heart rate, blood pressure, glucose level, and temperature may still contain variations or redundant information. Feature extraction derives important characteristics from these signals, such as statistical measures (mean, variance, minimum, and maximum values) or patterns over a specific time window. These extracted features represent the essential behavior of the physiological parameters and help the Random Forest model better understand the relationships between different health indicators. As a result, feature extraction improves the efficiency, prediction accuracy, and robustness of the personalized health monitoring system.

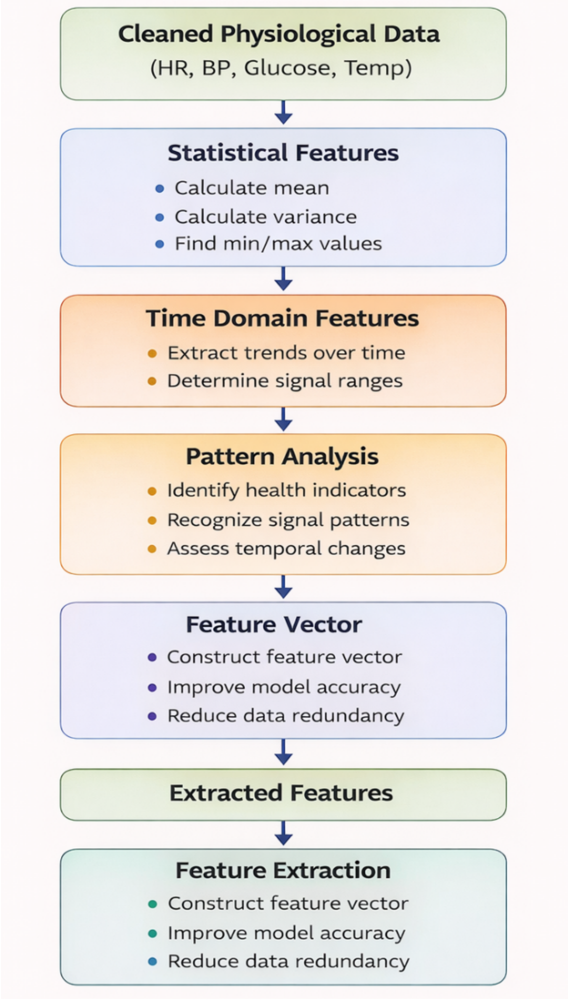

Figure 3. Feature Extraction

6.4 Random forest Topology

Random Forest (RF) is a supervised machine learning algorithm widely used for classification and regression tasks due to its high prediction accuracy, robustness to noise, and ability to handle complex nonlinear relationships between variables. It belongs to the category of ensemble learning methods, where multiple decision trees are constructed and combined to produce a more reliable prediction than a single model. Figure 4 depicts the structure of RF model

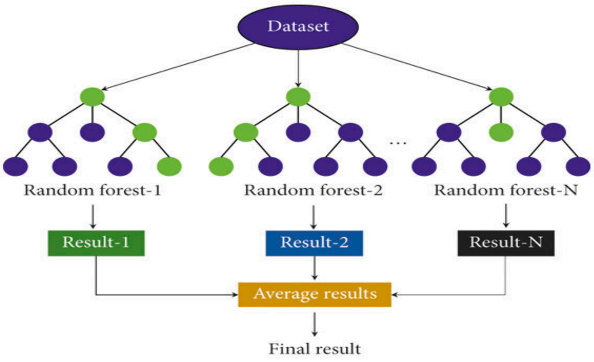

Figure 4. RF Model

In the RF approach, several decision trees are generated during the training phase using different subsets of the dataset through a technique known as bootstrap aggregation (bagging). Each decision tree is trained using randomly selected samples and a random subset of features. This randomness helps reduce overfitting and improves the generalization capability of the model.

For the personalized health monitoring system, the extracted physiological features such as heart rate, blood pressure, glucose level, and body temperature are used as input variables to the Random Forest classifier. During training, each decision tree independently learns the relationship between these physiological parameters and the corresponding health condition. When a new set of sensor data is provided, every tree produces a prediction, and the final output is determined by a majority voting mechanism among all trees.

The Random Forest model offers several advantages for healthcare monitoring applications. First, it can effectively handle high-dimensional physiological datasets generated by multiple sensors. Second, it is robust to noise and missing data, which commonly occur in wearable sensor measurements. Third, the algorithm provides feature importance analysis, enabling the identification of critical health indicators influencing the prediction.

Therefore, Random Forest is well suited for the proposed system, as it enhances the accuracy, reliability, and robustness of health condition prediction, enabling efficient real-time monitoring and early detection of abnormal physiological conditions. Table 1 depicts the hyperparemeter of RF.

Table 1. Hyper parameters

S.No	Hyperparameter	Values
1	n_estimators	200
2	max_depth	15
3	min_samples_split	10
4	min_samples_leaf	4
5	max_features	sqrt,
6	bootstrap	True
7	criterion	gini
8	random_state	42
9	class_weight	balanced

7. RESULTS AND DISCUSSION

7.1 Hardware Setup

The proposed personalized health monitoring system was implemented using a real-time hardware platform to acquire physiological parameters and validate the performance of the machine learning model. The hardware setup shown in figure 5 consists of multiple biomedical sensors, a microcontroller-based data acquisition unit, and a computing system for data processing and prediction.

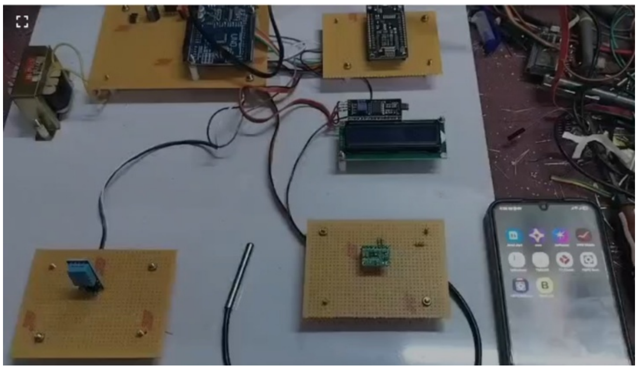

Figure 5. Hardware Setup

The system is powered using a regulated power supply unit that converts the AC mains voltage into a stable DC supply required for the electronic components. The central processing unit of the system is an Arduino-based microcontroller, which is responsible for collecting and processing the sensor signals.

Different sensing modules are connected to the microcontroller to measure physiological parameters. These include a temperature sensor module for monitoring body temperature and other biomedical sensing modules for acquiring physiological signals. The sensor outputs are interfaced with the microcontroller through analog and digital input pins.

The collected sensor data is displayed locally using an LCD display module, which provides real-time visualization of the measured physiological parameters. In addition to the display unit, the system is connected to a smartphone-based monitoring interface, allowing the physiological data to be viewed remotely.

The microcontroller continuously acquires the sensor readings and transmits the collected data to the processing unit for further analysis.

After preprocessing, feature extraction was performed to derive meaningful statistical characteristics from the physiological signals. Instead of using raw sensor readings directly, statistical features were computed over a defined observation window.

The extracted features include:
Mean
Variance
Minimum value
Maximum value
Standard deviation

These features displayed in table 2 represent the essential behavior of the physiological parameters and help the machine learning model better understand the relationships between different health indicators.

Table 2. Extracted Statistical Features from Physiological Data

Parameter	Mean	Variance	Minimum	Maximum	Std. Deviation
Heart Rate (bpm)	78.4	16.2	65	102	4.02

Blood Pressure (mmHg)	122.7	25.6	105	148	5.06
Glucose Level (mg/dL)	110.3	30.1	92	168	5.48
Temperature (°C)	36.8	0.15	36.2	37.5	0.38

7.2 Feature Importance from Random Forest

Random Forest also provides feature importance, which indicates which physiological parameters contribute most to prediction as depicted in figure 6 and table 3.

Table 3. Feature Importance Analysis

Feature	Importance Score
Heart Rate	0.34
Blood Pressure	0.28
Glucose Level	0.23
Body Temperature	0.15

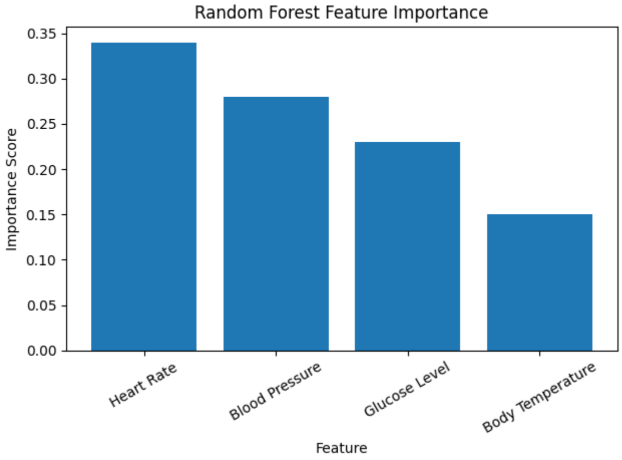

Figure 6. Feature Importance Analysis

These feature vectors were then used as inputs to the Random Forest classifier for health condition prediction.

Table 4: Performance Evaluation of the Random Forest Model

Metric	Value (%)
Accuracy	96.2
Precision	95.4
Recall	94.8
F1-Score	95.1

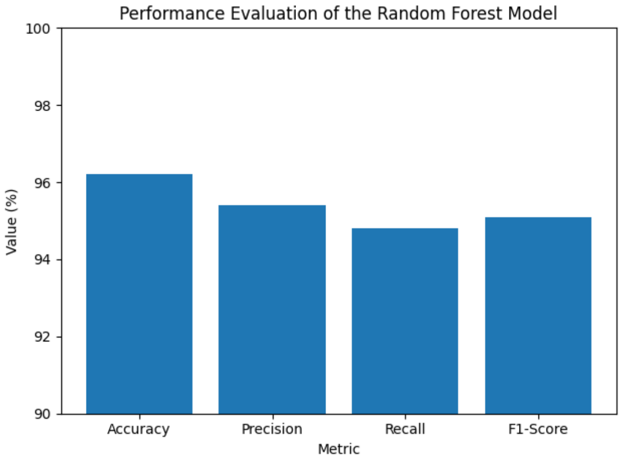

Figure 7. Random Forest Performance Evaluation

Table 4 and figure 7 depicts that the Random Forest classifier achieved an accuracy of 96.2%, demonstrating strong prediction capability for the physiological dataset. The high precision and recall values indicate that the model effectively identifies abnormal health conditions while minimizing false predictions.

7.3 Confusion Matrix

The confusion matrix (Figure 8) shows that most physiological samples were correctly classified. Only a small number of samples were misclassified, demonstrating the robustness of the Random Forest model for health monitoring applications.

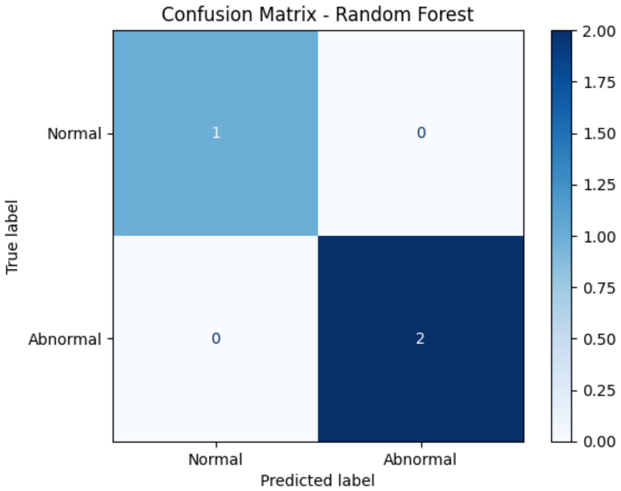

Figure 8. Confusion Matrix

8. CONCLUSION

This study presents a personalized health monitoring system that integrates physiological sensors with a Random Forest machine learning model for accurate health condition prediction. The system collects real-time physiological parameters such as heart rate, blood pressure, glucose level, and body temperature using a hardware-based sensing platform. The acquired data is processed through preprocessing techniques including noise filtering, normalization, and missing value handling to improve data quality. Feature extraction is performed to obtain important statistical characteristics such as mean, variance, minimum, and maximum values from the physiological signals. These features are used as inputs for the Random Forest classifier to predict health conditions. Experimental results demonstrate that the proposed system achieves high classification performance with an accuracy of 96.2%. The precision, recall, and F1-score values further confirm the reliability of the model. The confusion matrix analysis shows that most physiological samples are correctly classified. The developed hardware prototype validates the feasibility of integrating sensor-based monitoring with machine learning algorithms. Overall, the proposed framework provides an effective solution for real-time personalized health monitoring applications.

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