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Leveraging IoT with LoRa and AI for predictive healthcare analytics

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ABSTRACT

Progress in mobile technology, the internet, cloud computing, digital platforms, and social media has substantially facilitated interpersonal connections following the COVID-19 pandemic. As individuals increasingly prioritise health, there is an escalating desire for novel methods to assess health and well-being. This study presents an internet of things (IoT)-based system for remote monitoring utilizing a long range (LoRa), a low-cost and LoRa wireless network for the early identification of health issues in home healthcare environments. The project has three primary components: transmitter, receiver, and alarm systems. The transmission segment captures data via sensors and transmits it to the reception segment, which then uploads it to the cloud. Additionally, machine learning (ML) methods, including convolutional neural networks (CNN), artificial neural networks (ANN), Naïve Bayes (NB), and long short-term memory (LSTM), were utilized on the acquired data to forecast heart rate, blood oxygen levels, body temperature patterns. The forecasting models are trained and evaluated using data from various health parameters from five diverse persons to ascertain the architecture that exhibits optimal performance in modeling and predicting dynamics of different medical parameters. The models' accuracy was assessed using mean absolute error (MAE) and root mean square error (RMSE) measures. Although the models performed similarly, the ANN model outperformed them in all conditions.

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1. INTRODUCTION

Advancements in healthcare surveillance systems aim to acquire and analyze data from various sensors in recent years [1]. Furthermore, these gadgets monitor and assess patients' vital signs. The rising popularity of internet of things (IoT) has resulted in the proliferation of billions of interconnected devices utilized across several sectors for everyday applications. Industry leaders and researchers have created applications utilizing IoT technology to create smart environments [2]. The behavior of heart rate and blood oxygen temperature and other human vital parameters is associated with various underlying conditions and pathologies, including the risk of cardiovascular, respiratory diseases, anxiety, and depression [3]. Integrating IoT and deep learning technology has transformed medical systems in residential settings by facilitating remote health monitoring and early identification of health concerns. The implementation of IoT technology enables the acquisition of extensive physiological data, including blood oxygen levels, heart rate, and body temperature, via wearable devices or sensors. The gathered data is sent to a distant server for processing, utilizing deep learning techniques to identify patterns suggestive of diverse health concerns [4]. Over the past decade, there has been a significant increase in the accessibility and utilization of wristband-style wearable devices, particularly Fitbit and Apple Watch, with the market anticipated to expand further [5]. A multitude of remote patient monitoring, intelligent healthcare monitoring applications, and smart healthcare systems, predominantly founded on machine learning (ML), have been established. In recent years, artificial intelligence (AI) has gained prominence in the medical field, especially in illness detection and precision medicine [6]. Certain models have attained diagnosis accuracy equivalent to that of seasoned clinicians. The literature has extensively examined IoT Integration with AI for health monitoring in remote areas [7], [8]. In recent years, remote health monitoring, low-cost personal healthcare devices, and non-invasive methods of disease diagnosis have surfaced as viable tools for enhancing patient care and diminishing healthcare expenditures [9], [10] compared to conventional healthcare systems. IoT-enabled remote health monitoring and wearable smart healthcare devices offer several benefits [11]. Specifically, the low-power wide-area network (LPWAN) design enables the economical connection of wearable devices to the cloud across extensive distances [12].

Advancements in AI enable the analysis and interpretation of available data to formulate hypotheses and extract significant insights for early detection and tailored therapy for individual patients [13]. This project details the design and execution of an IoT-based patient monitoring system utilizing long range (LoRa) communication technology. This complete system facilitates fall detection and quantifies, exhibits, and sends essential health metrics, including heart rate and blood oxygen saturation levels body temperature, and electrocardiogram (ECG). The successful implementation and testing of this system illustrate its efficacy in real-time patient monitoring. By employing LoRa technology and IoT platforms, such as Adafruit IO, the solution guarantees that real-time health data is easily available to caretakers, hence improving patient care and facilitating prompt action when required [14]. The methodology and models presented in this study can be applied to various situations where the development of an accurate forecasting model for time-series data is essential. This work contributes to the rapidly growing body of literature that uses ML techniques in healthcare predictions [15]. For instance, the risk of illness initiation, including cardiovascular conditions, arrhythmia prevention, detection of heart disorders, or assessment of mortality risk in individuals who have a heart attack in the preceding year [16]. LoRa, a low-power wide area network (LPWAN), is favored in healthcare research because of its cost-effectiveness, energy efficiency, and extensive range capabilities [17]. Deploying IoT solutions utilizing LoRa-based sensors and gateways facilitates ongoing surveillance of high-risk patients or vital systems, guaranteeing that health and medical safety are prioritized without any lapses [18], [19].

Researchers have only partly explored the use of LoRa technology to build low-cost wearable devices with integrated IoT and ML [20], [21]. The use of ML to simultaneously model and predict heart rate, SpO2, temperature, body resistance, and many other vital parameter levels is underexplored. Also, from the literature, it is evident that preexisting ML models were built using publicly available datasets, not data from edge nodes. In order to build a healthcare system that is both efficient and inexpensive. The present study applies many ML algorithms to data acquired from sensor nodes.

2. MATERIALS AND PROPOSED DESIGN

2.1. Sensors and IoT devices

The health monitoring system utilizing IoT and LoRa is comprised of two unique components: the transmitter, which facilitates both IoT and LoRa connection, and the receiver, which exclusively supports LoRa communication. The design emulated a patient monitoring system, wherein the transmitter would assess the patient's vital parameters, upload the readings to an online Adafruit platform, and transmit the data to the doctor's monitoring channel via LoRa communication technology. Emergency notifications are transmitted uniformly to the recipient. Included materials are a microcontroller ESP 32, a power supply module, a MAX30100 pulse oxygen sensor, an MPU6050 accelerometer, a body temperature sensor, and a LoRa WAN radio module allows for long-range communication. Figure 1 represents a framework overview where the proposed work is prototyped and implemented in real-time.

2.2. Framework overview

Upon powering up, the transmitter circuit immediately establishes an internet connection; in the presence of Wi-Fi, it begins to collect data from the sensors and transmits it to both the LCD and the Adafruit cloud platform. Following the sensor reading, it verifies if the LoRa transmitter is linked to the receiver circuit; if not, it continues to attempt reconnection in the event that Wi-Fi is unavailable. After establishing a LoRa connection, the transmitter will transfer data collected by the sensors and display it on the receiver [22]. Upon completion of the data exchange, an alarm is sent to the physician in the event of abnormal readings;

otherwise, the sensor data continues to be shown on the LCD screen. Schematic for the transmitter which is a wearable device which can also be operated as remote node as shown in Figure 2. Where Figures 2(a) and 2(b) represents transmitter and receiver nodes respectively.

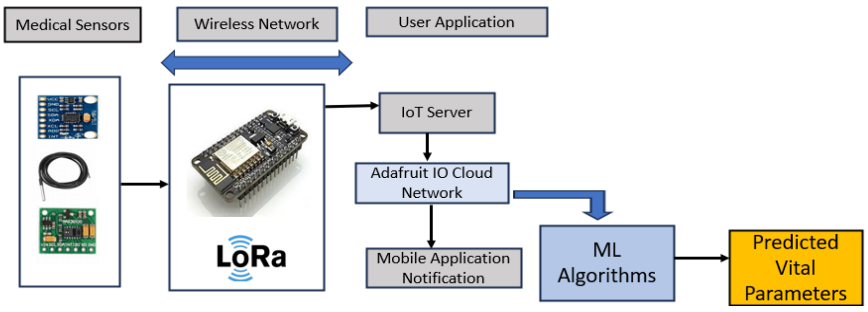

Figure 1. Graphical representation of proposed framework

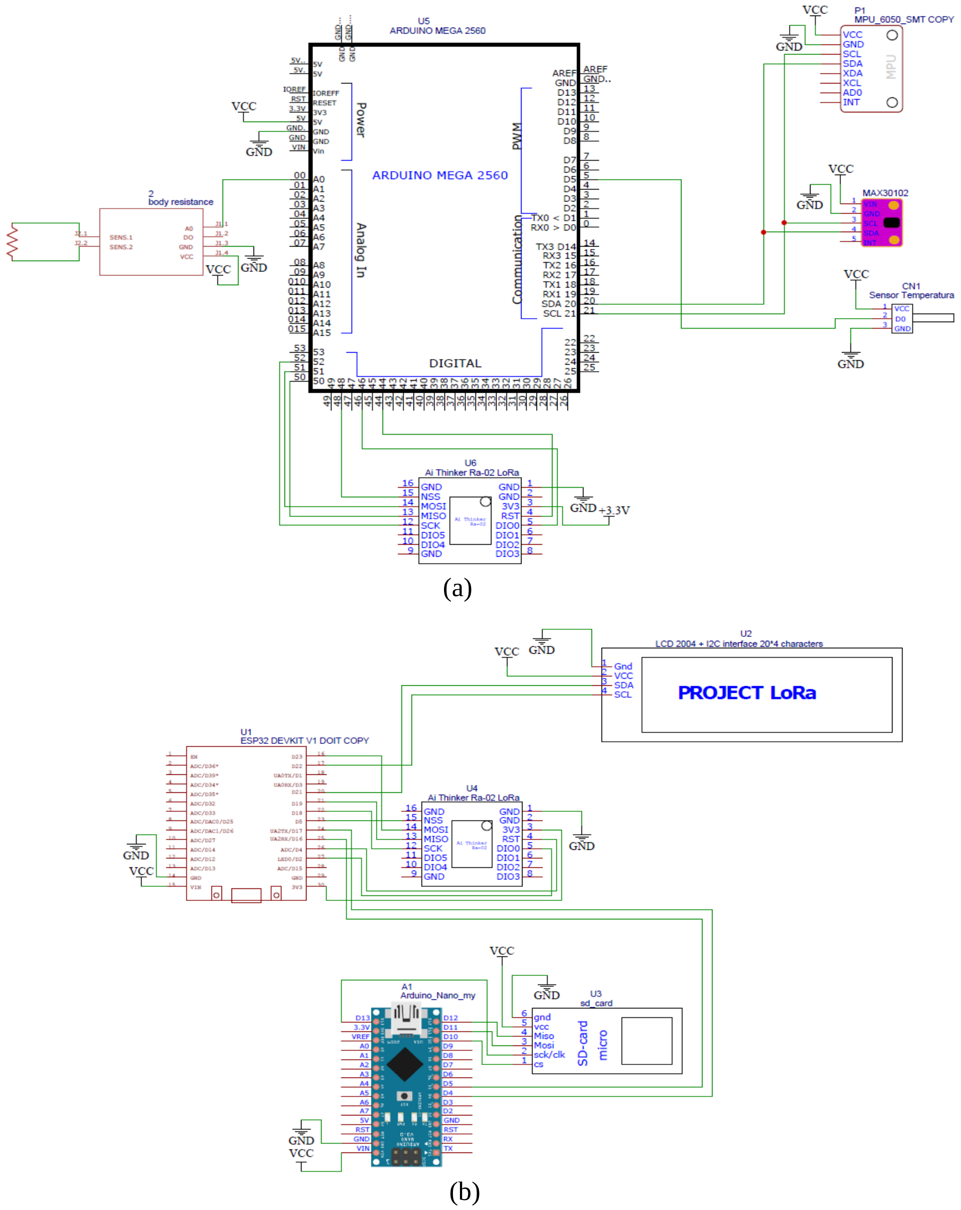

Figure 2. Schematic diagrams for (a) transmitter node and (b) receiver node

2.3. Research participants

The investigation was conducted in accordance with the relevant ethical guidelines and regulations of India. The original study and its objectives were thoroughly explained to all participants, and they subsequently provided written consent to participate. The inconsistency in device usage among participants resulted in gaps in the recorded vital parameters. Utilizing data from the entire research period is not a requirement for developing accurate models. Therefore, the research is limited to data gathered over a period of 7 days, encompassing a total of 1,400 observations for each participant.

3. RESEARCH METHOD

A number of preprocessing processes were carried out before the necessary signals were inputted into the pre-trained deep learning model [23]. The data was then divided 80/20 between a training set and a test set. The complexity of four separate architectures' artificial neural network (ANN), long-short term memory (LSTM), convolutional neural network (CNN), and Naïve Bayes (NB) algorithms was modeled to predict heart rate, body resistance, and SpO2 level. Python, Google Collab, and other tools were used for all data analysis. Table 1 gives a key summary of ML algorithms modeled in current research work.

Table 1. Summary of key ML algorithms

Model	Core concept	Key equations
NB	A probabilistic classifier using Bayes' Theorem assumes feature independence.	$\hat{Y}_{t+1} = Y_t$ Where $\hat{Y}_{t+1}$ indicates the estimated value for the next time interval Y_t Indicate the observed value that represents the measurement taken at the current step.
ANN	ANN consists of layers of artificial neurons that learn through hidden layers of transformations.	$Y_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i f\left(\sum_{i=1}^{p} \beta_{ij} Y_{t-1} + \beta_{0j}\right) + e_i$ Where 'αi'- weight from the hidden to output nodes, 'βij' - the input to the hidden node's Weight, e_i – error terms $'f'$ $represent$ activation function.
CNN	An enhanced ANN architecture that uses convolution layers to detect essential features from the data automatically.	$Y_t = \sigma\left(\sum_{i=1}^{q} W_i \mathrm{X}_i + \mathrm{b}\right)$ Where X_i denote the input features W_i denote the Weight b denotes the bias term σ denote the activation function
LSTM	A type of recurrent neural network (RNN) designed for sequential data and long-term dependencies.	Equations for gates and state: $i_t = \sigma\,(W_{xi} * X_t + W_{hi} * h_{t-1} + W_{ci} \circ C_{\,t-1} + b_i)$ $f_t = \sigma\,(W_{xf} * X_t + W_{hf} * h_{t-1} + W_{cf} \circ C_{t-1} + b_f)$ $C_t = f_t \circ C_{t-i} + i_t \circ tanh\,(W_{xc} * X_t + W_{hc} * h_{t-1} + b_c)$ $O_t = \sigma\,(W_{xo} * X_t + W_{ho} * h_{t-1} + W_{co} \circ C_t + b_o)$ $\mathrm{h}_t = o_t \circ tanh(C_t)$ Where i_t – Input gate; f_t - forget gates; O_t – output gate; C_t - cell status; h_t - output vector of the LSTM cell; X_t – Input vector; b(.) – bias vector; W_h , W_f , W_x - weight matrices; denotes element-wise product; σ – sigmoid activation function.

Table 1 compares NB, ANN, and LSTM ML algorithms. Based on Bayes' Theorem, NB is a simple probabilistic classifier for spam filtering and text categorization assuming feature independence. Artificial neurons in ANN pass data via input, hidden, and output layers to find patterns. CNN can autonomously extract meaningful information, making them useful for image identification. Finally, LSTM is a RNN for sequential data and time-series prediction [24]. Memory cells and gating mechanisms let it manage long-term dependencies, making it ideal for natural language processing and voice recognition [25]. Each model functions differently, from managing independent characteristics to processing complicated, sequential input. Relative accuracy is a statistic used to assess the efficacy of predictive models, specifically in regression analysis. It measures how well a model's anticipated values correspond to the actual observed values in terms of magnitude as in (1). The formula for calculating relative accuracy is:

$$Relative\ Accuracy = \left(1 - \frac{\sum_1^n |Y_i - \overline{Y_l}|}{\sum_1^n |Y_i|}\right) \tag{1}$$

4. RESULTS AND DISCUSSION

This research applied mean absolute error (MAE), root mean square error (RMSE), and relative accuracy to determine the optimal model for predicting human vital parameters. These metrics were computed for the model's overall performance and for each category of heartbeats in the ECG heartbeat categorization dataset. Each participant had their deep learning algorithm run 50 times. The ANN model was determined to have the highest performance; although the models produced very comparable findings, Table 2 illustrates the oxygen saturation, heart rate, and body resistance levels forecasts from the four models applied to a single participant's test set.

From Table 2, the results of the simulation study suggest that the ANN model generated a more precise forecast than the Naïve, Conv1D, and LSTM models in relation to the pulse rate oxygen saturation levels and body resistance of participant. The results indicated that the ANN model outperformed the other models, resulting in a more precise forecast with lower RMSE, and greater accuracy. Figure 3 depicts results obtained from ANN architecture which forecasted the heart rate and SpO2 levels for single participant. This research compared the predictions of four models ANN, CNN, NB, and LSTM for human vital data. Although all four ML models performed equally, the findings show that ANN predictions outperformed the competition by a statistically significant margin.

Table 2. Performance metrics of tested algorithms

Vital parameter	Algorithm name	MAE	RMSE	Accuracy
Heart rate	LSTM	1.0673	1.5321	98.9327
	ANN	**0.9885**	**1.3481**	**99.0115**
	Conv1D	1.0497	1.5775	98.9503
	Naive model	1.2456	1.7015	98.7544
SpO2	LSTM	2.0776	3.013	97.9224
	ANN	**2.0068**	**2.9581**	**97.9932**
	Conv1D	2.0203	2.9714	97.9797
	Naive model	2.594	1.8027	97.406
Body resistance	LSTM	1.6285	1.2342	98.3715
	ANN	**1.6126**	**2.5468**	**98.3874**
	Conv1D	1.9045	2.6137	98.0955
	Naive model	4.7062	4.2324	95.2938

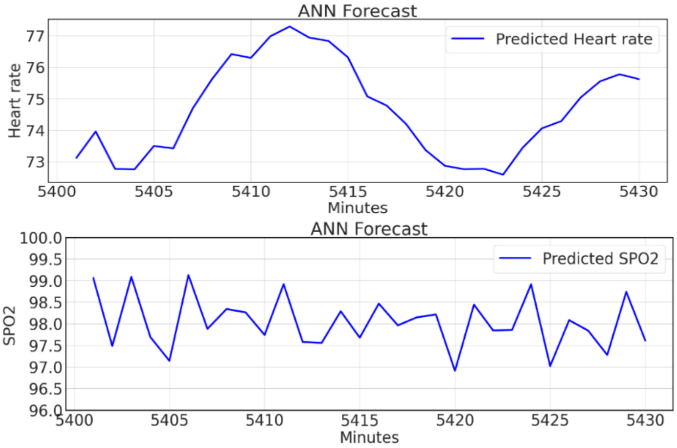

Figure 3. ANN forecasted plot for heart rate and SpO2 for single participant

5. CONCLUSION

Using the IoT and deep learning, our findings conclude with a new paradigm for health monitoring. Based on real-time data obtained from a low-cost device prototyped using LoRa as a communication network, this study has several potential expansions to monitor various health parameters. Further, these models can be utilized to assess the quality of life of employees in specific departments of a company and make adjustments to their daily routines based on their physiological reactions to stress, which is a well-known correlation with heart rate, blood oxygen level, and overall well-being. The need to safeguard the confidentiality and integrity of health data is growing in tandem with the amount of data gathered and transferred via IoT devices. Therefore, we may direct future studies to create strong paradigms for improving the safety and confidentiality of medical records.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Pillalamarri Lavanya	✓	✓		✓		✓	✓		✓	✓		✓	✓	
Selvakumar Venkatachalam		✓	✓	✓	✓			✓	✓	✓	✓			
Immareddy Venkata Subba Reddy				✓						✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [Pillalamarri Lavanya], upon reasonable request.

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