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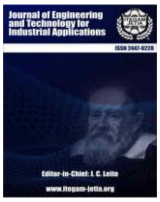

RESEARCH ARTICLE OPEN ACCESS

IOT-BASED REMOTE VITAL SIGNS MONITORING AND TEMPERATURE FORECASTING FOR PREGNANT WOMEN

Bilal Mokhtari[1], Fairouz Graine[2] and Abdelhak Merizig[3]

[1]Department of Computer Science, University of Mohamed Khider, Biskra, Algeria & LAMIE Laboratory, University of Batna 2, Batna, Algeria.
[2]Department of Computer Science, University of Mohamed Khider, Biskra, Algeria.
[3]LINFI Laboratory, Computer Science Department, Mohamed Khider University, Biskra, Algeria & LIMIA Laboratory, Mohamed Khider University, Biskra, Algeria.

[1]https://orcid.org/0000-0003-4888-8267, [2]https://orcid.org/0009-0004-6344-5928, [3]http://orcid.org/0000-0001-6817-323X

Email: bilal.mokhtari@univ-biskra.dz , pr.fairouzgraine@gmail.com, abdelhak.merizig@univ-biskra.dz

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ABSTRACT

The importance of maintaining optimal health during pregnancy for both the mother and fetus has driven the development of numerous artificial intelligence (AI)-based monitoring systems. These systems aim to address the growing need for continuous, reliable health tracking in pregnant women, ensuring early detection of complications and promoting better outcomes. While general-purpose health monitoring platforms exist, there remains a significant gap in solutions explicitly tailored for pregnancy. Addressing this need requires not only real-time monitoring but also predictive capabilities based on vital signs. In this work, we propose an IoT-based pregnancy monitoring system that continuously collects key physiological data, namely body temperature, heart rate, and blood oxygen saturation. The collected data is transmitted in real time and processed using a Long Short-Term Memory (LSTM) neural network to build a model capable of forecasting potential health anomalies. The system provides real-time insights and future predictions. This approach enhances proactive care, enabling timely intervention and improving maternal-fetal health outcomes. This system's approach shifts between personal and centralized monitoring, a capability particularly valuable where regular prenatal visits are difficult, thereby enhancing the overall effectiveness of prenatal care delivery.

I. INTRODUCTION

Nowadays, modern healthcare systems [1], [2] are increasingly focused on early monitoring to prevent and predict complications at an early stage. This approach has become a fundamental tool in preventive medicine, aiming to detect potential health issues early and enable timely intervention. By leveraging advanced techniques [3], [4] to analyze patient data, these systems contribute significantly to improving overall well-being. Monitoring pregnant women is one of the areas that benefits most from tailored health monitoring systems. The dynamic physiological changes during pregnancy can lead to various complications and, in some cases, may even threaten the mother's life. Traditionally, the health of pregnant women is monitored by healthcare professionals in clinical settings through physical examinations and laboratory tests. However, in most cases, these methods lack the ability to collect and utilize real-time data.

New technologies have emerged, particularly remote health monitoring and data analysis using artificial intelligence (AI) and IoT are becoming increasingly popular [5–8]. These innovations allow both patients and healthcare professionals to track and analyze real-time health data. For pregnant women, this means being able to detect any changes or patterns related to potential complications, enabling early intervention to prevent risks that could affect either the mother's or the fetus's health. A variety of techniques [6], [9] for collecting and analyzing health data are now being incorporated into remote healthcare monitoring, including the use of wearable devices, mobile applications, and other digital tools. These systems enable the continuous collection and analysis of vital signs such as heart rate, blood pressure, and body temperature.

By leveraging these sensors and technologies, it becomes possible to identify patterns, make predictions, and forecast future changes, allowing for the early detection of potential health risks and enabling timely interventions to maintain good health. In this work, we propose a new framework that combines IoT and AI-based techniques to enable healthcare professionals to remotely monitor the health of pregnant women. The system collects data from vital signs, analyzes them to detect potential risks, stores historical health records, and forecasts future changes.

IoT devices are used to track any abnormal variations in vital signs continuously, while an AI-based approach using a Long Short-Term Memory (LSTM) deep learning architecture serves as a predictive tool for early diagnosis by forecasting future changes in these parameters and estimating the likelihood of developing complications. The system provides real-time monitoring and predictive insights through an integrated web and mobile application, allowing both pregnant women and healthcare providers to access critical health information at any time.

I.1 RESEARCH CONTRIBUTIONS

The main contribution can be summarized as follows:

1. **Development of a Novel IoT-AI Framework:** A new system is proposed that integrates IoT and AI technologies specifically for the remote monitoring of pregnant women's health.
2. **Real-Time Vital Sign Monitoring:** IoT devices are used to continuously collect and track key physiological data (e.g., heart rate, temperature, oxygen saturation) for early detection of abnormal changes.
3. **Combining Health Monitoring Approaches**: This system shifts from personal to centralized monitoring, a capability particularly valuable in contexts where regular prenatal visits are limited or challenging.
4. **Predictive Health Analysis Using LSTM:** Implementation of a Long Short-Term Memory (LSTM) deep learning model to forecast future changes in vital signs and predict potential complications.
5. **Early Diagnosis and Risk Prevention:** The system enables early identification of health risks, allowing timely intervention and preventive care.
6. **Historical Data Storage and Trend Analysis:** The collection and storage of historical health data to analyze long-term patterns and support better clinical decision making.
7. **Multi-Platform Accessibility**: Real-time monitoring and predictive insights are made available through both web and mobile applications, improving accessibility for both patients and healthcare providers.

II. RELATED WORKS

II.1 HEALTH MONITORING SYSTEMS

Health monitoring involves observing and tracking various aspects of a person's condition to identify potential issues and address them early. It consists of continuously assessing changes related to an individual's well-being to prevent potential health risks [10]. Monitoring can be done in three different ways [11], namely on-site, remotely, or centralized. In onsite monitoring, healthcare providers collect data directly by medical sensors connected to the patient, and it is done locally. It ensures accurate clinical assessment but lacks continuity. Remote monitoring uses transmission technology to send health data to a central monitoring system, which enables healthcare providers to monitor patients' health regardless of time and location, but may lack immediate clinical interpretation. Centralized monitoring bridges the two by combining remote data collection with expert oversight. The data collected remotely and the analytical evaluation are done at a central location. It is considered a more reliable approach for studying health phenomena, conducting large-scale research, and guiding decision-making in general health management, for example, the spread of epidemics like COVID-19.

II.2 INTERNET OF THINGS (IoT) IN HEALTHCARE

To enable remote monitoring, IoT is the most widely used technology for collecting data via sensors, transmitting information through networks, and analyzing the data using intelligent cloud-based solutions, thereby supporting efficient healthcare systems. The study presented in [6] proposed a patient monitoring system that uses GSM and embedded IoT technology to store and transfer healthcare data to the cloud, making it accessible to multiple users anytime and anywhere. Another study in [12] introduced an IoT-based health monitoring system focused on two vital signs: body temperature and respiratory rate. The system analyzes these parameters and detects abnormal health conditions via a mobile application, which can be used by doctors and nurses in hospitals.

This allows them to monitor all patients in real time without needing to visit each one individually, except in emergencies or when intervention is necessary. Different types of data can be used to evaluate overall health via IoT. Vital signs, such as heart rate, blood pressure, and temperature, are key physiological indicators [13]. Physical activity monitoring, including movement and exercise tracking, as well as sleep analysis (e.g., duration and quality), helps detect issues like sleep disorders [14]. Monitoring specific parameters, such as blood pressure in cases of hypertension, is essential for managing chronic diseases. Emotional and behavioral tracking also enables the early detection of mental health problems [15].

II.3 VITAL SIGNS IN MATERNAL HEALTH

Among others, vital signs monitoring [16–18] allows healthcare professionals to make timely interventions by continuously observing and measuring a person's physiological functions. It helps detect any changes in their condition and identify potential issues before they become serious. Various physiological functions, such as blood pressure, heart rate, respiratory rate, temperature, and oxygen saturation, can be considered. These measurements, commonly referred to as vital signs, play a critical role in clinical evaluation and management [19]. Several researchers have studied the use of wearable devices for continuous monitoring the healthcare based on body temperature [17], [20], [21].

Body temperature is one of the key indicators for the body to detect early warning signals of inflammation, infection, and other health complications. In the study conducted in [22], it was shown how body temperature, captured using wearable sensors, can continuously and accurately monitor health conditions and, for instance, prevent cases of sepsis using machine learning techniques. Other vital signs, including blood pressure, heart rate, and blood Oxygen saturation (SpO2) is a key indicator of an individual's health status. Blood pressure reflects cardiovascular function. Heart rate and its variability reflect cardiac and nervous system adaptations during pregnancy and postpartum [23], and they help in detecting serious complications such as preeclampsia [24], as well as psychological conditions like depression [25]. Oxygen saturation (SpO2) predicts adverse maternal outcomes in preeclampsia [26].

The work presented in [27] describes systems designed to monitor these vital signs. These systems collect real-time physiological data and transmit it to healthcare providers for immediate monitoring. Furthermore, machine learning techniques are integrated to enable the early and timely detection of potential health issues, thereby helping to prevent complications. According to the World Health Organization, deaths during pregnancy and childbirth are often caused by severe bleeding, high blood pressure, and pregnancy-related infections, which can be directly linked to and identified through vital signs. In cases such as infection, which pose a serious risk to both the mother and her fetus and can lead to dangerous complications or even death, a high body temperature often serves as a primary symptom and indicator that the body is responding to the infection [28].

Thus, monitoring vital signs, including body temperature, is crucial to ensure the well-being of the mother and the healthy development of the fetus. There are several benefits to monitoring vital signs during pregnancy. These include the early detection and management of high-risk conditions by tracking pre-existing medical issues such as diabetes, hypertension, and heart disease, all of which can increase the risk of complications. Vital sign monitoring is also useful for assessing overall health and guiding treatment decisions in women taking medications, as changes in indicators like blood pressure and body temperature can signal the need for medical adjustments. Moreover, tracking vital signs provides valuable data for research, contributing to a better understanding of the causes and risk factors leading to pregnancy complications.

Vital signs thus play a significant role in supporting the well-being of pregnant women and informing their healthcare providers. For example, elevated body temperature, especially in the first trimester, can indicate infection and has been linked to an increased risk of congenital heart defects or neural tube defects (NTDs), which affect the brain, spine, or spinal cord of the newborn [29], [30]. A rapid heart rate may signal underlying conditions such as anemia or preeclampsia, and if combined with a high temperature, it may point to sepsis. High blood pressure (hypertension) is another serious condition that can severely affect both the mother's health and the development of the fetus. Healthy SpO_2 levels are essential for proper fetal development, as even short periods of oxygen deprivation can disrupt normal organ formation and elevate the risk of congenital defects, particularly cardiac and spinal abnormalities [31].

Various research efforts based on vital signs have been proposed to monitor the health of pregnant women. The work presented in [6] introduces a system that uses vital signs and data collected through IoT technology to measure fetal movement and maternal parameters such as blood pressure, heart rate, and body temperature. This data is then transmitted and visualized via a mobile phone to monitor the health status of both the mother and the fetus. The system addresses the challenge faced by pregnant women living in rural areas with limited access to medical facilities, offering low-cost healthcare coverage without requiring travel.

II.4 FORECASTING AND AI IN HEALTH MONITORING

Another similar work proposed in [5] analyzes various pregnancy-related biological factors such as the pregnant woman's heart rate, blood pressure, blood glucose level, body temperature, and the weight of the fetus. This system allows physicians to monitor the condition of both the mother and the fetus remotely and access critical data, supporting rapid decision-making and timely treatment in case of complications. In fact, advancements in digital health technologies, particularly the use of Internet of Things (IoT) devices, have enabled continuous and remote monitoring of patients' vital signs [32]. These systems are especially impactful in maternal healthcare, where real-time data collection from pregnant women provides critical insights into both maternal and fetal health.

However, data collection alone is not sufficient; intelligent analysis is required to extract meaningful patterns and predict potential complications before they become critical. This need has driven the integration of AI into healthcare systems to enhance early detection, diagnosis, and intervention [33]. In this context, forecasting refers to the use of data-driven models to predict future changes in a patient's health status based on current and historical vital signs, a key capability for identifying complications that may not show immediate symptoms [34]. Therefore, our contribution proposes an IoT-based framework for monitoring pregnant women, in which vital signs, mainly body temperature, are continuously collected and analyzed.

We use a Long Short-Term Memory (LSTM) deep learning model to forecast temperature trends, allowing for early prediction of abnormal patterns that may indicate infection or other risks. LSTMs are able to capture temporal dependencies in sequential data, making them particularly suitable for effectively forecasting vital signs that change over time[35]. This approach of forecasting physiological parameters with deep learning models supports timely intervention and improved maternal care, as it has been shown to enhance preventive healthcare by enabling proactive decision-making and personalized treatment plans [36].

III. MATERIALS AND METHODS

The proposed system includes an IoT infrastructure that connects sensors to a web application, enabling doctors to remotely monitor the health status of pregnant women through vital signs such as body temperature, heart rate, and SpO2. This setup helps in preventing potential health issues and associated risks. Additionally, the system forecasts future body temperature to anticipate and mitigate possible complications, acting as a preventive mechanism, adding an extra layer of safety. It provides both pregnant users and healthcare professionals with access to collected and analyzed health data. This section introduces our proposed architecture, describing the IoT-based monitoring and temperature forecasting model and the hardware components.

III.1 FRAMEWORK ARCHITECTURE AND COMPONENTS

The global architecture of the proposed framework is shown in Fig. 1. It provides an overview of the main components of the system. Four primary components are included: the sensing module, data collection and storage, temperature forecasting, and the web application.

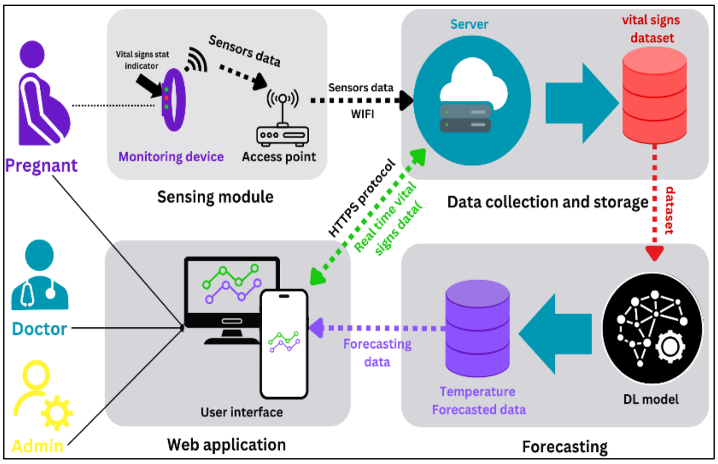

Figure 1: Overall framework architecture for pregnant women monitoring.
Source: Authors, (2026).

The main components of the framework are broken down as follows:

1. **Sensing Module:** The sensing module consists of IoT components used to collect vital signs related to real-time data of pregnant women. It includes sensors for temperature, heart rate, and oxygen levels, LED indicators, and a microcontroller to evaluate the corresponding values and send alerts in different situations (low, high, or normal). The data is transmitted to the cloud via IoT protocols, ensuring real-time communication so that both the pregnant woman and the doctor are promptly notified through their respective dashboards. The data is also stored for use by the forecasting model. Different sensors have been used to realize the sensing module.

- Temperature sensor: The LM35 temperature sensor is used, which outputs a voltage linearly proportional to the temperature in degrees Celsius. It measures temperatures ranging from -55 ◦C to 155 ◦C, with a voltage conversion rate of 10 mV/◦C. This sensor is suitable for remote monitoring because it does not require external calibration and offers reliable performance. Moreover, it is low-cost, highly accurate, and consumes little power.
- Pulse oximeter and heart rate sensors: The sensor MAX30102 sensor presented in Fig.3 is used to measure both the heart rate and oxygen saturation. It works on a 1.8 V power supply and measures heart rate and blood oxygen from wearable devices, which can be worn on the fingers, earlobe, and wrist.
- Microcontroller: To manage the different sensors and process the data, we used the NodeMCU microcontroller (Fig. 4), which is open-source and equipped with a CPU, RAM, and a Wi-Fi module.
- Light Emitting Diodes (LEDs): We used an RGB LED with three internal colors (Red, Green, and Blue) to produce visual alert messages. Any color can be generated by combining these three LEDs.

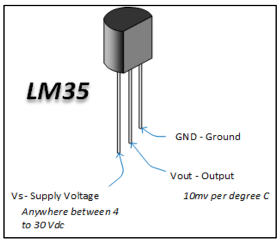

Figure 2: LM35 temperature sensor.
Source: [37].

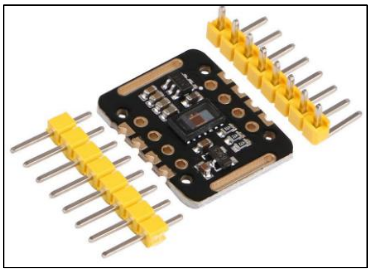

Figure 3: MAX30102 pulse oximeter and heart rate sensor.
Source: [38].

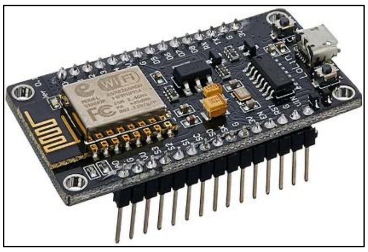

Figure 4: NodeMCU microcontroller.
Source: [39].

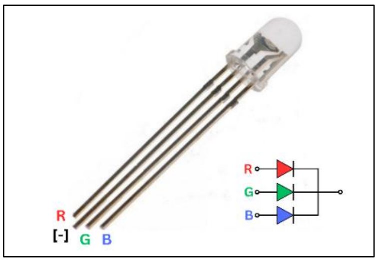

Figure 5: The used RGB LED.
Source: Authors, (2026).

2. **Data collection and storage:** To store and manage the collected data, we used the ThingSpeak IoT cloud platform, which includes a web service (REST API) for collecting and storing data from sensors in the cloud. It provides ample cloud storage capacity to manage real-time data and allows seamless access to the data from anywhere at any time. The NodeMCU microcontroller is used to transmit the gathered sensor data to this platform through its integrated Wi-Fi module. Each value, including temperature, heart rate, and SpO$_2$, is transmitted through a dedicated channel. The collected vital signs data is stored in CSV or JSON format, allowing for easy retrieval and use in historical visualization and forecasting.

3. **Body temperature forecasting:** In order to forecast future body temperature and predict any related complications, a deep learning (DL)-based forecasting model is proposed (described in detail in Section III-B). It uses the stored data in the cloud to build a learning model, which is then used to predict temperature for the upcoming hours. The predictions are displayed through the web application and can be accessed by doctors and pregnant users via their dashboards, with an appropriate display mode for each. The overall process is shown in Fig. 6.

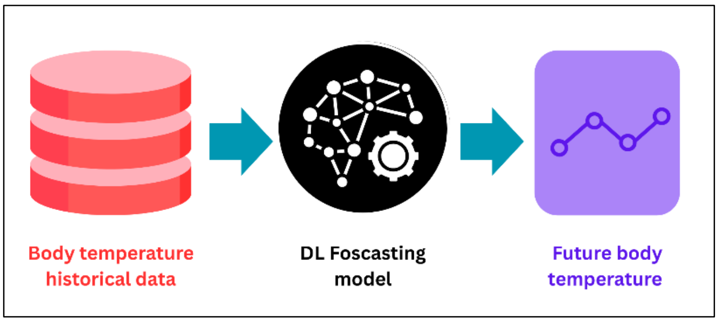

Figure 6: Body temperature forecasting processes.
Source: Authors, (2026).

4. **Web application:** The web application allows different actors to benefit from the information provided by the framework, each for a specific purpose. The three main actors are the admin, the pregnant user, and the doctor. The administrator can manage technical actions such as adding and updating user profiles. The doctor can perform standard operations, monitor patients' vital signs, view historical data, access forecasting information, and identify any potential risks. The pregnant user can check her vital signs to ensure everything is normal and add or update her personal information. The use-case diagrams presented in Fig. 7 summarizes the actions of each of the different actors.

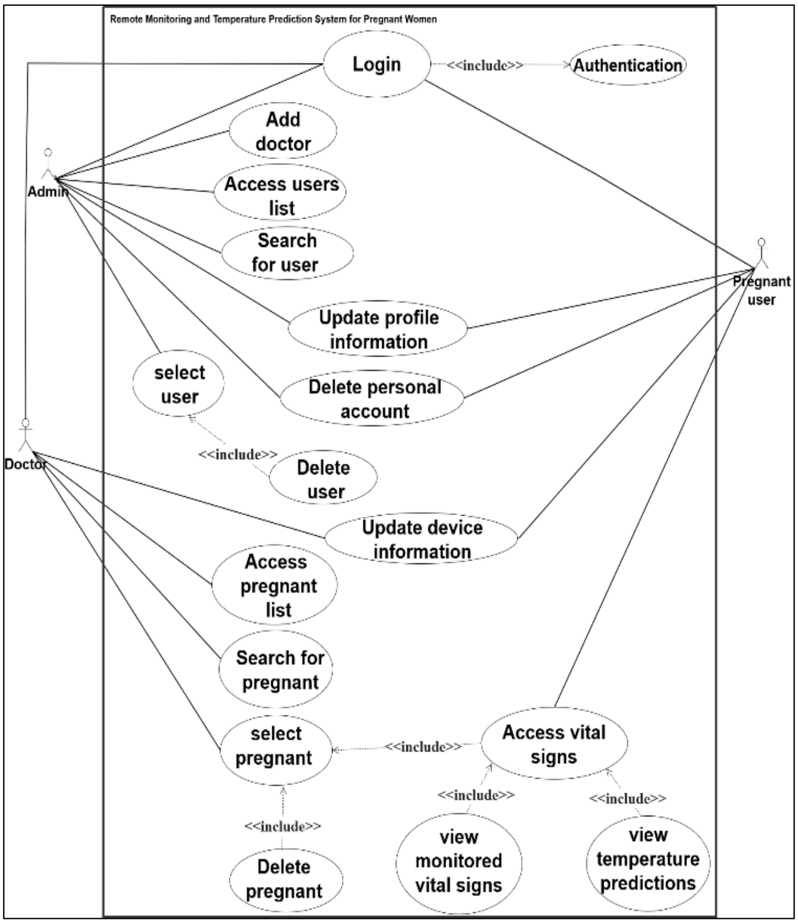

Figure 7: Use case diagram.
Source: Authors, (2026).

The block diagram shown in Fig. 8 resumes the overall working mechanism of the proposed framework.

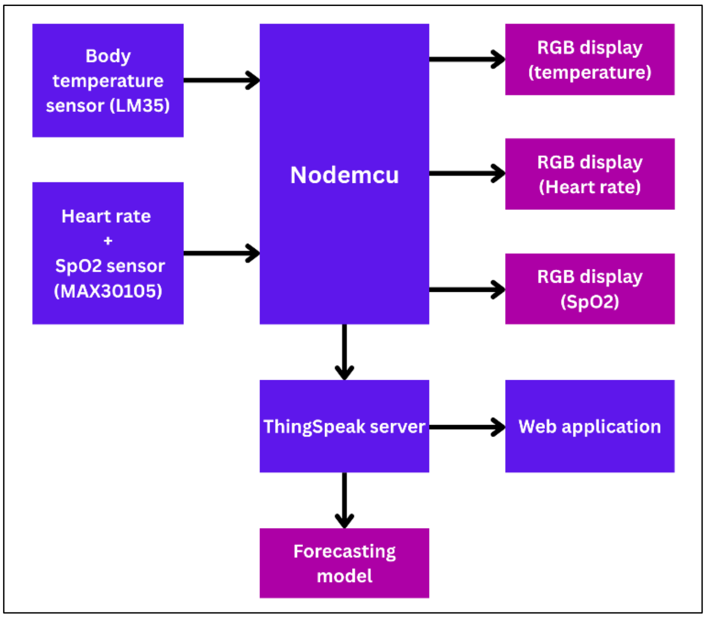

Figure 8: Use case diagram.
Source: Authors, (2026).

III.2 BODY TEMPERATURE FORECASTING

In order to forecast temperature over future time steps, we developed a sequence-to-sequence LSTM model tailored for multi-step output. Different LSTM-based architectures, namely LSTM, Bi-LSTM, and GRU, were considered and evaluated against various baseline models and performance metrics. This enabled us to identify the most suitable model for the forecasting task. The overall temperature forecasting process, including the LSTM architecture, is shown in Fig. 9.

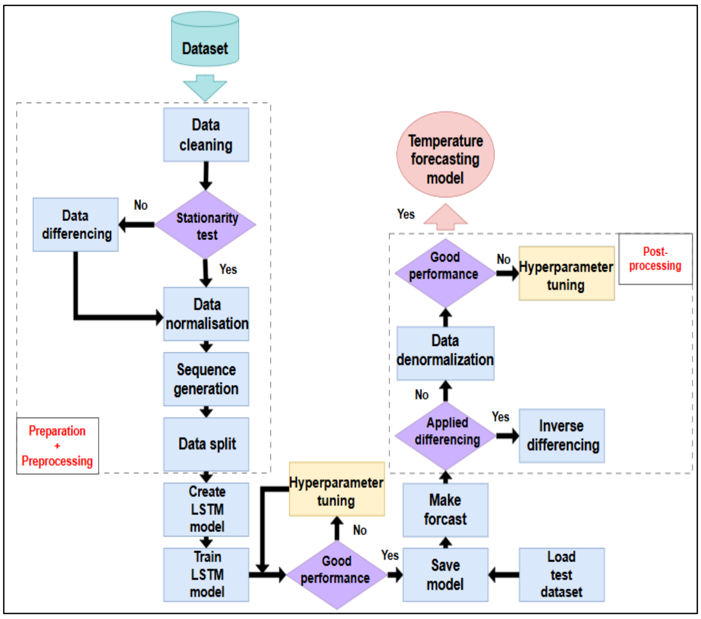

Figure 9: Use case diagram.
Source: Authors, (2026).

The process starts with preprocessing steps: filtering the data, checking for missing values, and handling them appropriately. Data normalization and scaling are then applied. Statistical tests such as the Augmented Dickey-Fuller (ADF) test, along with ACF and PACF plots, are used to visualize the data and verify stationarity. If necessary, first-order differencing is applied to remove trends and achieve stationarity. Next, sequences are created from the input and output data to fit a structured format suitable for a supervised learning task. A fixed number of previous time steps, referred to as the “look-back” window, serve as input features, while another fixed number of future time steps, referred to as the “target” window, serve as the predicted output generated by the model. The final step in the processing phase is to split the data into training and testing sets. Additionally, a validation set is created, used for hyperparameter tuning during training. It allows for assessing the model’s performance on unseen data while fine-tuning its hyperparameters. Afterward, the LSTM model with different architectures and configurations is deployed.

The first configuration consists of a one-dimensional LSTM that processes one-dimensional sequential temperature data. It includes an input layer, followed by three LSTM layers, three dense layers with ReLU activation functions, and a final single-unit output layer with a linear activation function. The second configuration is a Bi-LSTM model. It starts with an input layer shaped according to the input data (ninput, nfeatures), which then passes through three bidirectional LSTM layers with 100 units each—allowing the model to capture information from both past and future time steps. This is followed by two fully connected layers with 8 and 1 neurons, respectively, using ReLU and linear activation functions for feature extraction and regression output. The last configuration is a GRU-based architecture, starting with an input layer, followed by three stacked GRU layers with 100 units each, and an additional GRU layer with 50 units. Two dense layers are added afterward: the first with 64 units and a ReLU activation function, and the final output layer with a single unit and a linear activation function. The three architectures are presented in Fig. 10.

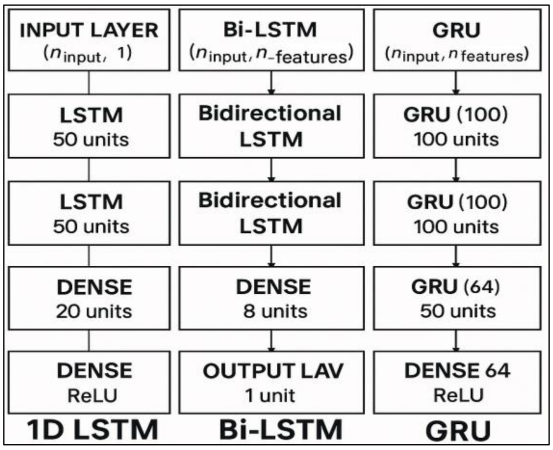

Figure 10: Used LSTM architectures for temperature forecasting.
Source: Authors, (2026).

After training and evaluating the model to determine the optimal parameters, the forecasting process is performed by specifying the size of the input sequence (forecasting look-back) and the length of the desired forecast output. Finally, the post- processing phase is crucial to convert the data back to its original standard time series format.

IV. RESULTS AND DISCUSSIONS

IV.1 HARDWARE IMPLEMENTATION

Our device prototype is built using an LM35 temperature sensor, a MAX30102 pulse oximeter and heart rate sensor, and a NodeMCU ESP8266 board. We also include three RGB LEDs (indicators for the three sensors) and nine resistors. The positive legs (anodes) of the LEDs are connected to the power supply (VCC). Each LED's positive pin is connected through a resistor to specific pins on the NodeMCU. Fig. 11 shows how all the components are connected, giving a clear overview of the monitoring system.

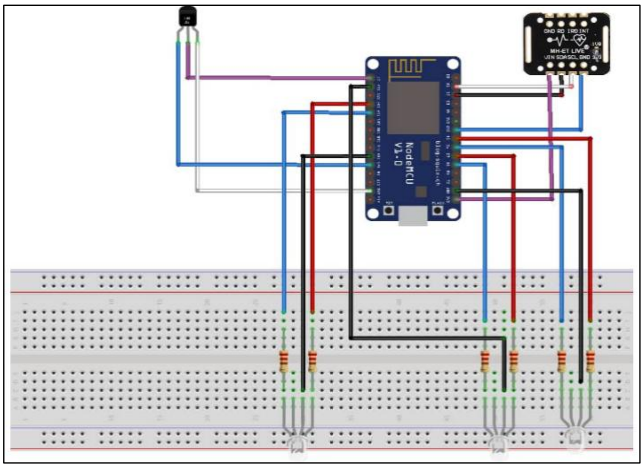

Figure 11: Device material connection.
Source: Authors, (2026).

The components of the circuit model are connected as described in Section III. The circuit integrates the LM35 temperature sensor and the MAX30102 pulse oximeter and heart rate sensor as inputs to the NodeMCU microcontroller. The microcontroller collects and analyzes the data, transmits it to the server, and controls the RGB LEDs as visual indicators. The LEDs display the status of the measured vital signs: green for normal, red for high, and blue for low. ThingSpeak is used to collect, store, and remotely access data by both users and devices. Several steps are followed to set up the server and connect it to the NodeMCU board. This includes creating a ThingSpeak account, setting up a new channel for data communication, and using the API key to upload data to the correct channel.

Finally, the different components are interconnected, and the server is configured accordingly. Afterward, the monitoring device operates according to the following process:

1. **Initialization and data collection:** The connected device initializes the sensors, continuously collects data using the Wi-Fi module, and establishes a connection with ThingSpeak for data transmission and communication.
2. **Data processing:** Ensure efficient data analysis, the collected data is first preprocessed and cleaned to make it usable for the next steps. This process also verifies that the vital signs are correctly detected, confirming that the user is wearing the device and that the data is accessible.
3. **Vital signs Assessment:** Based on the collected data, the connected device assesses the status of the vital signs by monitoring temperature, heart rate (HR), and SpO2 levels. Abnormal values are indicated using RGB LEDs: blue for low values, red for high values, and green for normal levels.
4. **Data Transmission:** The API key and channel ID are used to send the collected data to the ThingSpeak server. Each vital sign value (temperature, heart rate, SpO2) is assigned to a specific field within the channel.
5. **Data storage:** The data sent to the ThingSpeak server is stored in suitable formats for further use, including both CSV and JSON file formats.
6. **Continuous Loop:** The previous steps are executed in a continuous loop. Sensor data and the status of the vital signs are updated periodically.

Display outputs are integrated into the device to provide a more user-friendly interface. Once the device is connected, a message showing the network name is printed, along with a ”success” confirmation. The vital signs values are displayed in real time, and a notification is shown each time data is successfully sent to the server.

IV.2 FORECASTING MODEL RESULTS

To train the proposed models, we relied on a dataset obtained from a real experiment consisting of nearly 7-week-long wrist skin temperature measurements of a pregnant individual, collected using a smartwatch. The temperature is captured every 3 minutes for 24 hours. Fig. 12 below represents the visualization of this dataset.

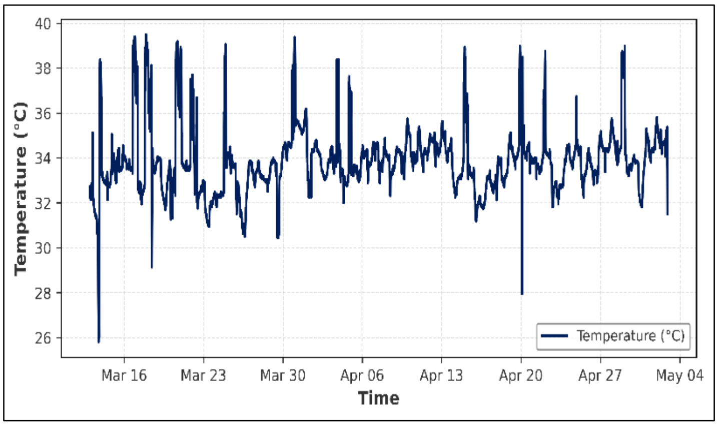

Figure 12: Seven-week wrist skin temperature of a pregnant individual.
Source: Authors, (2026).

The performance of the different forecasting models is evaluated, and the training results for each of the three configurations are shown in Figs. 13, 14, and 15.

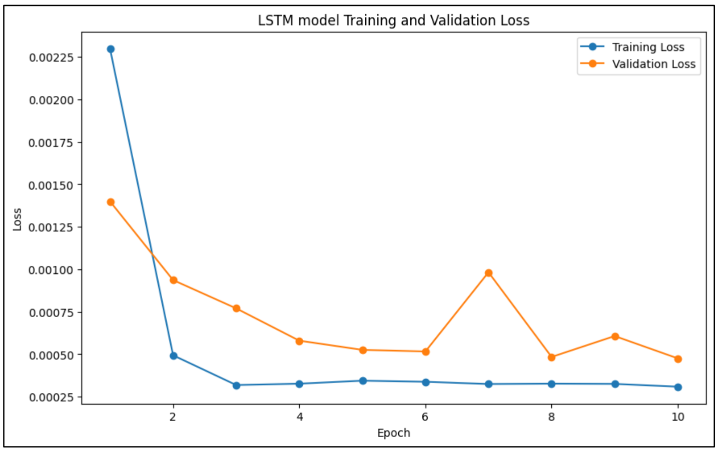

Figure 13: LSTM loss function evaluation.
Source: Authors, (2026).

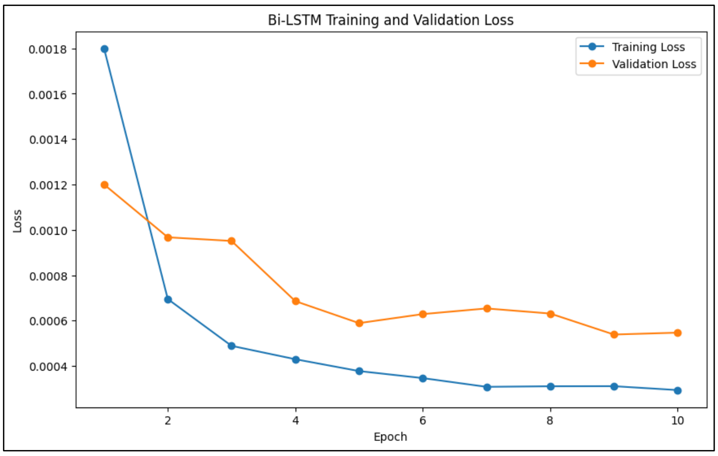

Figure 14: Bi-LSTM loss function evaluation.
Source: Authors, (2026).

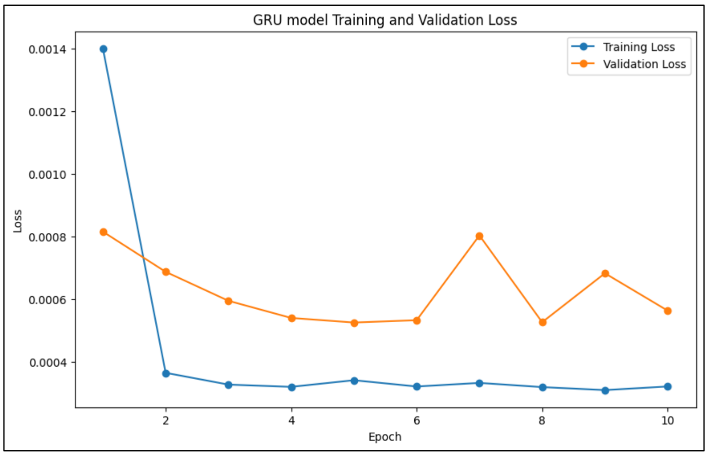

Figure 15: GRU loss function evaluation.
Source: Authors, (2026).

The loss function plots in these figures show distinct behaviors among the models. Although the 1D-LSTM starts with a higher initial loss, it exhibits a faster convergence rate compared to the other models. Ultimately, it achieves the lowest final loss for both the training and validation sets, indicating superior learning efficiency and generalization. In contrast, Bi-LSTM and GRU show similar overall performance trends. For training, the Bi-LSTM begins with a lower initial loss, suggesting a more favorable starting point. However, for validation, the GRU performs slightly better in the early epochs.

Despite these differences, both models eventually converge toward similar stationary loss values, implying comparable long-term performance. Interestingly, a minor increase in the loss is noted around epoch 7 for both the 1D-LSTM and GRU models. This could suggest a momentary overfitting or instability in learning, possibly due to learning rate dynamics or model sensitivity. Nonetheless, both models recover and resume a decreasing trend afterward, reinforcing the stability of their training process. To further evaluate the performance of the considered models, additional metrics, namely RMSE and MAE, are reused. Table I summarizes the obtained results.

Table 1: Training metrics scores.

Model	**Loss**	**RMSE**	**MAE**
LSTM	0.01 %	1.19 %	0.70 %
Bi-LSTM	0.02 %	1.29 %	0.78 %
GRU	0.02 %	1.45 %	0.95 %

Source: Authors, (2026).

Regarding the results shown in Table I, the 1D-LSTM model outperforms the other models, achieving the lowest values for all three metrics: loss, RMSE, and MAE. The Bi-LSTM model ranks second, showing better performance than the GRU model in terms of RMSE and MAE. The 1D-LSTM out performs the others by effectively capturing temporal patterns with less complexity. Bi-LSTM, though more powerful, may suffer from redundancy or overfitting. GRU, being simpler, lacks the memory depth needed for optimal performance in this context.

V. CONCLUSIONS

In the future, to increase the impact of the proposed work, other deep learning architectures could be considered to enhance the accuracy of the forecasting process and reduce the risk of medical errors. Additionally, a user-friendly mobile application could be developed alongside the web application, enabling faster access to the monitoring system and timely reception of related notifications. In this work, we focused on the mother’s primary vital signs as an initial step but considering there are many additional issues related to pregnancy, further monitoring devices with extended capabilities such as fetal heart rate and glucose level tracking can also be integrated to monitor a wider range of health indicators and to address the fetus’s condition more precisely

VI. AUTHOR’S CONTRIBUTION

Conceptualization: Fairouz Graine.
Methodology: Bilal Mokhtari and Fairouz Graine.
Investigation: Fairouz Graine.
Discussion of results: Fairouz Graine.
Writing – Original Draft: Bilal Mokhtari, Fairouz Graine and Abdelhak Merizig.
Writing – Review and Editing: Bilal Mokhtari and Fairouz Graine.
Resources: Fairouz Graine.
Supervision: Bilal Mokhtari.
Approval of the final text: Bilal Mokhtari.

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