

# AI DRIVEN WBAN IN HEALTHCARE USING MACHINE LEARNING

**Dr.Karthigai Lakshmi S <sup>1</sup>, Geetha A <sup>2</sup>, Shanjuvikasini J <sup>3</sup>**

Professor & Head <sup>1</sup>, Assistant professor <sup>2</sup>, PG Scholar <sup>3</sup>

Department of Electronics and Communication Engineering, SSM Institute of Engineering  
and Technology, Dindigul, Tamilnadu, India.

## ABSTRACT

*The convergence of Artificial Intelligence (AI) and Wireless Body Area Networks (WBANs) is reshaping healthcare monitoring by enabling non- invasive, intelligent systems. This study presents a simulation-based framework for predicting vital signs—Electrocardiogram (ECG), blood pressure, and body temperature—using machine learning, thus eliminating reliance on physical sensor hardware. Synthetic datasets were generated to emulate WBAN conditions, and three supervised learning algorithms—Linear Regression (LR), Support Vector Machine (SVM), and Random Forest (RF)—were employed for predictive analysis. Model performance was evaluated using Mean Squared Error (MSE) and the Coefficient of Determination ( $R^2$  score). Among the tested models, Random Forest demonstrated superior accuracy and robustness across all health parameters. The results highlight the potential of AI-driven simulation as a cost- effective and scalable solution for the development and preliminary testing of healthcare monitoring systems. Future efforts will aim to enhance model versatility with broader datasets and explore real- time implementation and anomaly detection capabilities.*

**Keywords:** Artificial intelligence (AI), Linear Regression, Support vector machine, Random forest, ECG, body temperature, Blood pressure.

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## 1. INTRODUCTION

Wireless Body Area Networks (WBANs) have emerged as a transformative technology in healthcare, enabling continuous monitoring of patients through wearable and implantable sensors. These networks facilitate real-time data collection, transmission, and analysis, leading to early disease detection, personalized treatment, and improved patient outcomes. To extract meaningful insights from the vast amount of physiological data. Generated by WBANs, machine learning (ML) techniques play a crucial role. Among the various ML models, Linear Regression, Random Forest, and Support Vector Machines (SVM) are widely used to analyze and predict key health parameters such as heart rate, blood pressure, glucose levels, and ECG signals.

## 2. LITERATURE SURVEY

Machine Learning (ML) has emerged as a transformative tool in the medical field due to its capacity to process vast volumes of data, uncover hidden patterns, and enhance the interpretability of complex information. Its adaptability and predictive capabilities are being increasingly utilized to improve diagnostic accuracy, system reliability, and overall healthcare outcomes. Numerous studies have demonstrated that ML algorithms can significantly aid in the early detection and diagnosis of various diseases by recognizing subtle correlations within clinical data that may not be easily apparent through traditional analysis methods.

In recent years, a growing body of literature has explored the application of ML in critical medical domains. These include oncology, where ML is used to predict cancer progression and treatment outcomes; neuroinformatics, particularly in brain imaging and cognitive disorder diagnostics; and medical chemistry, where algorithms support drug discovery and molecular analysis. ML has also found substantial use in the interpretation of complex medical images, aiding radiologists and specialists in identifying abnormalities with

increased precision. Furthermore, the advent of wearable technologies has introduced new dimensions for continuous health monitoring, where ML algorithms process physiological signals in real time for proactive healthcare management.

A crucial requirement for deploying ML in clinical settings is the structured and accurate encoding of patient data, typically extracted from electronic medical records. Well-encoded data enable ML models to autonomously analyze and correlate new cases with previously encountered scenarios, thereby supporting healthcare professionals in making rapid and informed decisions. These advancements also facilitate use by medical trainees and non-specialists, democratizing access to diagnostic tools and promoting consistent healthcare delivery.

### 3. METHODOLOGY

#### 3.1 ML Simulation Framework

This study proposes a simulation-driven framework for predicting health risk scores using machine learning techniques, namely Linear Regression (LR), Support Vector Machine (SVM), and Random Forest (RF). The framework operates entirely on synthetic datasets, thereby eliminating the dependency on wearable sensor hardware. This enables flexible and cost-effective experimentation with various algorithmic models for health parameter estimation.

The simulation begins with the generation of synthetic datasets representing key physiological indicators such as ECG values, blood pressure levels, and body temperature. These parameters are synthesized using statistical distributions designed to emulate realistic variability observed in actual clinical data. The synthetic features are then fed into the machine learning models to train regression models that estimate a composite health risk score.

Each model undergoes training and testing phases, where the dataset is split into appropriate subsets to evaluate generalization performance. The models' predictive outcomes are compared to actual values in the test dataset. Evaluation metrics include the Mean Squared Error (MSE) and the Coefficient of Determination ( $R^2$  score), both of which offer insights into the models' accuracy and reliability.

As visualized in the simulation results, the Random Forest model demonstrated the closest fit between predicted and actual health risk scores, showing superior performance in terms of both lower MSE and higher  $R^2$  scores. The accompanying bar chart further highlights the comparative performance, confirming Random Forest's advantage over Linear Regression and SVM.

This framework provides a replicable, sensor-free environment to benchmark machine learning methods in virtual WBAN applications, contributing toward future AI-assisted healthcare systems.

### 3.2. Google colab

To conduct the simulation and comparative evaluation of machine learning models, the entire experimental workflow was implemented using Google Colab. Google Colab provides a cloud-based development environment equipped with GPU/CPU support, enabling the efficient execution of machine learning tasks without requiring local computational resources.

The simulation process began with the generation of synthetic datasets using Python libraries such as NumPy and pandas. These datasets included simulated features representing health parameters like ECG values, blood pressure, and body temperature. The corresponding target variable was a health risk score, designed to represent a composite index derived from the aforementioned parameters.

## 4. RESULTS

The bar chart illustrates the coefficient of determination for each model—Linear Regression, Support Vector Machine (SVM), and Random Forest. Among the three, Random Forest demonstrates the highest  $R^2$  score, followed closely by Linear Regression and SVM. This suggests that while all three models are capable of explaining a significant portion of variance in the data, Random Forest offers superior generalization capability and robustness.

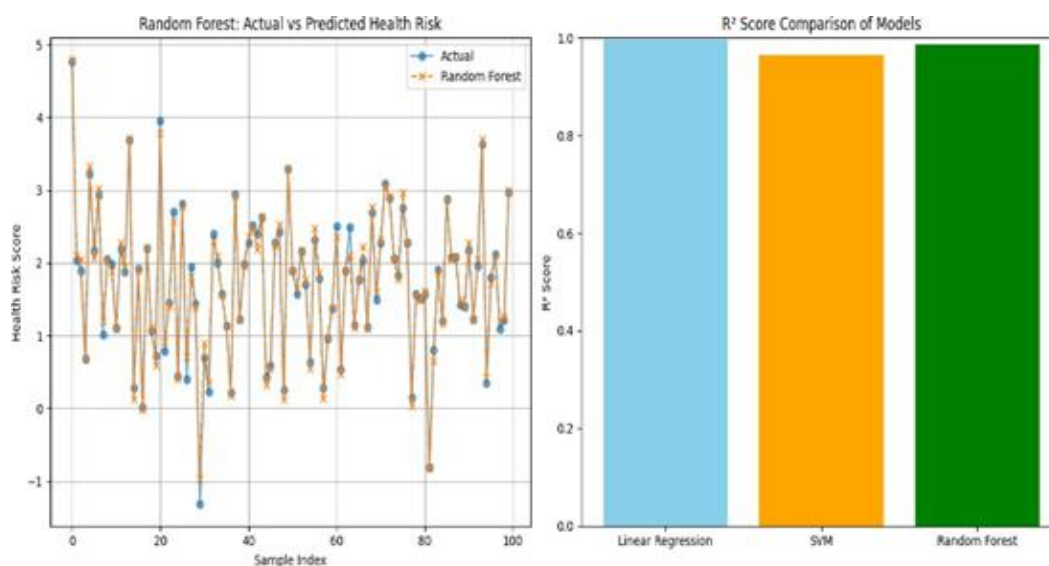


Fig 1 Proposed simulated output

## CONCLUSIONS

The use of synthetic data in this simulation offers a scalable, flexible, and cost-effective approach for testing predictive models in the absence of real-world wearable sensor data. This framework lays the groundwork for future integration of AI-driven health monitoring systems, especially in resource-constrained or early-stage development environments. Moving forward, real-time data integration and model deployment can enhance the system's clinical applicability and pave the way for smart healthcare innovations.

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✉ [editor@iaeme.com](mailto:editor@iaeme.com)