An Intelligent Health Surveillance System: Predictive Modeling of Cardiovascular Parameters through Machine Learning Algorithms Using LoRa Communication and Internet of Medical Things (IoMT)

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Abstract

In several nations, the majority of heart attacks lead to fatality prior to patients receiving any kind of medical intervention. The traditional healthcare system is mostly passive, requiring patients to initiate contact with healthcare services independently. People often do not request the treatment if they are unconscious during a heart disease episode. The use of Internet of Medical Things (IoMT) methods offers significant advantages in addressing the issue of caring for patients with cardiac problems. These techniques may transform service delivery into ubiquitous and activate healthcare services. Low-cost remote monitoring systems are essential to implementing a widespread healthcare service. In this article, we proposed a cost-effective Personal Health Care Device(PHCD) based on the Internet of Things (IoT). The PHCD transmits user somatic signals to data acquisition devices using a LoRa (Long-range and low-power) wireless communication network. The received data is uploaded to the cloud using IoT platforms like Adafruit IO. Further, various Machine learning (ML) algorithms, Naïve Bayes, ANN, CNN, and LSTM, were applied to collected data to predict heart rate and SpO_2 behavior. The performance results of different forecast models were compared to identify precise modeling and reliable forecasts to prevent emergency cardiovascular conditions.

Keywords: IoMT, Heart Rate, SpO_2, ANN, LSTM, LoRa.

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1 Introduction

In recent years, there have been numerous advancements in healthcare surveillance systems, which have been developed and proposed with the objective of gathering, processing, and analyzing data obtained from a variety of sensors (Dammak et al., 2022). Additionally, these devices monitor and observe patients' vital signs (Vital Signs). The increasing popularity of IoT has led to the proliferation of billions of interconnected devices that may be used in numerous sectors for daily purposes. By utilizing IoT technology, both industry experts and researchers have developed applications to implement smart environments (Fadda et al., 2022; Bilbao-Jayo et al., 2021; Wang et al., 2021). Remote monitoring of individuals' health and physical circumstances has greatly profited from this technology (Kadhim et al., 2020). Integration of wearable sensors with IoT enabled continuous monitoring of physiological parameters. Specifically, the significance of wearable devices in health care systems is prominent as these devices are capable of early diagnosis of health concerns and allow for the capacity to act before the situation worsens.

Moreover, these wearable devices may dynamically engage with the device's carrier by activating pre-configured warnings. To fully use their capabilities, most wearable devices on the market need connectivity to a primary device, often a smartphone (Sanchez-Iborra 2021). Therefore, the wearable unit's communication and processing abilities are severely limited regarding hardware resources, and it just serves as a data collector device. However, there has been a recent emergence of a new set of solutions in two key areas crucial for advancing wearables. The low-power wide-area network (LPWAN) architecture enables cost-effective connectivity of wearable devices with the cloud across long distances (Qaim et al., 2020). Despite much research on LPWANs in recent years, their application to wearable devices remains relatively unexplored. Conversely, equipping wearable gadgets with artificial intelligence would be very significant since it would enable them to become fully autonomous devices capable of making intelligent judgments based on the data they gather. Habitual use of fitness trackers provides valuable SPO_2 and heart rate information. However, they have lesser accuracy and precision than ECGs (Electrocardiographs) and oximeters (Benedetto et al., 2018). In recent times, Artificial Intelligence (AI) has emerged as a prominent and expanding tool in the field of medicine, proving to be exceptionally beneficial across numerous clinical domains, including disease diagnosis (Mohammed & Askar 2021). This implies that the effectiveness of contemporary medicine can potentially be enhanced by utilizing ML algorithms and their training on vast quantities of data. A plethora of Internet of Things (IoT) health apps and platforms have recently emerged, with the twin goals of automating and expanding access to health services and enabling the safe and efficient interchange of medical data across various stakeholders (Islam et al., 2020; Lousado et al., 2021). Nevertheless, this technical advancement is out of reach for many people living in remote regions and those who cannot afford expensive healthcare gadgets. Given this fact, this study's primary concern is to monitor people's vitals, especially their heart rate and blood oxygen saturation levels, to detect cardiovascular risk early.Numerous reasons cause physiological time series to be nonlinear and nonstationary. Consequently, Heartrate and SpO_2 time series are frequently considered challenging to forecast and manage. Therefore, an accurate forecast of vital health metrics is essential for preventing and managing certain cardiac conditions (Luo and Wu 2020; Bolhasani et al., 2021). It is evident that, the combination of health monitoring through IoT and ML has the potential to bring about a significant transformation in the healthcare industry (Shumba et al., 2022). This is achieved by enabling continuous monitoring of physiological signals and offering personalized feedback to the user. Future developments in wearable sensor technology will enhance healthcare systems' precision and effectiveness (Ayoub et al., 2018; Alugubelli et al., 2022).

2 Related Work

In recent years Wearable device-based Internet of Things (IoT) healthcare sector systems have been the subject of several architectural proposals. Ahamed et al. (2022) the authors established a universal framework that integrates IoT-enabled wearable devices with ML and Cloud Computing methodologies to forecast cardiac disease. Within this architectural framework, wearable devices communicate data directly to a Cloud platform that encompasses data storage, processing, and visualization. This platform may be accessed by patients or medical professionals from any location. Additional works by (Addante et al., 2019) also belong to this category in which, A system was developed that includes a wearable device worn on the forearm. This device uses a mix of accelerometers and gyroscopes to monitor movement, and EMG sensors to gather muscle mass information.In addition, BLE was used to transmit data between the measuring device and a mobile device that served as a host for an application. Another study by (Abdali-Mohammadi et al., 2020) utilized Cloud infrastructure for the diagnosis and monitoring of chronic illnesses, with a specific emphasis on diabetes. This framework enables all types of data processing to be conducted on the Cloud.In their work,the researchers used a blend of wearable and implanted sensors to gather physiological data from patients. This data was then transferred to the Cloud using 3G/4G communication technology. The implemented system incorporates the capability to detect crises and promptly inform surrounding hospitals, enabling the provision of emergency medical assistance. Within the healthcare system, the conventional means of obtaining data include Bluetooth, Internet, and Wi-Fi. Bluetooth technology has a limited range drawback while offering the benefit of reduced power consumption (Shen et al., 2008). Utilizing Wi-Fi or Internet connectivity on a smartphone allows data acquisition without being restricted by distance. However, this method necessitates consumes a substantial amount of battery (Su et al., 2014). Currently, Internet of Medical Things (IoMT), using LoRa communication networks is a rapidly developing technology (Ahmed et al., 2018). Even in challenging environments, LoRa communication technology allows for long-distance, low-power transmissionsIt works reliably even in challenging conditions, allowing for communication up to 15 km in countryside or 7 km in metropolitan areas (Workgroup). Additionally the use of Internet of Things (IoT) and Machine Learning (ML) in personal health care devices has garnered significant interest in recent years. Nnumerous researchers have applied ML algorithms to forecast physiological parameters (Thakur and Han 2021; Gupta et al., 2023; Shuzan et al., 2023; Saeed et al., 2011; Reddy et al., 2024) developed a handheld SpO_2 blood oxygen saturation monitor and analyzed essential design factors in relation to typical uses. The fact that the system's root-mean-square error for the SpO_2 estimate was just 1.8 demonstrates good functioning, according to the experimental data. An additional noteworthy investigation employing a photo plethysmography-based methodology has been put forth by (Reiss et al. 2019). This study initially introduces a non-contact approach to quantify respiratory rate precisely and subsequently constructs machine learning models to forecast its outcomes. In another study (Christini et al., 1995) compared the performance of nonlinear and bilinear models with linear autoregressive (A.R.) and linear autoregressive-moving average (ARMA) models in fitting heart rate data and analyzed heart rate dynamics.A cardiac sensor and an Arduino board were used by E. Moghadas et al. to track and categorize people's health in relation to cardiac illness. The K-Nearest Neighbor (k-NN) method was used for validation and classification in this study (Moghadas et al., 2020). In conclusion, IoT and WSN IoT & WSN enable the potential for intelligent monitoring and management system contributing to the development of more streamlined and cost-effective Health Care Services.

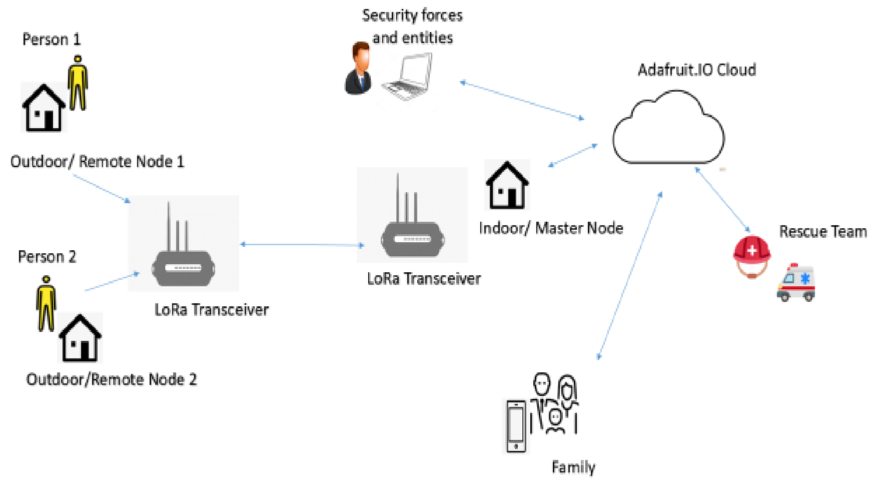


Figure 1: Conceptual scheme of proposed work

Research Gap and Major Contributions of the Work

Limited researchers explored the implementation of LoRa technology to develop low-cost wearable devices integrated into IoT and ML. Additionally, there is limited literature on ML implementation to model and simultaneously predict Heart rate and SpO_2. Moreover, existing ML models were developed on publicly available data sets and not on data from edge nodes. The present study aims to develop a cost-effective Personal Health Care Device (PHCD) and implement various ML algorithms on data acquired from sensor nodes.

3 Materials and Methods

Framework Overview

The methods and materials presented in this paper may be used in any circumstance where it is crucial to create a low-cost wearable device that results in an accurate forecasting model for time-series data. The conceptual Scheme of the proposed work is shown in Figure 1. The proposed system enables the utilization of readily available wristbands to monitor individuals' vitals. The collected data is then transmitted to a server via the LoRa network. The acquired data from outdoor or remote nodes may be used to assess personal risk. Upon receiving the individual physiological information, the indoor or master node transmits data to the cloud. The system includes a web application for data administration and an interactive dashboard for administrators to monitor the system alerts. Multiple modules comprise the application suite that supports the system for remote health monitoring, prediction, and alerting.

An inventory of the materials and apparatus was conducted to evaluate the model. Subsequently, an operational LoRa Gateway was implemented. Ultimately, a prototype was constructed, serving as a LoRa node, consisting of many equipment and sensors. The LoRa gateway components are:

- ESP32 Microcontroller IC
- LoRa 868/915 MHZ LoRa Module
- MAX30102 heartrate and pulse oximeter sensor
- MPU 6050 sensor
- Internet Connection (3G/4G/ Wi-Fi)

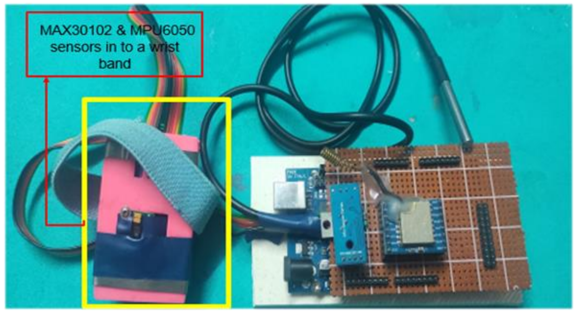


Figure 2: Low-cost personal health care device

Data Acquisition and Transmission

The research was carried out in adherence to India's ethical principles and regulatory frameworks. Each participant was furnished with comprehensive information regarding the initial study and its objectives and subsequently gave their written consent to partake. The proposed PHCD wearable device in Figure 2. was provided to the participants for the experiment. Users are then asked to wear the wristband for about 30 seconds to measure their Heart rate and oxygen saturation readings. Around 5400 data samples of heartrate and SpO_2 of different age groups were collected. The collected data was sent to the indoor master node through the LoRa communication network. Figure 3 shows a real-time prototype implementation where the indoor master node transmits the received sensor data to Adafruit IO, an IoT platform to store and process the data. Further, the free version of the Adafruit IO platform allows data storage for two months. The stored data in the Adafruit IO cloud can be obtained in JSON and CSV file formats.

LoRa Communication Network

Recent years have seen tremendous progress in the IoT ecosystem, with one of the most notable being the emergence of transmission technologies that enable long-distance communications with shallow energy usage Semtech. (LoRa and LoRaWAN). LoRa technology utilizes unlicensed frequency bands 868 to 915 MHz and is distinguished by its minimal power consumption, which is quantified in milliwatts (mW). Consequently, specific battery-operated devices can operate for ten years. The technology group known as LPWAN is now attracting significant interest in Health Care Systems (Stranieri et al., 2022).

Figure 3: Real-time implementation of prototype

Models

The developed prototype was implemented to evaluate the proposed PHCD's functionality. Five research subjects with diverse traits and varying heart rate patterns have been chosen. In contrast to previous studies that utilized commercially available devices such as Fitbit and Apple Watch to gather data, the participants were provided with the proposed PHCD wearable device, which assessed SpO_2 and heart rate. However, it is important to note that due to its design as a single piece, there are limitations to its usage, the participants were instructed to wear the device for a specified duration of time each day. In order to develop precise models, it is not essential to utilize observations collected throughout the entire duration of the study. In particular, the study only looks at data collected over seven days, which adds up to 5400 observations per participant. Subsequently, the gathered data was divided into two sets: a training set and a test set, with a proportion of 80:20. This approach is justifiable considering the huge amount of data and has been shown to be effective in real-world scenarios. People whose lifestyles were mostly the same (but not exactly the same) during the study period were chosen. All analyses were performed using Python Google Colab. Four distinct architectures were evaluated in terms of their ability to forecast heart rate and SpO_2 levels of complexity. A concise overview of the four architectures is provided in the following section, along with a detailed explanation of the reasons behind the modeling decisions.

Naive Bayes

Naive Bayes (N.B.) is a classification strategy that relies on the Bayes Theorem and assumes that the predictors are independent. Simply, a Naive Bayes classifier operates on the assumption that the existence of a specific characteristic in a category is independent of the existence of any other feature (John and Langley 1995). It is very practical and applicable for binary and multi-class categorizations in several realistic scenarios, such as text or document classification, spam filtering, and more (Sarker, 2019. The NB classifier may be used to accurately categorize the instances with noise in the data and create a resilient prediction model.

$$\text{Mathematically } \hat{X}_{t+1} = X_t \tag{1}$$

Where $\hat{X}_{t+1}$ Indicates the estimated value for the next time interval

X_t Indicate the observed value that represents the measurement taken at the current step.

Artificial Neural Networks & Convolution Neural Networks

Artificial Neural Networks consist of artificial components known as neurons. The units are organized in a sequence of layers, forming the whole Artificial Neural Network inside a system (Pedregosa et al., 2011). Artificial Neural Networks typically consist of an input layer, an output layer, and one or more hidden layers (Han et al., 2011). The input layer gets heart rate and SpO_2 data that the neural network must assess and learn from. Subsequently, the data undergoes a series of transformations in one or more concealed levels, resulting in significant information for the output layer (Selvakumar et al., 2023). An improvement on the original ANN architecture is the convolution neural network (CNN) (LeCun et al., 1998). CNN is seen as more potent than traditional ANN due to its larger computing weight ability to recognize essential characteristics automatically, without human interaction (Goodfellow et al., 2016).

An equation that illustrates the connection between the heart rate and SpO_2 inputs $(x_{t-1}, x_{t-2}, \dots \dots, x_{t-p})$ and the outputs (x_t) is,

$$x_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i f\left(\sum_{i=1}^{p} \beta_{ij} x_{t-1} + \beta_{0j}\right) + e_i \tag{2}$$

The weight from the hidden to output nodes is denoted by 'αi', whereas the input to hidden node's weight is denoted by 'βij.' The activation function is represented by $'f'$.

Long Short-Term Memory

Another artificial recurrent neural network (RNN) architecture used in deep learning is long short-term memory (LSTM) (Hochreiter and Schmidhuber 1997). In contrast to more traditional networks, LSTMs excel in learning sequential data, making predictions based on time series data, and performing tasks like classification and processing (Zhu et al., 2022). LSTM equations are denoted below.

$$\left.\begin{aligned}
i_t &= \sigma\,(W_{xi} * X_t + W_{hi} * h_{t-1} + W_{ci} \circ C_{t-1} + b_i) \\
f_t &= \sigma(W_{xf} * X_t + W_{hf} * h_{t-1} + W_{cf} \circ C_{t-1} + b_f) \\
C_t &= f_t \circ C_{t-i} + i_t \circ tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c) \\
O_t &= \sigma(W_{xo} * X_t + W_{ho} * h_{t-1} + W_{co} \circ C_t + b_o) \\
H_t &= o_t \circ tanh(C_t)
\end{aligned}\right\} \tag{3}$$

Where i_t, O_t and f_t denotes the input, output, and forget gates, respectively. C_t is the cell status; h_t is the output vector of the LSTM cell.

X_t is the input vector to the LSTM cell; W_x, W_h, W_c and $b(\cdot)$ are the weight matrices and bias vector parameters to be tuned during the training process; ◦ denotes the element-wise product, and σ is the sigmoid activation function.

Prediction Algorithm

Input:

- Heart rate and SpO_2 data.
- Set of selected models.

Output:

- Performance evaluation of selected models.

Steps:

Step1: Data Preprocessing

Step 2: Model Selection

- Select a Model to train and test the data set Heart rate and SpO_2 of each participant.

Step 3: Training and Testing

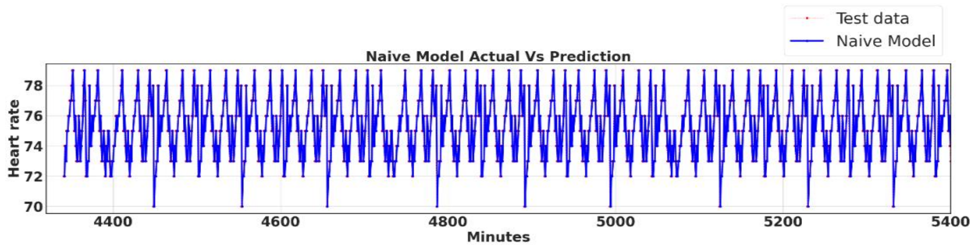
- Train the selected model on a portion of Heart rate and SpO_2 data.
- Test the chosen model on the remaining portion of Heart rate and SpO_2 data.

Step 4: Performance Evaluation of the models

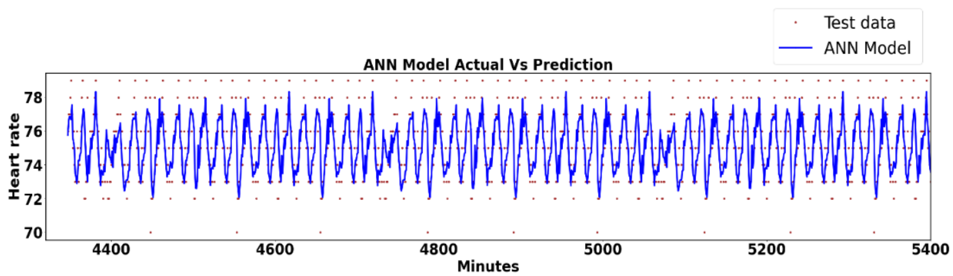
- Compare the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) of the tested models to achieve a model with superior predictive performance.

4 Results and Discussion

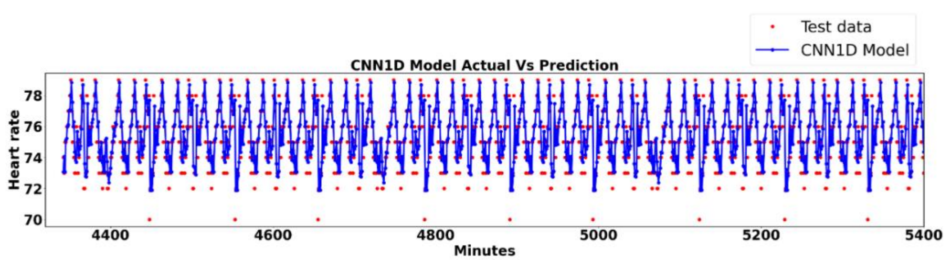
This section provides an overview of the performance of various machine learning algorithms (Ferreira et al., 2021). Here, a set of selected models are trained and evaluated. The model exhibiting the highest performance is subsequently chosen under the procedures described in the prediction Algorithm based on equations (1), (2) and (3). We used five performance metrics: MAE, RMSE, MSE, and MASE. Table 1 displays the performance metrics comparison across all four models. All four models were applied to the test data of Participant 1 to provide a heart rate forecast, as shown in Figure 4.



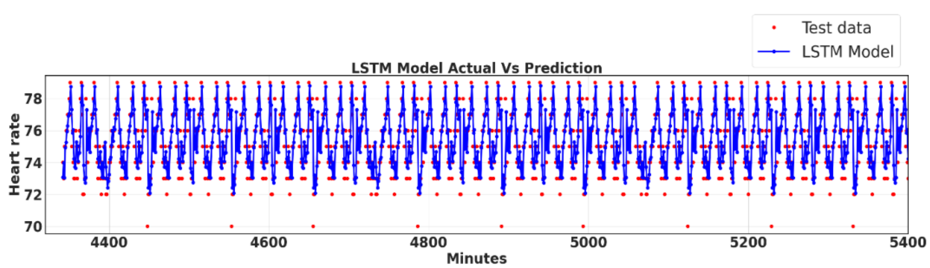
4(a) Naive Bayes



4(b) ANN



4(c) CNN1D



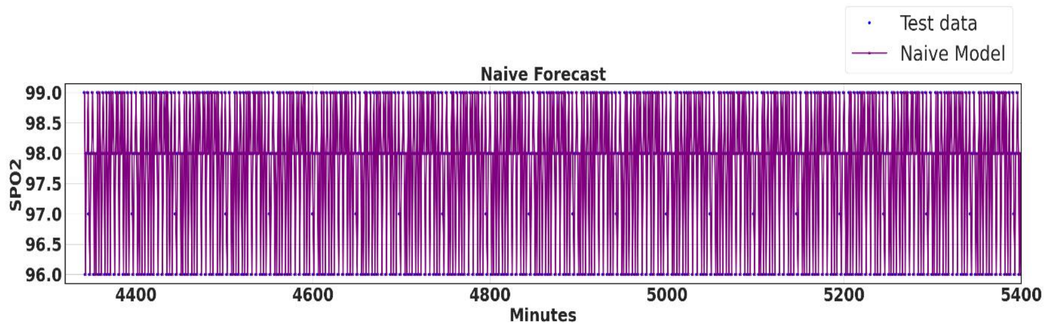
4(d) LSTM

Figure 4: Actual Vs. Predicted heart rate for various models a) Naïve Bayes b) ANN c) CNN1D d) LSTM of Participant 1

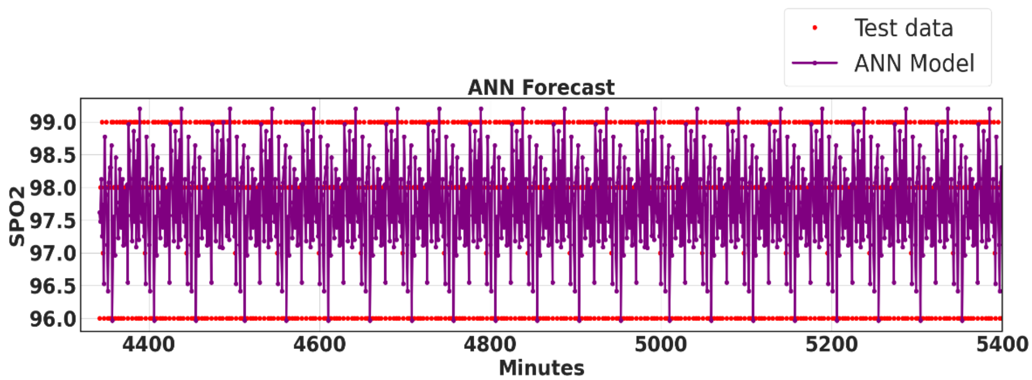
Table 1: Heart rate (in minutes) Comparison of Performance Metrics of Models for Various Participants

Heart Rate	Models	MAE	MSE	RMSE	MAPE	MASE
Participant 1	**Naive Model**	1.3457	3.2456	1.8016	1.7936	1.0025
	Conv1D	1.0497	2.1829	1.4775	1.4012	0.7827
	ANN	**0.9986**	**2.1288**	**1.4591**	**1.3283**	**0.7446**
	LSTM	1.0773	2.3200	1.5231	1.4357	0.8033
Participant 2	**Naive Model**	2.4940	12.9926	3.6045	3.1513	1.0028
	Conv1D	2.0203	8.7106	2.9514	2.5856	0.8171
	ANN	**2.0078**	**8.8096**	**2.9681**	**2.5744**	**0.8121**
	LSTM	2.0776	9.0784	3.0130	2.6631	0.8403
Participant 3	**Naive Model**	1.1501	1.7006	1.3041	1.8291	0.9999
	Conv1D	0.7648	1.0577	1.0284	1.2121	0.6645
	ANN	**0.6792**	**0.8688**	**0.9321**	**1.0763**	**0.5901**
	LSTM	0.8031	1.1535	1.0740	1.2772	0.6977
Participant 4	**Naive Model**	1.7646	3.8721	1.9678	3.2529	1.0006
	Conv1D	0.8812	1.4172	1.1904	1.6437	0.4997
	ANN	**0.8000**	**1.3196**	**1.1488**	**1.4917**	**0.4537**
	LSTM	0.9446	1.5234	1.2342	1.7566	0.5357
Participant 5	**Naive Model**	4.7062	28.3281	5.3224	7.8521	0.9999
	Conv1D	1.9045	6.8314	2.6137	3.1775	0.4053
	ANN	**1.7217**	**6.0446**	**2.4586**	**2.8669**	**0.3664**
	LSTM	1.6285	5.8931	2.4276	2.7090	0.3466

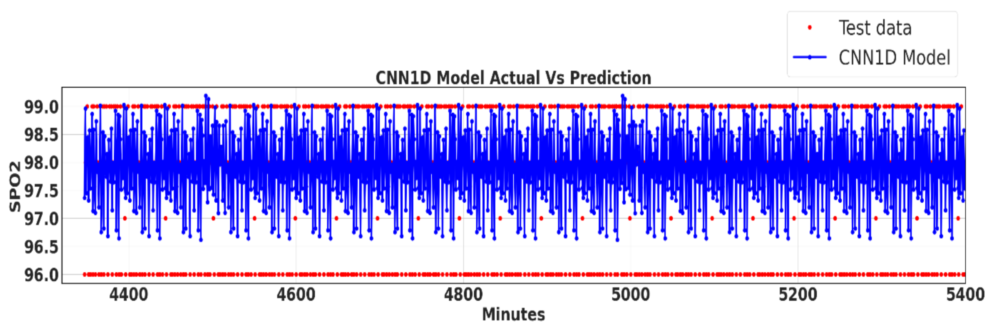
Findings from the simulation study indicate that the ANN model produced a more accurate forecast than the Naïve model, Conv1D model, and LSTM model regarding the heart rate of five participants using cloud data from the LoRa network shown in Table 1. The results showed that the ANN model outperformed the other models, yielding a more precise forecast with lower MAE, MSE, RMSE, MAPE, and MASE values. Due to the stochastic nature of neural networks during training, their results will likely differ with each run. The deep learning algorithm was executed 50 times for each participant as part of the study. Figure 5 shows the SpO_2 forecast generated by all four models on test data for Participant 1.



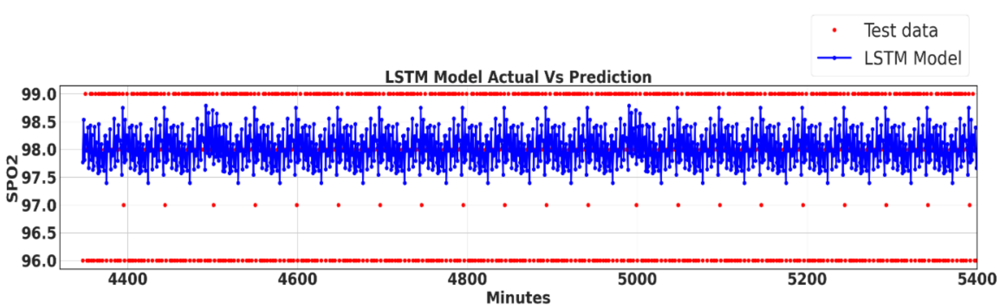
5(a) Naive Bayes



5(b) ANN



5(c) CNN1D



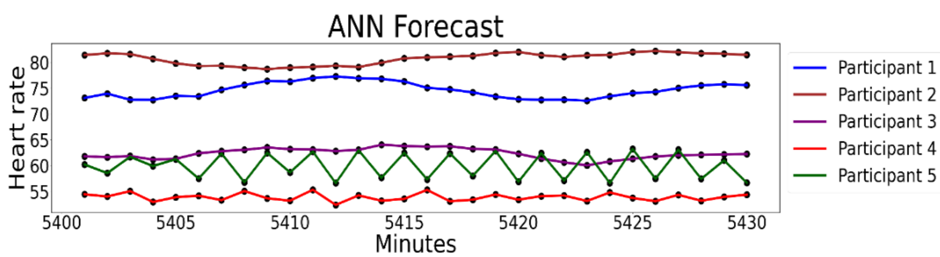
5(d) LSTM

Figure 5: Actual Vs. Predicted SpO_2 various Models a) Naïve Bayes b) ANN c) CNN1D d) LSTM for Participant 1

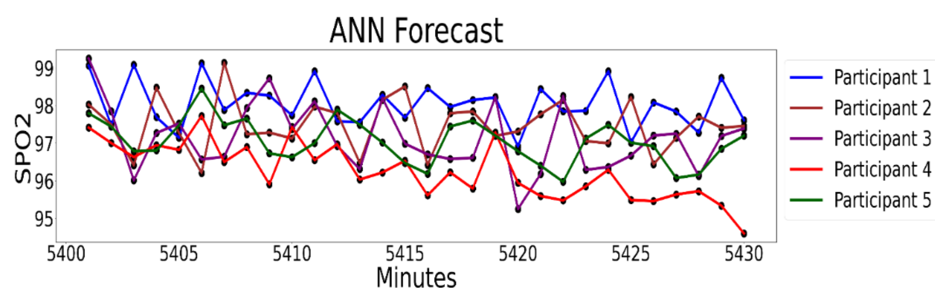
Table 2: SpO_2 (in minutes) Comparison of Performance Metrics of Models for Various Participants

SpO_2	Models	MAE	MSE	RMSE	MAPE	MASE
Participant 1	Naive Model	1.6719	3.4717	1.8633	1.7154	1.0007
	Conv1D	0.6719	0.6518	0.8074	0.6900	0.4019
	ANN	0.6281	0.5796	0.7613	0.6453	0.3757
	LSTM	0.8542	1.2045	1.0975	0.8795	0.5109
Participant 2	Naive Model	1.6432	3.4115	1.8470	1.6873	0.9996
	Conv1D	0.7756	0.8975	0.9473	0.7969	0.4720
	ANN	0.6560	0.6193	0.7870	0.6726	0.3993
	LSTM	0.8216	1.0041	1.0021	0.8456	0.5001
Participant 3	Naive Model	1.1501	1.7006	1.3041	1.8291	0.9999
	Conv1D	0.7648	1.0577	1.0284	1.2121	0.6645
	ANN	0.6792	0.8688	0.9321	1.0763	0.5901
	LSTM	0.8031	1.1535	1.0740	1.2772	0.6977
Participant 4	Naive Model	1.6756	3.4995	1.8707	1.7198	0.9996
	Conv1D	0.7499	0.9649	0.9823	0.7732	0.4470
	ANN	0.6434	0.6775	0.8231	0.6619	0.3835
	LSTM	0.8437	1.1885	1.0902	0.8688	0.5029
Participant 5	Naive Model	1.3281	2.0695	1.4386	1.3716	1.0005
	Conv1D	0.7350	0.9016	0.9495	0.7613	0.5534
	ANN	0.6420	0.5794	0.7612	0.6633	0.4834
	LSTM	0.7190	0.7672	0.8759	0.7434	0.5414

Through a comparison of performance metrics and accurate predictions shown in Table 2, the simulation study's findings demonstrated that the ANN model demonstrated the utmost performance for the SPO_2 data received from the LoRa network. Figure 6 further shows that the ANN plot almost coincides with the reported values for all the participants.



6(a). Heart rate



6(b). SpO_2

Figure 6: Forecasted ANN plots of (a) Heart rate and (b) SpO_2 for all five participants

5 Conclusion

This study introduces a low-cost Personal Health Care Device that utilizes LoRa technology in the context of the IoT. The device continuously analyses the users' physiological parameters, including heart rate and SpO_2 levels. In addition, a prototype has been developed to offer a comprehensive demonstration of the technology. The objective was to identify the best architecture to predict human vitals effectively. The findings obtained suggest that all four designs performed similarly. However, it is worth noting that the predictions generated by the ANN model were statistically considerably superior to those of the other models.

Further, the results were validated in a diverse group of five participants, considering their ages, genders, and lifestyle behaviors. It is worth noting that heart rate and blood oxygen levels are influenced by an individual's inherent traits and lifestyle choices. The results indicate that wearable devices have the potential to employ a simple model to provide valuable information to users, enabling them to monitor abnormalities in their heart rate readings and mitigate the risk of developing diseases. The research was limited by the absence of an evaluation of the predicting models in participants with confirmed cardiac abnormalities despite data from five participants.

References

[1] Abdali-Mohammadi, F., Meqdad, M.N., & Kadry, S. (2020). Development of an IoT-based and cloud-based disease prediction and diagnosis system for healthcare using machine learning algorithms. *IAES International Journal of Artificial Intelligence*, *9*(4), 766–771.

[2] Addante, F., Gaetani, F., Patrono, L., Sancarlo, D., Sergi, I., & Vergari, G. (2019). An innovative AAL system based on IoT technologies for patients with sarcopenia. *Sensors*, *19*(22), 4951. https://doi.org/10.3390/s19224951

[3] Ahamed, J., Manan Koli, A., Ahmad, K., Jamal, A., & Gupta, B.B. (2022). CDPS-IoT: cardiovascular disease prediction system based on IoT using machine learning. *International Journal of Interactive Multimedia and Artificial Intelligence*, *7*, 78–86.

[4] Ahmed, Z.U., Mortuza, M.G., Uddin, M.J., Kabir, M.H., Mahiuddin, M., & Hoque, M.J. (2018). Internet of Things based patient health monitoring system using wearable biomedical device. *In international conference on innovation in engineering and technology (ICIET)*, 1-5.

[5] Alugubelli, N., Abuissa, H., & Roka, A. (2022). Wearable Devices for Remote Monitoring of Heart Rate and Heart Rate Variability—What We Know and What Is Coming. *Sensors*, *22*(22), 8903. https://doi.org/10.3390/s22228903

[6] Ayoub, W., Samhat, A.E., Nouvel, F., Mroue, M., & Prévotet, J.C. (2018). Internet of mobile things: Overview of lorawan, dash7, and nb-iot in lpwans standards and supported mobility. *IEEE Communications Surveys & Tutorials*, *21*(2), 1561-1581.

[7] Benedetto, S., Caldato, C., Bazzan, E., Greenwood, D.C., Pensabene, V., & Actis, P. (2018). Assessment of the Fitbit Charge 2 for monitoring heart rate. *PloS one*, *13*(2), e0192691. https://doi.org/10.1371/journal.pone.0192691

[8] Bilbao-Jayo, A., Almeida, A., Sergi, I., Montanaro, T., Fasano, L., Emaldi, M., & Patrono, L. (2021). Behavior modeling for a beacon-based indoor location system. *Sensors*, *21*(14), 4839. https://doi.org/10.3390/s21144839

[9] Bolhasani, H., Mohseni, M., & Rahmani, A.M. (2021). Deep learning applications for IoT in health care: A systematic review. *Informatics in Medicine Unlocked*, *23*, 100550. https://doi.org/10.1016/j.imu.2021.100550

[10] Christini, D.J., Bennett, F.H., Lutchen, K.R., Ahmed, H.M., Hausdorff, J.M., & Oriol, N. (1995). Application of linear and nonlinear time series modeling to heart rate dynamics analysis. *IEEE transactions on Biomedical Engineering*, *42*(4), 411-415.

[11] Dammak, B., Turki, M., Cheikhrouhou, S., Baklouti, M., Mars, R., & Dhahbi, A. (2022). Lorachaincare: An iot architecture integrating blockchain and lora network for personal health care data monitoring. *Sensors*, *22*(4), 1497. https://doi.org/10.3390/s22041497

[12] Fadda, E., Perboli, G., Rosano, M., Mascolo, J.E., & Masera, D. (2022). A decision support system for supporting strategic production allocation in the automotive industry. *Sustainability*, *14*(4), 2408. https://doi.org/10.3390/su14042408

[13] Ferreira, A.P., Gupta, C., Inácio, P.R., & Freire, M.M. (2021). Behaviour-based Malware Detection in Mobile Android Platforms Using Machine Learning Algorithms. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA)*, *12*(4), 62-88.

[14] Ghazal, S., Sauthier, M., Brossier, D., Bouachir, W., Jouvet, P. A., & Noumeir, R. (2019). Using machine learning models to predict oxygen saturation following ventilator support adjustment in critically ill children: A single center pilot study. *PloS one*, *14*(2), e0198921. https://doi.org/10.1371/journal.pone.0198921

[15] Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). *Deep learning.* Cambridge: MIT Press.

[16] Gupta, P., Chouhan, A.V., Wajeed, M.A., Tiwari, S., Bist, A.S., & Puri, S.C. (2023). Prediction of health monitoring with deep learning using edge computing. *Measurement: Sensors*, *25*, 100604. https://doi.org/10.1016/j.measen.2022.100604

[17] Han, J., Pei, J., & Kamber, M. (2011). *Data mining: concepts and techniques*. Amsterdam: Elsevier.

[18] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, *9*(8), 1735-1780.

[19] Islam, M.M., Rahaman, A., & Islam, M.R. (2020). Development of smart healthcare monitoring system in IoT environment. *SN computer science*, *1*, 1-11.

[20] John, G.H., & Langley, P. (1995). Estimating continuous distributions in Bayesian classifers. *In: Proceedings of the Eleventh conference on Uncertainty in artifcial intelligence*, 338–345.

[21] Kadhim, K.T., Alsahlany, A.M., Wadi, S.M., & Kadhum, H.T. (2020). An overview of patient's health status monitoring system based on internet of things (IoT). *Wireless Personal Communications*, *114*(3), 2235-2262.

[22] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, *86*(11), 2278-2324.

[23] Lousado, J.P., Pires, I.M., Zdravevski, E., & Antunes, S. (2021). Monitoring the health and residence conditions of elderly people, using lora and the things network. *Electronics*, *10*(14), 1729. https://doi.org/10.3390/electronics10141729

[24] Luo, M., & Wu, K. (2020). Heart rate prediction model based on neural network. In *IOP Conference Series: Materials Science and Engineering*, *715*(1), 012060. https://doi.org/10.1088/1757-899X/715/1/012060

[25] Moghadas, E., Rezazadeh, J., & Farahbakhsh, R. (2020). An IoT patient monitoring based on fog computing and data mining: Cardiac arrhythmia usecase. *Internet of Things*, *11*, 100251. https://doi.org/10.1016/J.IOT.2020.100251.

[26] Mohammed, C.M., & Askar, S. (2021). Machine learning for IoT healthcare applications: a review. *International Journal of Science and Business*, *5*(3), 42-51.

[27] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., & Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. *The Journal of machine Learning research*, *12*, 2825-2830.

[28] Qaim, W.B., Ometov, A., Molinaro, A., Lener, I., Campolo, C., Lohan, E.S., & Nurmi, J. (2020). Towards energy efficiency in the internet of wearable things: A systematic review. *IEEE Access*, *8*, 175412-175435.

[29] Reddy, I.S., Lavanya, P., & Selvakumar, V. (2024). Machine learning classifiers for fall detection leveraging LoRa communication network. *International Journal of Reconfigurable and Embedded Systems (IJRES)*, *13*(1), 76-84.

[30] Reiss, A., Indlekofer, I., Schmidt, P., & Van Laerhoven, K. (2019). Deep PPG: Large-scale heart rate estimation with convolutional neural networks. *Sensors*, *19*(14), 3079. https://doi.org/10.3390/s19143079

[31] Saeed, M., Villarroel, M., Reisner, A.T., Clifford, G., Lehman, L.W., Moody, G., & Mark, R.G. (2011). Multiparameter Intelligent Monitoring in Intensive Care II (MIMIC-II): a public-access intensive care unit database. *Critical care medicine*, *39*(5), 952-960.

[32] Sanchez-Iborra, R. (2021). Lpwan and embedded machine learning as enablers for the next generation of wearable devices. *Sensors*, *21*(15), 5218. https://doi.org/10.3390/s21155218

[33] Sarker, I.H. (2019). A machine learning based robust prediction model for real-life mobile phone data. *Internet of Things*, *5*, 180-193.

[34] Selvakumar, V., Achanta, A., & Sreeram, N. (2023). Machine Learning based Chronic Disease (Heart Attack) Prediction. *In International Conference on Innovative Data Communication Technologies and Application (ICIDCA)*, 1-6.

[35] Semtech. LoRa and LoRaWAN: A Technical Overview, 2019. https://lora-developers.semtech.com/uploads/documents/files/LoRa_and_LoRaWAN-A_Tech_Overview-Downloadable.pdf

[36] Shen, X., Cheng, W., & Lu, M. (2008). Wireless sensor networks for resources tracking at building construction sites. *Tsinghua Science and Technology*, *13*(S1), 78-83.

[37] Shumba, A.T., Montanaro, T., Sergi, I., Fachechi, L., De Vittorio, M., & Patrono, L. (2022). Leveraging IOT-aware technologies and AI techniques for real-time critical healthcare applications. *Sensors*, *22*(19), 7675. https://doi.org/10.3390/s22197675

[38] Shuzan, M.N.I., Chowdhury, M.H., Chowdhury, M.E., Murugappan, M., Hoque Bhuiyan, E., Arslane Ayari, M., & Khandakar, A. (2023). Machine learning-based respiration rate and blood oxygen saturation estimation using photoplethysmogram signals. *Bioengineering*, *10*(2), 167. https://doi.org/10.3390/bioengineering10020167

[39] Stranieri, A., Venkatraman, S., Minicz, J., Zarnegar, A., Firmin, S., Balasubramanian, V., & Jelinek, H.F. (2022). Emerging point of care devices and artificial intelligence: Prospects and challenges for public health. *Smart Health*, *24*, 100279. https://doi.org/10.1016/j.smhl.2022.100279.

[40] Su, X., Tong, H., & Ji, P. (2014). Activity recognition with smartphone sensors. *Tsinghua science and technology*, *19*(3), 235-249.

[41] Thakur, N., & Han, C.Y. (2021). A study of fall detection in assisted living: Identifying and improving the optimal machine learning method. *Journal of sensor and actuator networks*, *10*(3), 39. https://doi.org/10.3390/jsan10030039

[42] Vital Signs. https://my.clevelandclinic.org/health/articles/10881-vital-signs

[43] Wang, Y., Yang, B., Hua, Z., Zhang, J., Guo, P., Hao, D., & Huang, J. (2021). Recent advancements in flexible and wearable sensors for biomedical and healthcare applications. *Journal of Physics D: Applied Physics*, *55*(13), 134001. https://doi.org/10.1088/1361-6463/ac3c73

[44] Workgroup, T.M. A Technical Overview of LoRa®and LoRaWAN TM What Is It?. https://www.tuv.com/content-media-files/master-content/services/products/1555-tuv-rheinland-lora-alliance-certification/tuv-rheinland-lora-alliance-certification-overview-lora-and-lorawan-en.pdf

[45] Zhu, Y., Al-Ahmed, S.A., Shakir, M.Z., & Olszewska, J.I. (2022). LSTM-based IoT-enabled CO_2 steady-state forecasting for indoor air quality monitoring. *Electronics*, *12*(1), 107. https://doi.org/10.3390/electronics12010107.

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