Performance Evaluation of Wearable Sensor Systems in Android based Medical Smartbands

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Abstract: Android-based medical smartbands equipped with wearable sensors have emerged as effective tools for continuous health monitoring and preventive healthcare. These smartbands integrate multiple sensors such as heart rate, accelerometer, SpO_2, temperature, and motion sensors to collect real-time physiological and activity data. This paper presents a performance evaluation of wearable sensor systems used in Android-based medical smartbands, focusing on key parameters such as accuracy, response time, reliability, power consumption, and data transmission efficiency. Sensor data is processed through Android applications, enabling real-time visualization, alerts, and remote health monitoring. The study highlights the effectiveness of sensor-based smartbands in medical care applications including fitness tracking, chronic disease monitoring, and elderly care. Experimental analysis demonstrates that optimized sensor integration and Android-based data handling can enhance system performance while maintaining low power consumption. The results indicate that wearable sensor systems in Android-based smartbands offer a cost-effective, portable, and reliable solution for modern healthcare monitoring.

Keywords: Wearable Sensors, Android-Based Smartbands, Medical Health Monitoring, Performance Evaluation, IoT Healthcare, Real-Time Data Monitoring, Smart Wearable Devices, Remote Patient Monitoring

Introduction

Recent advancements in wearable technology have significantly transformed the field of healthcare monitoring. Among these technologies, Android-based medical smartbands have gained considerable attention due to their portability, affordability, and ability to provide continuous health monitoring. These smartbands are equipped with various wearable sensors that collect physiological and activity-related data, enabling real-time analysis and remote medical supervision.Wearable sensor systems integrated into smartbands typically include heart rate sensors, accelerometers, gyroscopes, SpO_2 sensors, temperature sensors, and, in advanced models, electrocardiogram (ECG) sensors. These sensors continuously capture vital health parameters and transmit the data to Android applications through wireless communication technologies such as Bluetooth Low Energy (BLE). Android platforms offer a flexible and user-friendly interface for data visualization, storage, and alert generation, making them suitable for medical and healthcare applications.

Performance evaluation of these wearable sensor systems is essential to ensure accuracy, reliability, low power consumption, and timely data transmission, which are critical factors in medical care. Inaccurate or delayed sensor data may lead to incorrect health assessments and reduced trust in wearable medical devices. Therefore, analyzing sensor performance under different usage conditions is necessary to validate their effectiveness for continuous health monitoring. This study focuses on evaluating the performance of wearable sensor systems used in Android-based medical smartbands. Key performance parameters such as measurement accuracy, response time, energy efficiency, and data communication reliability are analyzed. The objective is to assess the suitability of these smartbands for medical applications such as preventive healthcare, chronic disease monitoring, fitness tracking, and elderly care. The outcomes of this evaluation aim to contribute to the development of reliable and efficient wearable healthcare solutions.

2 Existing Methods

A contingency table as a confusion matrix or a matching matrix was used to evaluate the datasets in order to test the machine learning algorithms for classifying sensor data. Four machine learning methods were used in this study. Algorithms that can be employed include Random Forest, Bagging, Decision Trees, and Hyperpipes.

2.1 Random Forest

As an ensemble learning method for classification and regression tasks, random forests or random decision forests construct a large number of decision trees during the training phase and output the class that represents the mode of all classes (classification) or the mean/average prediction of all trees (regression). The tendency of decision trees to overfit their training set is corrected by random decision forests. However, the accuracy of random forests is lower than that of gradient-boosted trees. Their performance can, however, be influenced by the data's features.

2.2 Bagging

In the context of statistical classification and regression, bootstrap aggregating, often known as bagging (from the word "bootstrap"), is a meta-algorithm for machine learning ensembles that aims to increase the stability and accuracy of machine learning algorithms. It also decreases variability and prevents overfitting. Aside from decision tree approaches, it may be utilized with any other sort of analysis. The model averaging technique is extended to include bagging as a specific instance.

2.3 Decision Tree

It is possible to utilize Decision Trees to solve both Classification and Regression issues, however they are more commonly employed for Classification problems. Internal nodes reflect the dataset's attributes and branches represent decision rules; each leaf node represents an outcome. This is a tree-based classifier. The Decision Node and the Leaf Node are both nodes in a decision tree. There are two types of nodes in a network: those that make decisions, and those that don't make any decisions at all. Decisions or tests are made based on the dataset's characteristics. It is a visual depiction of all possible solutions to a particular problem/decision. As with a tree, it begins with the root node and grows outwards in a tree-like form, thus the name "decision tree."

2.4 Hyper Pipes

In the context of statistical classification and regression, bootstrap aggregating, often known as bagging.

3. Proposed Method

By monitoring physiological and other indicators, wearable sensors are possible to spot abnormal or unexpected events and conditions. Fig. 1 shows a wearable sensor-based system for tracking human activities, with data sent to and analysed in real time through mobile computing and remote web-based graphical user interface. To build these technologies, we must first gather and evaluate user data. Wi-Fi, Bluetooth, and sensors, such as heart rate monitors, may all provide up-to-date data about human health issues and requirements. This data is saved in the devices' memory. Using this information, the hospital and the patient may interact more effectively.

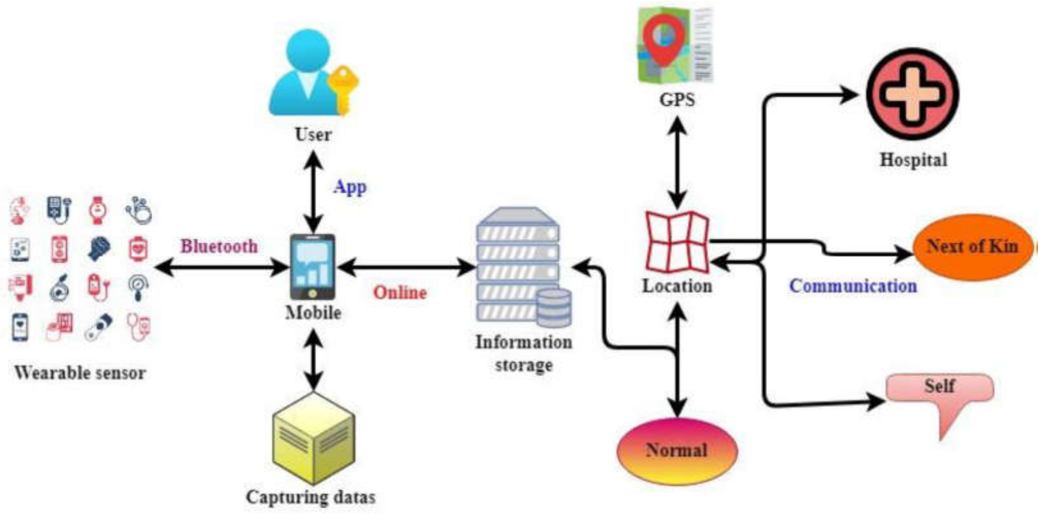

Figure 1: Proposed method for health monitoring by sensor

It is possible to measure and record physical characteristics such as blood pressure, heart rate and skin temperature using sensors, as seen in figure 3.1. When the system gets a command, the Bluetooth and GSM are both initiated and connected to the smart band's Bluetooth terminal. The IR sensor monitors the heart rate of the patient once the patient places their finger between the IR transmitter and an IR sensor.

4. Experimental Analysis and Discussion

A medically exact and validated blood sample is required when using a smart band to determine blood pressure. A pressure cuff that functions as a smart blood pressure cuff. As shown in Table 1, the results of blood pressure measurements made using a smart phone are shown and tabulated.

Table 1: Blood Pressure Generated

Date	Duration	BP
12/24/2024	14.29	150/56
01/09/2025	10.29	162/95
01/09/2025	10.3	146/84
01/09/2025	8.03	117/70
01/09/2025	10.27	155/90
01/09/2025	10.32	128/77
12/24/2025	14.27	132/70

Data from the Smart band watch, which is employed, should be analyzed in a precise way. In this case, the bingo f0 device is utilized to record the information. A blood pressure monitor, heart rate monitor, and other capabilities on these smart bracelets can help identify health problems before they occur. Allows users to categories their physical attributes into distinct categories. Smart bands have sensors that can detect if a person's health is normal, abnormal, or high-risk. The range which is considered normal is 90≤120. The range which is considered abnormal is 150≤ 170 and the range which is considered high risk is greater than or equal to 190. Various datasets from different parts of the users' bodies are collected through sensory data. There are 11 characteristics in the sensor datasets that are considered critical for forecasting the severity obtained from Kaggle dataset as depicted in table 2.

Table 2: Feature for Classification

Type	Number	Description
Data Instances	1423	Patient data is collected over a period of two months.
Class Variable	3	Class 1: Normal Level Class 2: Abnormal Level Class 3: High Risk Level
Attributes (various sensors)	4	3 Axis accelerometer, Altimeter, oxymeter sensor, bioimpedence sensor
Evaluation Metrices	5	Correctly classified instances, incorrectly classified instances
Machine Leaning Algorithms	4	Random forest, bagging, decision tree and hyper pipes

The figure 2 depicts a comparison of four separate classifiers using evaluation metrics, including Correctly Classified Instances, wrongly Classified Instances, Relative absolute error, Root relative squared error, with x-axis and y-axis data plotted for each metric. All four parameters were evaluated and the random forest method came on top.

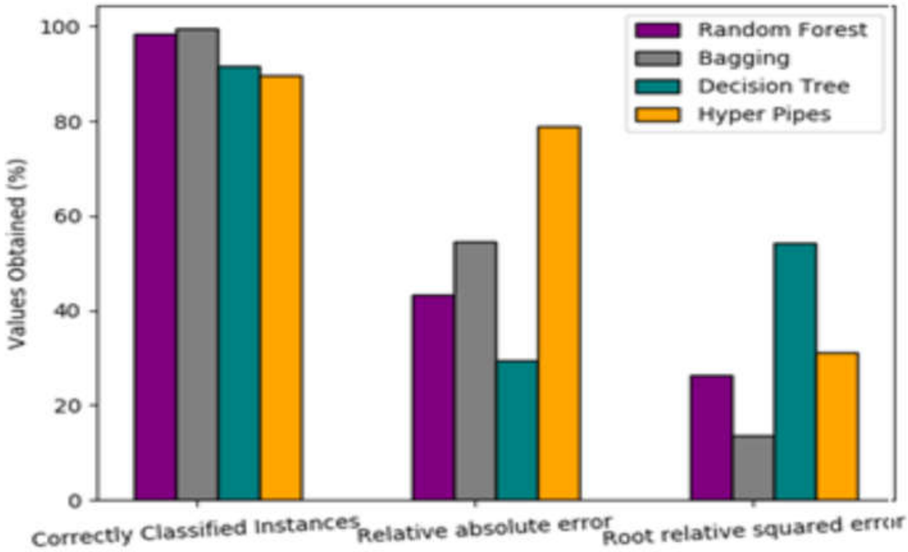

Figure 2: Comparison of Classifier Output

The performance of four classifiers applied to three classes is presented after adjusting the sensors, including the 3 Axis Accelerometer, Altimeter, oxymeter sensor, and bioimpedence sensor. The results indicate that the random forest method outperforms the other three classifiers across all three categories. Figure 3 depicts the relationship between false positive and true positive rates, with the former being shown on the x-axis and the latter on the y-axis respectively.

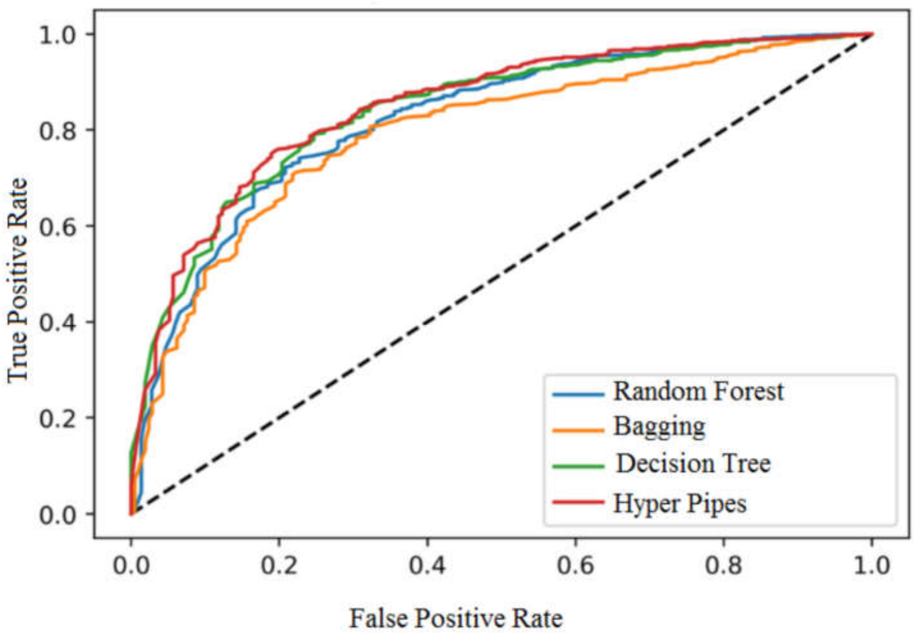

Figure 3: Comparison of Accuracy Levels

5. Conclusion

Given its versatility and ability to handle even the most complicated issues, the Random Forest algorithm consistently outperforms other categorization methods related to performance and accuracy. To accomplish, avoid over fitting and produce easy-to-set parameters, the programme uses a supervised learning algorithm technique that uses a large number of decision trees. By utilizing an approach like this, the Random Forest is able to accurately and effectively learn the whole training dataset. The Random Forest method was chosen because it may be modified during training to incorporate more data. Classification of a large number of fresh datasets may be done much more quickly with this method. According to our significant study, Random Forest performs better than other categories since it provides more accurate results. All the existing methods are compared with the proposed method. The comparison between the results are Random Forest 98% , Bagging 96%, Decision Tree 95% and Hyper Pipes 93% proves Random Forest as the effective method.

References

[1] Toorani M, "Mobile Health Technology Evaluation", *Published by Elsevier Inc.on behalf of American Journal of Preventive Medicine*, 2013.

[2] Suranga Seneviratne, Yining Hu, Tham Nguyen, Guohao Lan, Sara Khalifa, "A Survey of Wearable Devices and Challenges", *IEEE Communications Surveys & Tutorials,* vol.19, no.4, 2017.

[3] Jonas Tanai, Maria Forssi, Thomas Hellstén, "The use of wearables in healthcare – challenges and opportunities", *Arcada Working Papers*, 2017.

[4] Iván García-Magariño, Dilip Sarkar and Raquel Lacuesta, "Wearable Technology and Mobile Applications for Healthcare", *Mobile Information Systems*, 2019.

[5] Priyanka Kakria N. K. Tripathi and Peerapong Kitipawang, "A Real-Time Health Monitoring System for Remote Cardiac Patients Using Smartphone and Wearable Sensors", *International Journal of Telemedicine and Applications*, 2015.

[6] Witte A. K and Zarnekow R, “Transforming Personal Healthcare through Technology-A Systematic Literature Review of Wearable Sensors for Medical Application”, *Proceedings of the 52nd Hawaii International Conference on System Sciences*, 2019.

[7] Lisha Yu, Wai Man Chan, Yang Zhao, Lisha Yu, Wai Man Chan, Yang Zhao, “Personalized Health Monitoring System of Elderly Wellness at the Community Level in Hong Kong”, *IEEE Access*, vol.6, pp.35558-35567, 2018.

[8] Movassaghi S, Abolhasan M and Lipman J, “A Review of Routing Protocols in Wireless Body Area Networks”, *Journal of Networks,* vol.8, no.3, pp.559-575, 2013.

[9] MalhiK, Mukhopadhyay S, Schnepper J, Haefke M, Ewald H, “A zigbee-based wearable physiological parameters monitoring system”, *IEEE Sensors*, vol.12, no.3, pp.423-430, 2012.

[10] Nahed Jalloulm, “Wearable sensors for the monitoring of movement disorders”, *Biomedical Journal*, vol. 41, no. 4, pp. 249-253, 2018.

[11] Tuba Yilmaz, Robert Foster, Yang Hao, “Detecting Vital Signs with Wearable Wireless Sensors”, *Sensors*, vol.10, no.12, pp.10837-10862, 2010.

[12] Appelboom G, Camacho E, Abraham M. E, Bruce S. S, Dumont E. L, Zacharia B. E and Connolly E. S, “Smart wearable body sensors for patient self assessment and monitoring”, *Archives of public health*, vol.72, no.1, pp.1-9, 2014.

[13] Bandodkar, Amay J, William JJeang, Roozbeh Ghaffari and John A.Rogers,“Wearable sensors for biochemical sweat analysis”, *Annual Review of Analytical Chemistry*, vol.12,pp.1-22, 2019.

[14] Baldus H, Corroy S, Klabunde K and Schenk T, “Human-centric connectivity enabled by body-coupled communications”, *IEEE Communications Magazine*, pp.172-178, 2009.

[15] Winterhalter C. A, “Development of electronic textiles to support networks, communications, and medical applications in future u.s. military protective clothing systems”, *IEEE Transactions on Information Technology in Biomedicine*, vol.9, no.3, pp.402-406, 2005.

[16] Wegmueller M. S, Kuhn A, Froehlich J, Oberle M, Felber N and Fichtner W, “An attempt to model the human body as a communication channel”, *IEEE Transactions on Biomedical Engineering,* vol.54, no.10, pp.1851-1857, 2007.

[17] Somani N. A and Patel Y, “Zigbee: A low power wireless technology for industrial applications”, *International Journal of Control Theory and Computer Modelling (IJCTCM)*, vol.2, no.3, pp. 27-33, 2012.