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RESEARCH ARTICLE

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CLINICAL VALIDATION OF A NON-INVASIVE SYSTEM FOR MONITORING PHYSIOLOGICAL PARAMETERS IN HUMANS BASED ON THE INTERNET OF THINGS AND MACHINE LEARNING

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ABSTRACT

The monitoring of physiological parameters in individuals undergoing frequent clinical follow-up continues to rely, in many cases, on invasive procedures or equipment that makes continuous monitoring outside the hospital setting difficult. In light of this situation, the present study evaluated a non-invasive system for measuring glucose, oxygen saturation, heart rate, and body temperature, supported by the Internet of Things and machine learning. The research was conducted in 2025 at a private clinic in the Buena Fe canton, Los Ríos province, Ecuador, using a quantitative, exploratory, descriptive, and quasi-experimental design, with a sample of 120 patients selected from a population of 174 users. Data collection was performed under controlled conditions, and each measurement obtained by the system was compared with values from commercial reference devices. For predictive processing, models such as linear regression, support vector machines, decision trees, and neural networks were analyzed and evaluated using performance metrics including R^2 , MSE, RMSE, accuracy, F1-score, and AUC. The findings showed that the system performed well in estimating physiological signals, with better performance in the more complex machine learning-based models. The neural network achieved the highest performance indicators, with an accuracy of 95.42% and an F1-score of 98.13%, while the system exhibited low percentage errors in the clinical comparison for oxygen saturation. It is concluded that non-invasive physiological monitoring supported by IoT and machine learning constitutes a viable option for continuous clinical monitoring, with potential for use in telemedicine and in healthcare settings with limited resources.



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I. INTRODUCTION

The monitoring of physiological parameters plays a key role in healthcare, particularly in the management of chronic diseases and conditions that require frequent follow-up. Variables such as glucose, oxygen saturation, heart rate, and body temperature provide useful information for clinical assessment and monitoring of a patient's progress [1], [2], [3], [4], [5]. Despite this, some of the methods routinely used still involve punctures, disposable supplies, or intermittent measurements, which can cause pain, discomfort, and higher costs during long-term monitoring [1], [2], [6], [7], [8]. The growth of digital health has facilitated the emergence of connected devices capable of capturing biomedical data and transmitting it in real time to visualization and analysis platforms [1], [2], [9]. The Internet of Things applied to healthcare enables the integration of sensors, microcontrollers, and communication services to facilitate remote monitoring, record review, and early detection of physiological abnormalities [10], [11], [12], [13], [14], [9], [15]. Added to this is machine learning, whose utility in the analysis of biomedical signals has been reported in tasks involving classification, estimation, and support for the recognition of clinical patterns [16] [17], [18], [19], [20].

In the case of non-invasive monitoring, recent literature has described advances in optical sensors, photoplethysmography, near-infrared spectroscopy, and wearable technologies for capturing physiological variables without the need to penetrate tissues. These approaches have proven useful in home monitoring, telemedicine, and continuous monitoring of patients with chronic diseases [6], [7], [21], [22], [23]. IoT systems designed for vital sign monitoring and early detection of abnormalities have also been described, with the ability to send information to remote platforms for review by healthcare personnel [24], [12]. [13], [9], [15], [25]. Within the field of metabolism, glucose measurement represents one of the most sensitive challenges, as conventional glucometers rely on capillary samples and test strips [21], [19], [26], [13]. This requirement can hinder patient adherence when repeated measurements are necessary [21], [25], [22]. Recent studies have explored non-invasive systems based on optical sensors and predictive models to estimate glucose, with results that open up a promising line of work for less intrusive monitoring of individuals at metabolic risk or with diabetes [26], [23], [27]. At the same time, oxygen saturation, heart rate, and temperature remain clinical indicators in daily use; therefore, integrating them into a single system can enhance the practical value of monitoring. [13], [28], [29].

In Ecuador, the need for lower-cost and more accessible technological alternatives is of particular interest to small and medium-sized healthcare facilities [30]. The baseline research reports that the study was conducted at a private clinic in the Buena Fe canton, Los Ríos province, where traditional methods for physiological monitoring were still in use and where the challenge was to obtain physiological data in real time and in a non-invasive manner. The document also defines as a general objective the development of a non-invasive system for real-time monitoring of physiological parameters, supported by the Internet of Things and machine learning. Based on this, the research question can be formulated as follows: What level of clinical accuracy does a non-invasive system based on the Internet of Things and machine learning demonstrate for monitoring glucose, oxygen saturation, heart rate, and temperature, when compared to commercial reference devices in patients treated at a private clinic in Ecuador during 2025? The scientific value of the study lies in examining the accuracy and feasibility of a physiological monitoring solution from a clinical and methodological perspective, rather than from the technical construction of the device. The central focus is on comparing measurements, analyzing agreement with reference devices, and the potential to generate local evidence to support future digital health applications.

II. MATERIALS AND METHODS

II.1 STUDY LOCATION AND CONTEXT

The research was conducted at a private clinic located in the Buena Fe canton, Los Ríos province, Ecuador. The study was carried out in a real-world clinical setting, which allowed for the collection of physiological measurements from patients under controlled conditions and their comparison with data obtained using certified commercial medical equipment. The choice of this setting responded to the need to assess the clinical applicability of a non-invasive system for physiological monitoring in a population routinely seen in outpatient care.

II.2 TYPE AND RESEARCH APPROACH

The study was an exploratory and descriptive investigation with a quantitative approach. The exploratory phase allowed for a review of the scientific literature, available technologies, and previous applications regarding non-invasive monitoring of physiological parameters supported by the Internet of Things and machine learning. The descriptive phase allowed for an examination of the behavior of the evaluated system based on empirical measurements, comparing the values captured by the device with those obtained by reference medical instruments. The quantitative approach allowed us to work with numerical data from clinical trials, as well as to estimate the system's accuracy using statistical and predictive metrics.

II.3 STUDY DESIGN

A quasi-experimental design was employed. This design allowed for the evaluation of the non-invasive system's performance under real-world clinical conditions, without absolute control over all environmental factors, though with systematic observation of the obtained measurements. The comparison was conducted on the same subjects, using both the evaluated device and commercially available, certified equipment for each physiological parameter.

II.4 RESEARCH METHODS

Several research methods were applied to organize and analyze the study. The observational method allowed us to record the system's behavior during physiological data collection and examine the sensors' response to variations in measurements. The inductive method allowed us to draw conclusions from the results obtained in the clinical trials. The deductive method facilitated the review of previous contributions on non-invasive monitoring technologies and their comparison with the study's findings.

II.5 SOURCES OF INFORMATION

The research utilized secondary sources of information. Scientific articles, books, theses, technical documents, regulations, essays, and digital resources related to biomedical sensors, the Internet of Things, machine learning, physiological signal processing, and non-invasive clinical monitoring were reviewed. This review helped substantiate the research problem, organize the background, and define the methodological structure of the study.

II.6 POPULATION, SAMPLE, AND SELECTION CRITERIA

The population consisted of 174 patients treated at the private clinic selected as the study setting. The sample was calculated using simple random sampling, with a 95% confidence level and a 5% margin of error, resulting in a total of 120 patients. Included were individuals over 18 years of age who agreed to participate by signing an informed consent form and who, upon visual inspection, did not have allergies or lesions in the areas of contact with the sensors. Excluded were patients with implanted electronic devices, active dermatological conditions at the measurement sites, or those who refused to participate in the study.

II.7 STUDY VARIABLES

The independent variable was “*non-invasive system based on the Internet of Things and machine learning.*” The dependent variable was “accuracy in monitoring physiological parameters in humans.” For the clinical validation phase, four physiological variables were analyzed: “*heart rate,*” “*oxygen saturation,*” “*glucose,*” and “*body temperature.*” Each of these was recorded by the device under evaluation and by a commercial reference medical device. In the predictive modeling phase, both numerical and categorical variables were used. The numerical variables were “BPM,” “SpO2,” “Glucose,” and “Temperature.” The categorical variables were “BPM_Category,” “SpO2_Category,” “Glucose_Category,” and “Temperature_Category,” coded into three clinical risk levels: 1 = normal, 2 = moderate, and 3 = high.

II.8 DATA COLLECTION TECHNIQUES AND INSTRUMENTS

The primary method was the clinical field trial. Measurements were taken under controlled conditions, with each patient at rest for at least three minutes prior to the start of the procedure. To capture physiological signals, sensors were placed on specific anatomical sites: the MAX30100 sensor on the index finger and the temperature sensor in parallel, following the established procedure for the prototype. Research tools included a literature and document review, observation in a clinical setting, and direct comparison with certified commercial medical devices. An anonymized database was also used to organize the records obtained during the tests.

II.9 METHODOLOGICAL PROCEDURE

The methodological development of the study was carried out in a systematic sequence that allowed us to move from the theoretical review to the quantitative evaluation of the system under real-world clinical conditions. Initially, scientific literature and technical documentation on non-invasive physiological monitoring, biomedical sensors, IoT communication, data processing, and machine learning were reviewed. This review served to identify prior clinical applications, recognize technology selection criteria, and use the parameters employed in similar studies as a reference. Building on this foundation, the theoretical and methodological foundations of the study were organized, defining the clinical evaluation criteria, the sampling procedure, and the planned strategy for validating the predictive model. With this structure in place, the study moved to the patient phase, where the system was applied to the selected sample, and simultaneous measurements were recorded using both the non-invasive device and the reference medical equipment. During this stage, data corresponding to “*estimated glucose,*” “*oxygen saturation,*” “*heart rate,*” and “*body temperature,*” were collected and stored in an anonymized database to protect the participants’ identities. Once data collection was complete, a quantitative analysis of the results was performed. To do this, the values obtained by the system were compared with those provided by the reference devices, and at the same time, the performance of the machine learning models trained on the physiological records was evaluated. This process allowed for an assessment of both the system’s performance in measuring the studied variables and its level of fit and classification within the validation framework established in the research.

II.10 DATA PREPROCESSING AND HANDLING

For training the predictive models, a dataset of 1,500 physiological records was used, manually collected by authorized clinical staff using certified medical devices. Each record included four numerical variables: “BPM,” “SpO2,” “Glucose” and “Temperature”. The data were organized in tabular format and subjected to double-checking to detect missing values, duplicate records, or inconsistencies. Min-Max normalization was then applied to scale the variables between 0 and 1 and promote the stability of the algorithm training. The target variable corresponded to the “clinical risk level,” coded into three classes: 1 = normal risk, 2 = moderate risk, and 3 = high risk. This categorization was assigned by clinical professionals based on established diagnostic criteria for each physiological parameter.

II.11 CLASS BALANCING

The original class distribution showed an imbalance between categories. To correct this, the synthetic oversampling (SMOTE) technique was applied. This procedure allowed for the generation of new instances of the less frequent classes, avoiding simple duplication of cases and reducing bias during classifier training. Reviewing the imbalance index revealed greater disparity in “Temperature” and “BPM” while “SpO2” exhibited a more balanced distribution across classes. The use of SMOTE improved the proportionality of the dataset prior to model validation.

II.12 MACHINE LEARNING MODELS

Several machine learning algorithms were evaluated to estimate and classify physiological parameters. The models considered were a multilayer neural network trained using the Levenberg–Marquardt and backpropagation methods, linear regression, support vector machines in regression mode, and decision trees. Comparing the models allowed us to determine which one offered the best fit and the best classification ability for clinical risk levels. The multilayer neural network underwent iterative testing by modifying the number of neurons in the hidden layer until the architecture with the best performance was selected.

II.13 EVALUATION METRICS

The predictive component was validated using regression and classification metrics. To estimate the fit between predictions and actual values, the mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and Pearson’s correlation coefficient or coefficient of determination were used, depending on the model applied. In the classification phase, “Accuracy”, “F1-score”, the multiclass ROC curve, area under the curve, and confusion matrix were used. These measures allowed us to examine the discriminatory capacity of each algorithm with respect to clinical risk categories.

II.14 COMPARISON BETWEEN THE NON-INVASIVE DEVICE AND REFERENCE EQUIPMENT

The clinical evaluation of the system was performed through a direct comparison of the values obtained by the prototype and by certified commercial medical devices. Two main metrics were used for this purpose: “*absolute error*” and “*relative error*”. The former expressed the numerical difference between the two values, and the latter represented that difference as a percentage relative to the reference device. This comparison was applied to “*heart rate*”, “*oxygen saturation*”, “*glucose*” and “*body temperature*” with the aim of estimating the system’s level of accuracy under real clinical conditions.

II.15 STATISTICAL HYPOTHESIS TESTING

To test the hypotheses, Student’s t-test for paired samples was used, since the measurements from the non-invasive system and those from the traditional method were taken from the same participants. Before applying this test, the normality of the differences was verified using the Shapiro–Wilk test. The analysis was performed with a significance level of $\alpha = 0.05$. This procedure allowed us to determine whether there were statistical differences between the two measurement methods for each physiological parameter evaluated.

II.16 ETHICAL CONSIDERATIONS

Patient participation was voluntary and supported by informed consent. Records were anonymized to protect the participants’ identities and safeguard the confidentiality of clinical information. The study adhered to medical and ethical criteria during patient selection, data collection, and the handling of the information obtained.

III. RESULTS AND DISCUSSIONS

III.1 IDENTIFICATION OF INTERNET OF THINGS COMPONENTS AND TECHNOLOGIES FOR THE INTEGRATION OF NON-INVASIVE SENSORS

The selection of system components was based on a technical review focused on the integration of Internet of Things technologies applied to physiological monitoring. At this stage, microcontrollers were evaluated based on their wireless communication capabilities, low power consumption, compatibility with biomedical sensors, and ease of programming. Table 1, summarizes the analyzed devices and their main characteristics.

Table 1: Microcontrollers for IoT Integration.

Type	Dimensions and voltage	Inputs/outputs	Main characteristics
Arduino Nano	45 × 18 mm ² ; 7 V–12 V	16 digital / 6 analog	Features similar to the Arduino UNO, in a compact format.
Arduino Micro	48 × 18 mm ² ; 7 V–12 V	20 digital / 12 analog	Includes TWI, SPI, and 2 UART communication.
Arduino UNO	68.6 × 53.4 mm ² ; 6 V–12 V	16 digital / 6 analog	Features I2C, SPI, and a UART module..
ESP32	55 × 28 mm ² ; 3.3 V–5 V	18 analog inputs / 2 digital-analog outputs	Incorporates Wi-Fi, Bluetooth, 36 GPIO pins, and a 160–240 MHz clock
ESP8266	34 × 25 mm ² ; 3.0 V–3.6 V	9 digital GPIO / 1 analog	Integrated Wi-Fi module, low power consumption, suitable for IoT applications, and compatible with Arduino IDE.

Source: Authors, (2026).

As shown in Table 1, the ESP32 and ESP8266 modules offered the best conditions for developing a connected solution. The comparative analysis showed that the ESP8266 offered advantages related to its small size, integrated wireless connectivity, and ease of implementation in data transmission applications. From the prototype’s operational perspective, this choice allowed for a reduction in the system’s overall size and simplified the communication architecture. The selection of the microcontroller had direct implications for the device’s feasibility, as a compact module enhances portability and reduces assembly complexity. In healthcare applications, this is valuable because a small, lightweight device facilitates its use in clinical and home settings. Based on this analysis, the ESP8266 was deemed suitable for transmitting physiological data to a remote interface.

III.1.1 Non-invasive sensors for measuring physiological parameters

The second phase of technology identification consisted of evaluating non-invasive sensors to record “*heart rate*”, “*oxygen saturation*”, “*glucose*” and “*body temperature*”. The review included optical sensors, thermal sensors, and modules with potential for integration into IoT architectures. Table 2, presents the reviewed sensors and their most important specifications.

Table 2: Non-invasive sensors for measuring physiological parameters.

Sensor	Main parameter or use	Technology	Voltage / interface	Dimensions	Main features
MAX30100	<i>Heart rate</i> ” and “ <i>SpO₂</i> ”	Photoplethysmography (PPG)	1.8 V–3.3 V / I2C	14 × 17 mm	High accuracy, low power consumption, and optical detection with integrated infrared LED.
NIR Sensor (TSD-MG1)	Non-invasive estimation of “ <i>glucose</i> ”	Near-infrared spectroscopy	3.3 V–5 V / analog or I2C	20 × 15 mm	Useful for machine learning-assisted applications.
DHT22	Ambient temperature and humidity	Capacitive and thermal sensor	3.3 V–5 V / digital	28 × 12 mm	Easy integration with microcontrollers.
Type K thermocouple with MAX6675	“ <i>Body temperature</i> ”	Thermoelectric sensor (Seebeck effect)	3.3 V–5 V / SPI	25 × 15 mm	Accurate readings over wide ranges; requires an amplifier module.

Source: Authors, (2026).

According to the results presented in Table 2, the MAX30100 sensor offered a favorable combination of accuracy, size, and power consumption, making it suitable for recording “heart rate” and “oxygen saturation.” Furthermore, due to its optical principle and the literature reviewed, it was also used to support the estimation of “glucose” in conjunction with the predictive model. On the other hand, the technical analysis showed that the K-type thermocouple, together with the MAX6675 module, provided stable readings for “body temperature.” The decision to integrate it was based on its operating range and its ability to provide readings under controlled clinical conditions. From a functional standpoint, the combination of the MAX30100, NIR sensor (or optical approach), and thermal sensor enabled the construction of a multivariable measurement platform within a compact system. The discussion of these findings aligns with previous studies on non-invasive monitoring. Recent research has reported that the incorporation of optical and thermal sensors into IoT platforms facilitates continuous physiological monitoring and remote data transmission. In the present study, the technological selection enabled the implementation of a distributed measurement model capable of recording variables of clinical interest and integrating them into a digital analysis workflow.

III.2 DESIGN OF THE NON-INVASIVE ELECTRONIC DEVICE FOR COLLECTING PHYSIOLOGICAL PARAMETERS

III.2.1 Development of the Proposal

The functional architecture of the system was defined based on the components selected during the previous stage. The general workflow included physiological signal acquisition, microcontroller processing, data transmission, and remote visualization. Figure 1 presents the general structure of the system.

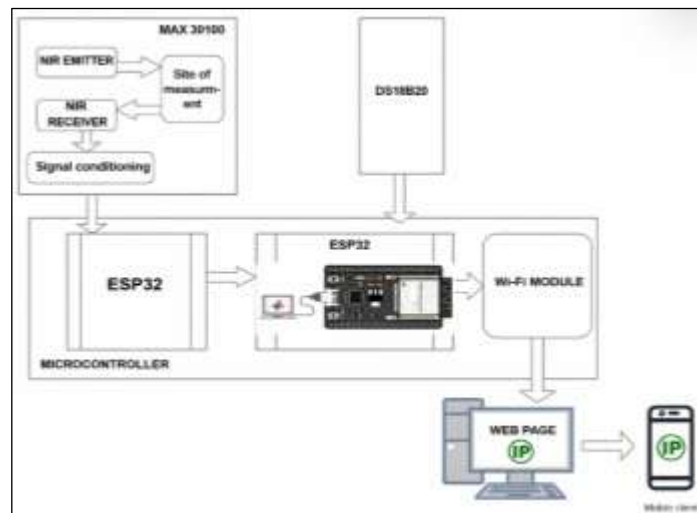


Figure 1: Block diagram of the non-invasive system for physiological monitoring.

Source: Authors, (2026).

As shown in Figure 1, the design was based on a modular organization. This approach allowed for the separation of signal acquisition, processing, and visualization, a condition that enhances the system’s scalability. The use of the ESP32 D1 Mini was driven by its wireless connectivity capabilities and compact size, which helped maintain a portable structure.

III.2.2 Physical Structure of the Device

The device was organized into two physical components: a clamp for the optical sensor and a main processing and power supply module. The configuration aimed to improve ergonomics and accessibility during measurements. Table 3 and Table 4 present the main dimensions of the housing.

Table 3: Clamp Dimensions..

Component	Length	Width	Height
Sensor clamp	3.2 cm	1.2 cm	1.5 cm

Source: Authors, (2026).

Table 4: Wristband Dimensions.

Component	Length	Width	Height
Wristband-type module	3.2 cm	2.9 cm	1.5 cm

Source: Authors, (2026).

According to Table 3, the structure designed for the optical sensor maintained compact dimensions to facilitate contact with the index finger. Table 4 shows that the main module retained a compact shape, with sufficient space to integrate processing, power supply, and internal connections. The result was a physical design intended for practical use, easy maintenance, and an improved user experience.

III.2.3 Device Circuit Diagram

The electronic integration relied on two ESP32 D1 Mini modules, a MAX30100 optical sensor, a thermal sensor, and a power supply system with lithium polymer batteries and TP4056 charging modules. Figure 2 shows the logical layout of the electronic components, while Figure 3 presents the printed circuit board (PCB) design.

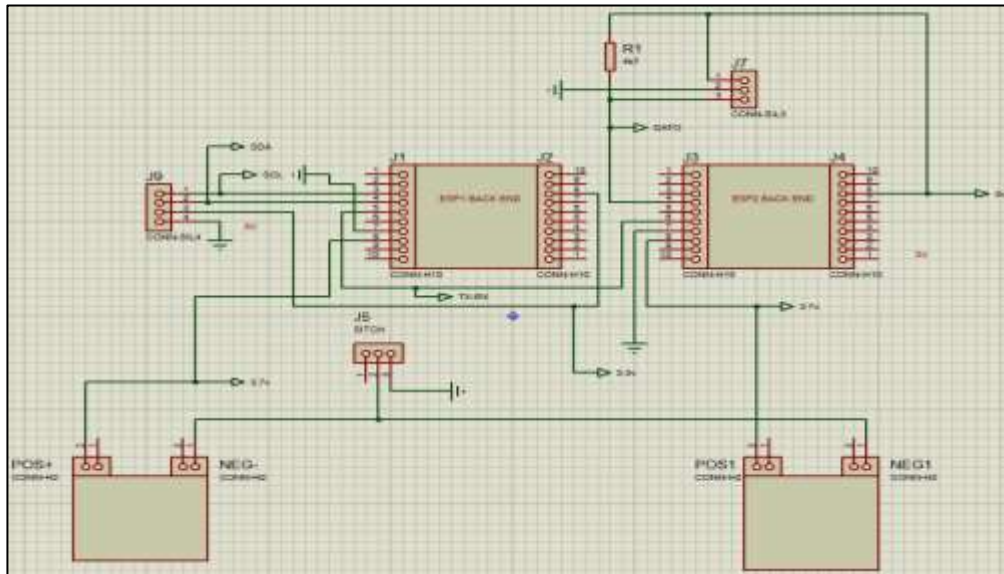


Figure 2: Electronic design of the non-invasive system for physiological signal acquisition.
Source: Authors, (2026).

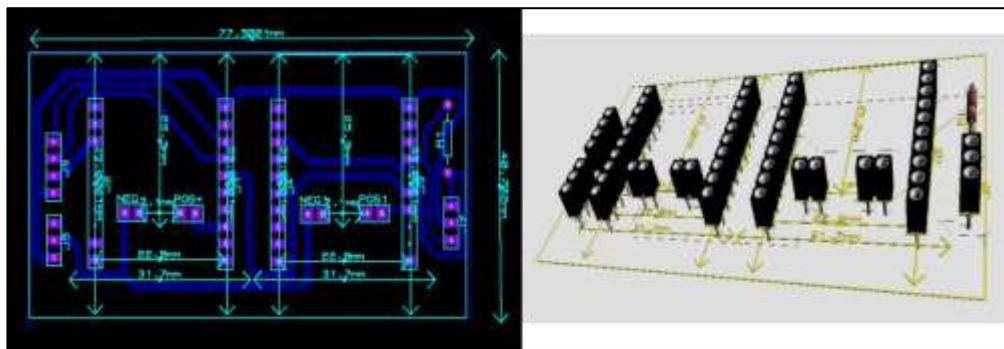


Figure 3: Printed circuit board design of the proposed system.
Source: Authors, (2026).

Figure 2 shows an integration architecture designed to support continuous measurements and wireless transmission. At this stage, the DS18B20 digital sensor was also used to read “body temperature,” given its electrical compatibility with the ESP32. The circuit incorporated a 4.7 kΩ pull-up resistor on the data line, which facilitated stable communication between the sensor and the microcontroller. Figure 3 shows a double-layer board measuring 45 × 30 mm. This design helped reduce electromagnetic interference and improve system stability under real-world operating conditions. From a functional perspective, the miniaturization of the circuit enhanced the device’s portability and improved the prototype’s internal layout.

III.2.4 Use Case Diagram

The system included a remote query interface to display “estimated glucose”, “blood oxygenation”, “heart rate” and “body temperature” in real time. Figure 4 illustrates user interaction with the web platform.

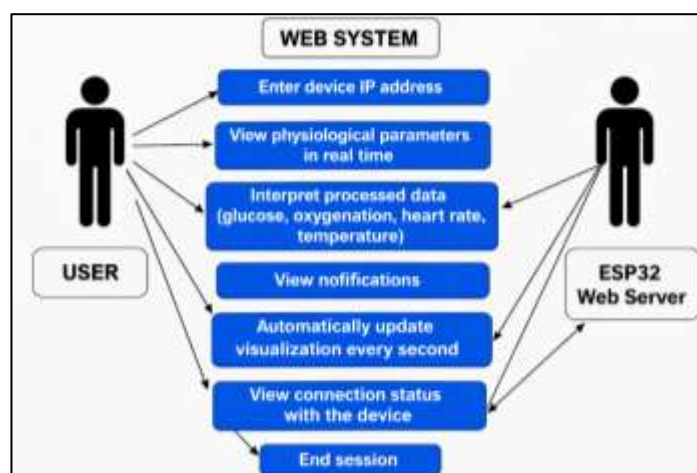


Figure 4: User interaction with the physiological monitoring web system.
Source: Authors, (2026).

Figure 4 represents the flow between data capture, algorithm processing, and remote querying. The second ESP32 acted as a central node for executing the backpropagation algorithm, responsible for interpreting the signals and classifying the physiological information before sending it via MQTT.

III.2.5 Implementation of the graphical interface

The display of results was implemented using a web page generated with the SendHTML function in the Arduino IDE. Figure 5 shows the panel where the four physiological parameters are displayed in real time.

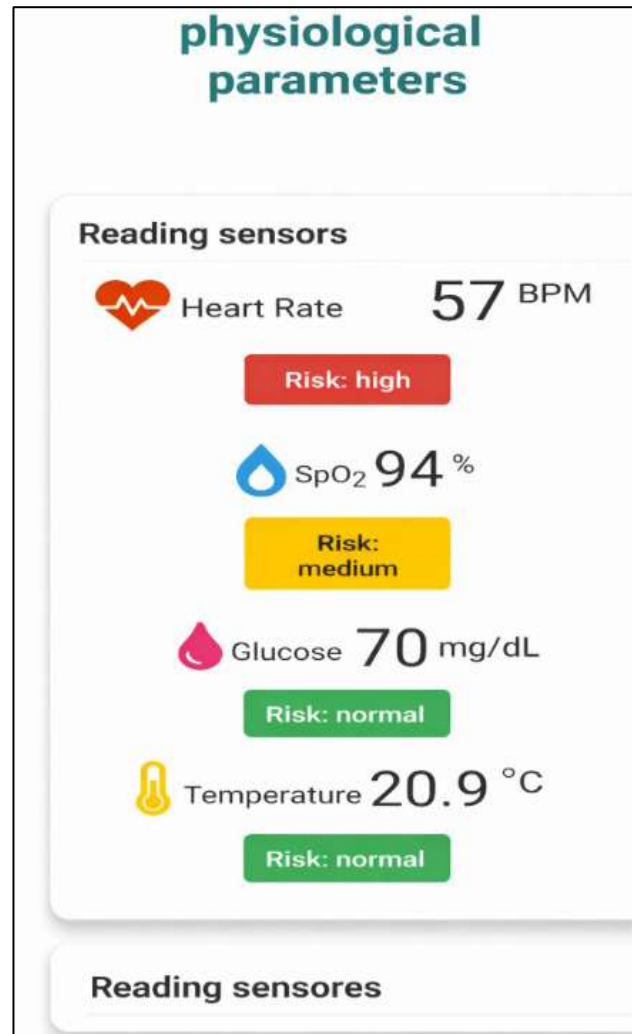


Figure 5: Web dashboard for real-time visualization of physiological parameters.
Source: Authors, (2026).

As shown in Figure 5, the information was organized in a clear and user-friendly manner. The interface was designed to be responsive across different devices and operated with a 60-second timer to smooth out the measurements. This decision helped protect the privacy of medical information by preventing permanent storage on the user interface.

III.2.6 Experimental Validation of the Device

The clinical validation of the device was conducted on 120 patients treated at a private clinic in the Buena Fe district. The tests included the variables "heart rate," "oxygen saturation," "glucose," and "body temperature." Measurements were obtained under controlled conditions, with patients at rest prior to recording, and were then compared with certified commercial equipment used as a reference. This procedure allowed us to assess the similarity between the two methods and estimate the level of accuracy achieved by the non-invasive system in a real clinical setting. In this phase, the presence of patients diagnosed with diabetes was also considered, in order to observe the prototype's performance in different physiological scenarios.

III.2.7 Results and Margin of Error for "Heart Rate"

The "heart rate" evaluation was based on the IEC 60601-2-27:2011 standard, which establishes acceptable error ranges for cardiac monitoring devices. Table 5 summarizes a representative sample of the recordings obtained with the traditional device and the prototype. Data collection was performed at different times and with patients of different ages, which allowed us to examine the system's stability under varying measurement conditions.

Table 5: Patient measurements for “heart rate”.

Patient number	Time of measurement	Age	Gender	Type	Traditional HR (bpm)	Prototype HR (bpm)
1	11:45	35	Female	Healthy	63	68
2	18:30	43	Male	Healthy	77	73
3	14:30	27	Female	Healthy	92	89
4	14:00	53	Female	Healthy	76	79
5	10:30	40	Male	Diabetes	84	83
6	14:00	48	Male	Healthy	92	97
8	17:45	53	Female	Healthy	63	61
9	06:15	38	Male	Diabetes	87	84
10	17:15	50	Male	Healthy	64	69
11	18:45	36	Male	Healthy	66	71
36	10:30	34	Female	Healthy	64	68
37	07:15	47	Female	Diabetes	90	86
38	08:15	42	Female	Healthy	83	82
49	12:45	35	Male	Diabetes	90	85
50	18:30	36	Male	Diabetes	88	84
51	13:45	24	Female	Healthy	79	80
52	16:30	31	Male	Healthy	96	100
53	07:30	43	Male	Healthy	64	67
117	17:00	29	Male	Healthy	85	81
118	18:15	50	Female	Healthy	73	71
119	11:15	37	Male	Healthy	99	103
120	17:15	27	Female	Healthy	62	60

Source: Authors, (2026).

Table 5 shows that the prototype maintained values close to those obtained by the reference clinical device. In most cases, the differences were small and distributed evenly, with readings slightly higher or lower than those of the traditional device. This behavior suggests that the system responded stably during measurement and was able to capture the physiological signal with adequate accuracy. The inclusion of healthy patients and patients with diabetes helped broaden the assessment of the device’s performance across different clinical profiles.

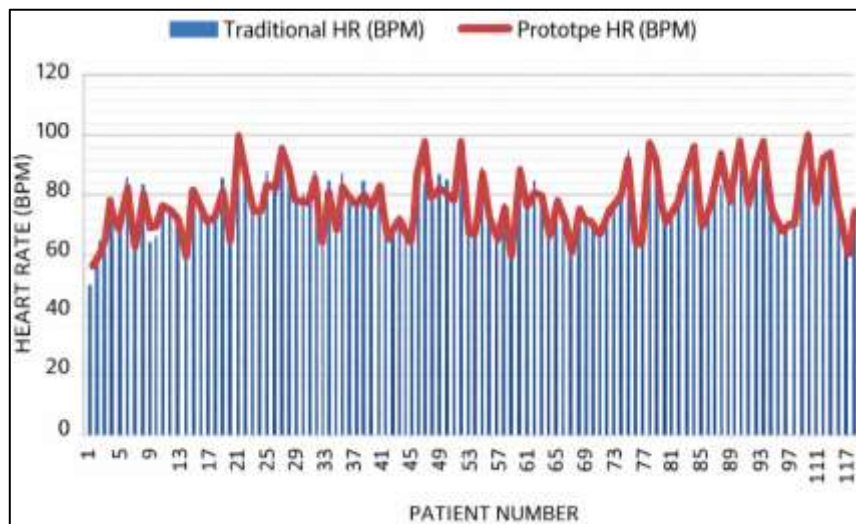


Figure 6: Absolute error in heart rate measurement between the prototype and the reference device.

Source: Authors, (2026).

Figure 6 represents the absolute error recorded in the observations. The dispersion of values shows small differences between the two methods and supports the system’s stability during measurement. It can also be seen that there is no marked concentration of high errors, which reinforces the overall consistency of the prototype. From a clinical perspective, this indicates that the device offers a useful solution for basic real-time monitoring of the “heart rate” variable. Table 6 presents the absolute error and relative error calculated for a representative subset of patients. These metrics allowed for a direct examination of the difference between the prototype’s measurement and that of the commercial device used as a reference.

Table 6: “Heart Rate” Error Margin.

Patient Number	Traditional HR (BPM)	Prototype HR (BPM)	Absolute error	Relative error (%)
1	63	68	5	7.94
2	77	73	4	5.19
3	92	89	3	3.26
4	76	79	3	3.95
5	84	83	1	1.19
6	92	97	5	5.43
7	72	72	0	0.00

8	63	61	2	3.17
9	87	84	3	3.45
10	64	69	5	7.81
11	66	71	5	7.58
12	81	79	2	2.47
13	74	79	5	6.76
14	74	75	1	1.35
40	88	83	5	5.68
41	80	79	1	1.25
71	79	77	2	2.53
72	83	80	3	3.61
88	94	93	1	1.06
89	96	100	4	4.17
116	93	93	0	0.00
117	85	81	4	4.71
118	73	71	2	2.74
119	99	103	4	4.04
120	62	60	2	3.23
Overall average				3.63

Source: Authors, (2026).

Table 6 shows an average relative error of 3.63%, a value that remained within the acceptable range for this type of measurement. The presence of low absolute errors in most patients indicates that the prototype's performance was consistent. Furthermore, several readings showed minimal or no deviations, indicating good point-by-point agreement in certain cases. Overall, the results suggest that "heart rate" measurement can be considered one of the variables with favorable response within the proposed system.

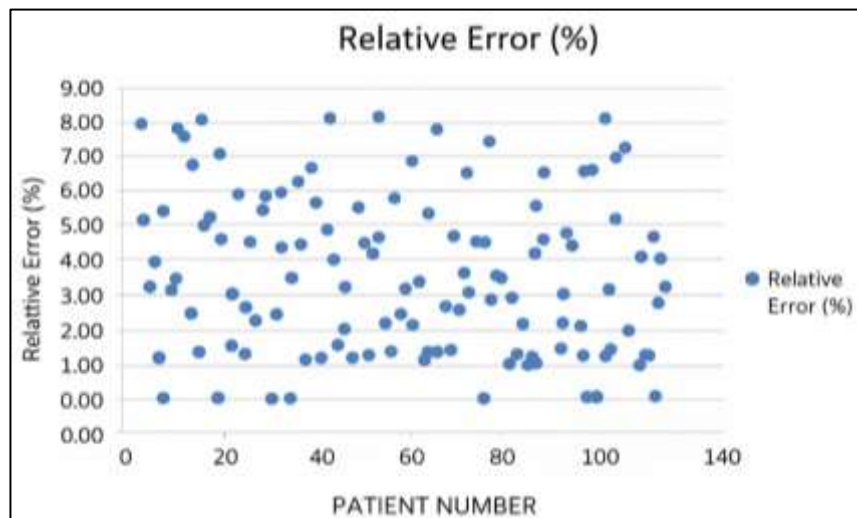


Figure 7: Relative error in heart rate measurement.

Source: Authors, (2026).

Figure 7 illustrates the distribution of relative error and confirms that most observations fell within low deviation levels. The graph also shows that the highest errors were rare and did not dominate the overall behavior of the sample. In clinical terms, this result supports the utility of the device for basic monitoring of the "heart rate" variable and suggests that the signal captured by the system maintains acceptable agreement with that of the conventional method.

III.2.8 Results and Margin of Error for "Oxygen Saturation"

The evaluation of "oxygen saturation" was based on the ISO 80601-2-61:2017 standard. Table 7 presents a comparison of the readings from the traditional device and the designed system. Measurements were taken under resting conditions to minimize interference caused by movement or postural instability.

Table 6: "Patient measurements for "oxygen saturation".

Patient number	SpO ₂ traditional device	SpO ₂ designed device
1	98	96
2	95	97
3	99	100
4	97	98
5	99	101
6	95	97
7	98	96
8	99	100

13	98	98
40	100	101
41	98	96
48	97	97
60	100	100
61	100	99
98	96	98
99	98	96
100	96	97
101	99	98
112	98	98
117	97	98
118	97	96
119	99	101
120	96	97

Source: Authors, (2026).

Table 7 highlights a high degree of agreement between the two methods. The observed differences were small, suggesting a stable system response to oxygenation measurements at rest. In most cases, the difference between the two values was one or two points, a pattern that reinforces the reliability of the data. This behavior is important because the “oxygen saturation” variable is often used as an immediate clinical indicator in the monitoring of respiratory and cardiovascular conditions.

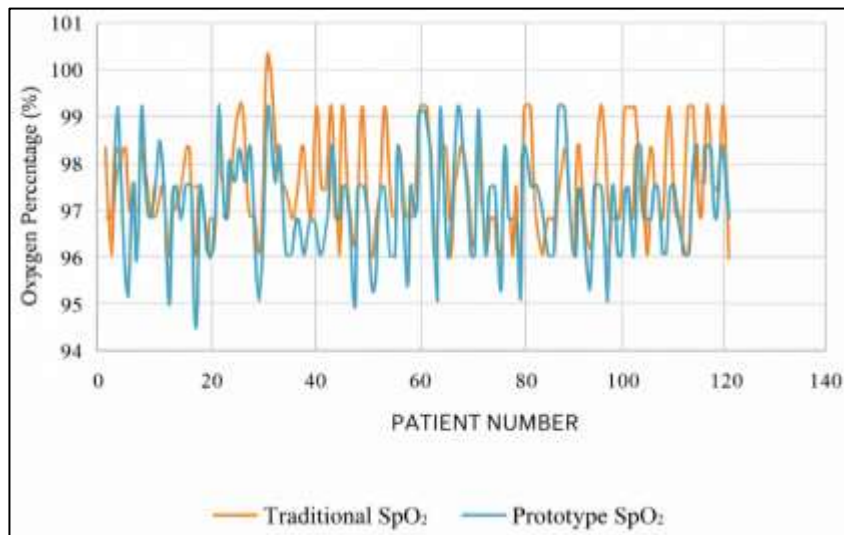


Figure 8: Absolute error in oxygen saturation measurement.

Source: Authors, (2026).

Figure 8, shows that absolute errors remained low and concentrated around a minimal difference. This behavior is favorable in terms of noninvasive monitoring, as it reflects appropriate agreement with the commercial oximeter used as a reference. A uniform distribution of errors is also observed, with no abrupt changes between patients, which contributes to the stability of the overall analysis of this variable. Table 8 summarizes the absolute error and relative error calculated for “oxygen saturation” measurements. This analysis allowed us to determine whether the system remained within the margin expected by the reference standard.

Table 7: Margin of error for “oxygen saturation”.

Patient number	Traditional SpO ₂	SpO ₂ from designed device	Absolute error	Relative error (%)
1	98	96	2	2.04
2	95	96	1	1.05
3	98	99	1	1.02
7	97	95	2	2.06
8	98	99	1	1.02
9	97	96	1	1.03
10	96	97	1	1.04
11	97	98	1	1.03
12	95	94	1	1.05
13	97	97	0	0.00
14	97	96	1	1.03
15	98	97	1	1.02
48	96	97	1	1.04
49	99	97	2	2.02
50	95	94	1	1.05
79	97	96	1	1.03

88	98	99	1	1.02
89	96	95	1	1.04
90	95	96	1	1.05
110	95	97	2	2.11
116	99	98	1	1.01
117	97	98	1	1.03
118	97	96	1	1.03
119	99	98	1	1.01
120	95	96	1	1.05
Overall average				1.33

Source: Authors, (2026).

Table 8 shows an average relative error of 1.33%, a value that falls within the margin accepted by the reference standard. This finding indicates adequate precision for the “oxygen saturation” variable. When compared to the other variables analyzed, this result places oxygenation among the best-performing parameters within the system. The low magnitude of the errors reinforces the idea that the sensor and the applied processing were able to maintain a stable measurement under controlled clinical conditions.

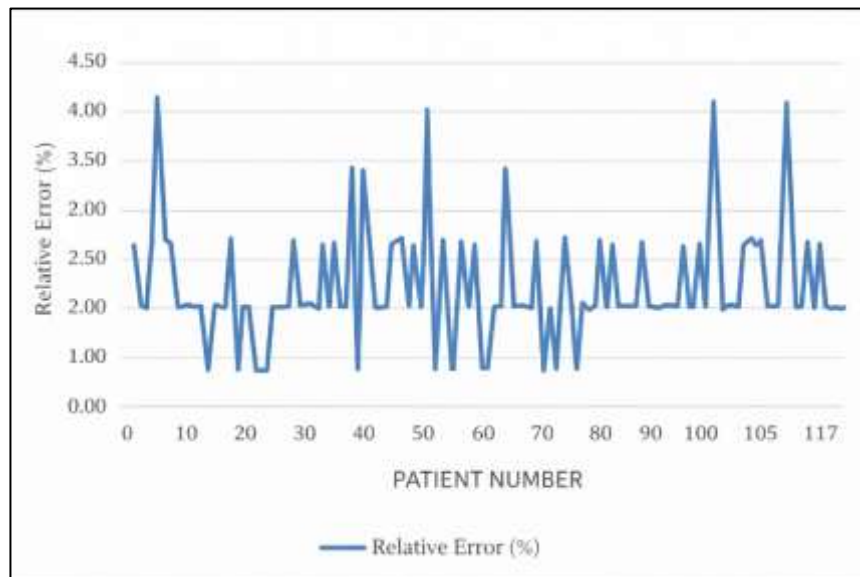


Figure 9: Relative error in oxygen saturation measurement.

Source: Authors, (2026).

Figure 9 confirms that most observations were concentrated in small deviations. From a clinical perspective, this behavior reinforces the device’s ability to estimate oxygenation with a limited difference compared to a commercial pulse oximeter. The observed distribution also suggests that variability among patients was low, which lends consistency to the system when used for continuous monitoring of this variable.

III.2.9 Results and Margin of Error for “Glucose”

“Glucose” measurements were compared against the criteria of ISO 15197:2015. Table 9 presents the records of a representative sample of patients. For this variable, patients with both normal and elevated values were included, allowing for an analysis of the system’s performance across a broader physiological range.

Table 8: “Glucose” measurements.

Patient Number	Time	Age	Gender	Type	Traditional Glucose (mg/dL)	Prototype Glucose (mg/dL)
1	11:45	35	Female	Healthy	82	70
2	18:30	43	Male	Healthy	179	168
3	14:30	27	Female	Healthy	102	109
4	14:00	53	Female	Healthy	132	123
5	10:30	27	Male	Diabetes	232	218
6	14:00	48	Male	Healthy	121	117
7	18:15	21	Male	Healthy	87	99
8	17:45	53	Female	Healthy	181	188
9	06:15	38	Male	Diabetes	163	162
34	11:00	49	Female	Healthy	165	178
35	06:15	60	Female	Healthy	123	118
37	07:15	47	Female	Diabetes	182	177
38	08:15	42	Female	Healthy	133	128
39	17:00	40	Male	Healthy	132	122

44	09:15	29	Female	Healthy	95	101
45	17:15	32	Female	Diabetes	183	194
48	14:00	57	Female	Healthy	154	165
51	13:45	24	Female	Healthy	140	137
61	16:00	27	Female	Healthy	146	134
62	12:15	23	Male	Diabetes	168	166
97	14:15	42	Female	Healthy	139	150
98	14:00	57	Female	Diabetes	184	182
105	06:45	31	Female	Healthy	86	74
117	17:00	29	Male	Healthy	77	91
118	18:15	50	Female	Healthy	160	148
119	11:15	37	Male	Healthy	199	212
120	17:15	27	Female	Healthy	121	135

Source: Authors, (2026).

Table 9 shows that the system covered normal, intermediate, and elevated values, including patients diagnosed with diabetes. This range of readings supported the evaluation of the system across different metabolic scenarios. Unlike other variables, a wider dispersion is observed here among some pairs of values, which was expected given the complexity of estimating “glucose” using non-invasive methods. Nevertheless, the set of measurements suggests that the system was able to follow the general trend of the values recorded by the reference device.

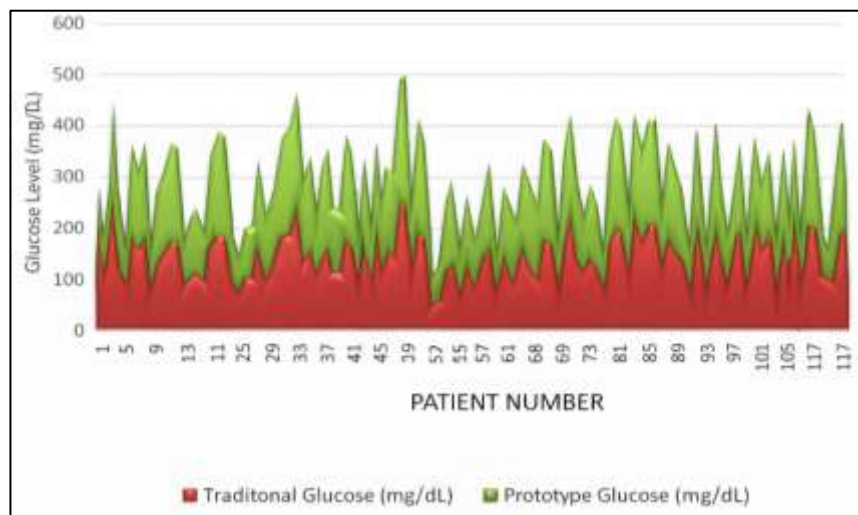


Figure 10: Absolute error in non-invasive glucose estimation.

Source: Authors, (2026).

Figure 10 shows the magnitude of the absolute error per observation. Although the variability was greater than for “heart rate” and “oxygen saturation,” the results remained within a clinically acceptable range for this type of non-invasive approach. The graph shows that the highest errors were not predominant, although there was greater dispersion, confirming that this variable remains one of the most challenging in terms of indirect measurement.

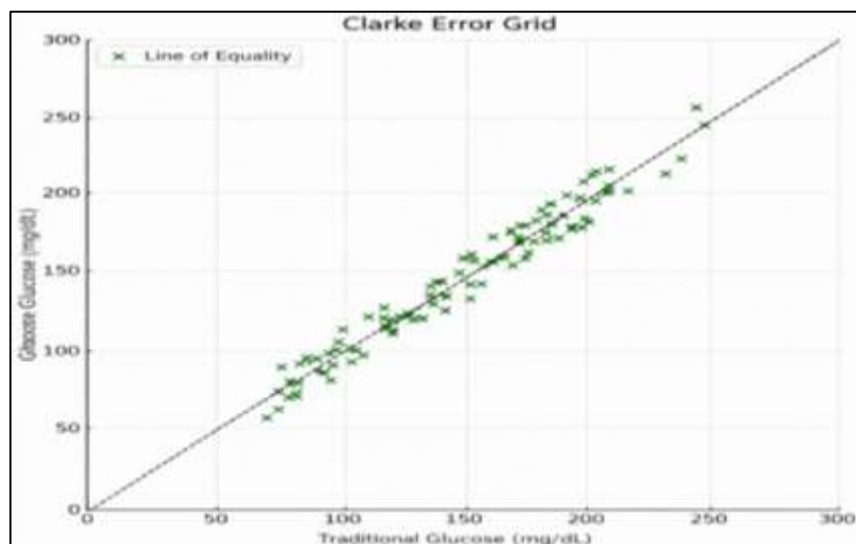


Figure 11: Error Grid analysis of glucose estimates from the non-invasive device.

Source: Authors, (2026).

Figure 11 indicated that the system's measurements fell within Zone A, supporting its clinical acceptability. This result is significant because the "glucose" variable typically presents greater estimation difficulty when non-invasive methods are used. Remaining within this zone suggests that, despite the observed dispersion, the differences did not compromise the system's clinical utility as a monitoring tool. Table 10 presents the absolute error and relative error of the measurements obtained for the "glucose" variable. This comparison allowed for a more precise quantification of the deviation between the prototype and the traditional method.

Table 9: Margin of error for "glucose".

Patient number	Traditional glucose (mg/dL)	Prototype glucose (mg/dL)	Absolute error	Relative error (%)
1	82	70	12	14.63
2	179	168	11	6.15
3	102	109	7	6.86
9	163	162	1	0.61
10	185	192	7	3.78
12	141	153	12	8.51
28	116	125	9	7.76
29	144	141	3	2.08
30	194	185	9	4.64
31	197	202	5	2.54
55	76	73	3	3.95
56	132	133	1	0.76
57	142	153	11	7.75
63	85	79	6	7.06
64	139	144	5	3.60
66	166	164	2	1.20
99	92	102	10	10.87
100	201	187	14	6.97
101	155	140	15	9.68
103	89	102	13	14.61
104	185	175	10	5.41
105	86	74	12	13.95
108	121	124	3	2.48
117	81	91	14	12.35
118	160	148	12	7.50
119	199	212	13	6.53
120	121	135	14	11.57
Overall average				5.72

Source: Authors, (2026).

Table 10 shows an average relative error of 5.72%. Although this variable exhibited greater variability than the others, the system's performance remained within acceptable limits according to the regulatory criteria adopted for the analysis. The results indicate that estimating "glucose" requires more complex signal processing and a predictive response that is more sensitive to individual variability. Nevertheless, the obtained average suggests that the system remains useful for monitoring and preliminary clinical observation.

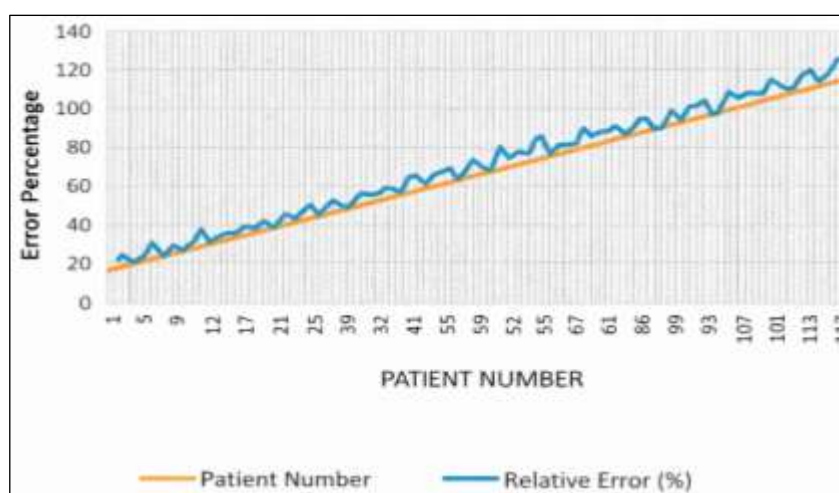


Figure 12: Relative error in glucose estimation.

Source: Authors, (2026).

Figure 12 shows that the relative deviations were more heterogeneous. This situation was to be expected, given that the non-invasive estimation of "glucose" depends on more complex physiological relationships and the response of the predictive model. Nevertheless, the overall performance suggests that the system retains useful capability for indicative monitoring. The observed dispersion does not invalidate the proposal, but it does highlight the need to continue refining the model and expanding the sample to improve stability for this variable.

III.2.10 Results and Margin of Error for “Body Temperature”

The evaluation of “body temperature” was performed based on ASTM E1112-00 and ISO 80601-2-56:2017. Table 11 presents a sample of the compared values. This variable was selected for its importance as a basic physiological sign and for its utility in monitoring general clinical conditions.

Table 10: “Body temperature” measurements.

Patient Number	Time	Age	Gender	Type	Traditional Temperature (°C)	Prototype Temperature (°C)
1	11:45	35	Female	Healthy	36	37
2	18:30	43	Male	Healthy	37	37
3	14:30	27	Female	Healthy	36	36
4	14:00	53	Female	Healthy	37	37
5	10:30	27	Male	Diabetes	37	37
37	07:15	47	Female	Diabetes	37	37
38	08:15	42	Female	Healthy	36	37
39	17:00	40	Male	Healthy	37	38
40	09:45	57	Male	Healthy	36	36
49	12:45	35	Male	Diabetes	36	36
75	15:45	53	Male	Healthy	37	37
76	13:00	59	Male	Healthy	36	37
81	13:00	41	Female	Diabetes	37	37
82	10:45	52	Female	Healthy	36	36
83	18:00	55	Female	Diabetes	37	37
94	09:15	23	Female	Healthy	37	37
113	13:15	28	Male	Healthy	37	37
114	11:00	30	Female	Healthy	37	37
115	06:30	39	Female	Healthy	37	37
116	09:45	41	Male	Healthy	37	37
117	17:00	29	Male	Healthy	37	37
118	18:15	50	Female	Healthy	36	36
119	11:15	37	Male	Healthy	37	37
120	17:15	27	Female	Healthy	37	37

Source: Authors, (2026).

Table 11 shows a high degree of agreement between the reference device and the prototype. The observed stability suggests that the “body temperature” variable was one of the best-performing variables during testing. In most readings, the prototype’s value matched or remained very close to that obtained by the commercial device, indicating a stable signal and a reliable reading process under controlled conditions.

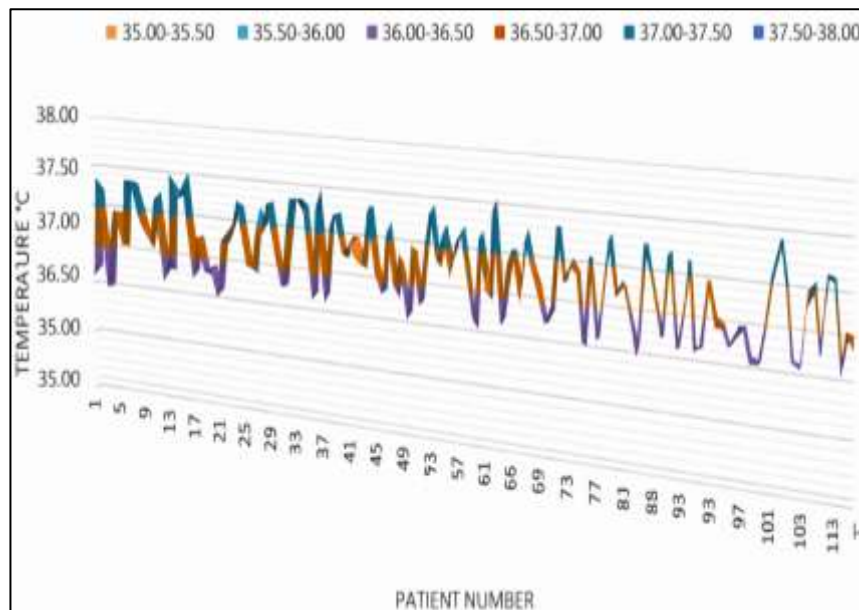


Figure 13: Absolute error in body temperature measurement.

Source: Authors, (2026).

Figure 13 shows very small absolute errors, with minimal differences between the two methods. This behavior is consistent with the less variable nature of temperature when the measurement is taken under controlled resting conditions. The graph supports the idea that this variable was one of the most consistent and that the system managed to maintain high accuracy in its recording. Table 12 presents the absolute error and relative error calculated for the “body temperature” variable. This analysis allowed us to quantify the deviation of the prototype from the reference method.

Table 11: Margin of error for “body temperature”.

Patient number	Traditional temperature (°C)	Prototype temperature (°C)	Absolute error	Relative error (%)
1	36.20	36.26	0.06	0.17
2	37.40	37.20	0.20	0.53
5	37.00	36.95	0.05	0.14
6	36.60	36.53	0.07	0.19
7	37.40	37.35	0.05	0.13
8	37.40	37.33	0.07	0.19
22	36.10	36.15	0.05	0.14
23	36.80	36.70	0.10	0.27
24	36.90	36.88	0.02	0.05
65	37.20	37.25	0.05	0.13
66	36.60	36.80	0.20	0.55
67	36.50	36.40	0.10	0.27
68	37.50	37.60	0.10	0.27
69	36.20	36.23	0.03	0.08
70	36.90	36.70	0.20	0.54
71	37.10	37.05	0.05	0.13
72	36.50	36.70	0.20	0.55
73	37.20	37.30	0.10	0.27
74	36.90	36.89	0.01	0.03
75	36.60	36.68	0.08	0.22
88	36.90	36.80	0.10	0.27
89	36.50	36.44	0.06	0.16
90	36.00	36.09	0.09	0.25
115	37.20	37.20	0.00	0.00
116	36.60	36.50	0.10	0.27
117	36.70	36.70	0.00	0.00
118	36.10	36.10	0.00	0.00
119	36.70	36.50	0.20	0.54
120	36.50	36.60	0.10	0.27
Overall average				0.21

Source: Authors, (2026).

Table 12 shows an average percentage error of 0.21, indicating a very small difference between the prototype and the commercial device. This result places “body temperature” as the variable with the best agreement among the parameters analyzed. The small magnitude of the error also suggests that the system can maintain this measurement with high stability, even when considering patients of different ages and clinical profiles.



Figure 14: Relative error in body temperature measurement.

Source: Authors, (2026).

Figure 14 confirms the low dispersion of the error. Most readings fell within minimal deviation values, supporting the device’s reliability for this variable. From a practical standpoint, this result strengthens the possibility of using the system to support continuous physiological monitoring, especially when temperature is part of routine clinical follow-up.

III.2.11 Integrated Discussion of Experimental Validation

The joint analysis of clinical variables shows better performance for “body temperature” and “oxygen saturation,” followed by “heart rate” and, with greater variability, “glucose.” The results summarize an average relative error of 3.63% for “heart rate,” 1.33% for “oxygen saturation,” 5.72% for “glucose,” and 0.21% for “body temperature.” This distribution suggests that the system performed more consistently for variables with a more direct physiological signal and lower inference complexity. The comparison between variables shows that the device’s performance was not uniform, but it maintained acceptable performance across all of them. The accuracy achieved for “body temperature” and “oxygen saturation” reinforces the system’s utility for parameters that depend on less complex and more stable signals. In the case of “heart rate,” the mean difference also remained within a low range, confirming that the system can provide functional readings for basic monitoring. The “glucose” variable, however, showed greater dispersion, which aligns with the physiological complexity of its non-invasive estimation. Comparison with previous literature indicates that “glucose” estimation remains the most sensitive component within non-invasive systems.

Previous studies have described wide deviations in areas of low concentration or in scenarios with high individual variability. In this study, the observed average error was lower than that reported in certain prior studies, which reinforces the utility of the proposed approach. It should also be noted that the commercial devices used as references have their own tolerances; therefore, the analysis should be interpreted within that technical margin and not as an absolute equivalence. Overall, the experimental validation shows that the system offers a functional solution for continuous non-invasive monitoring. From an applied clinical perspective, the results indicate that the proposal can be used to support physiological monitoring, telemedicine, and preventive surveillance, particularly in contexts where portability and remote consultation have operational value. At the same time, the findings suggest that future improvements should focus on refining the “glucose” estimate and increasing the sample size to strengthen the model’s accuracy in more heterogeneous populations.

III.2.12 Hypothesis Testing

To determine whether there were differences between the measurements from the IoT system and those from the traditional method, Student’s t-test for paired samples was applied. Table 13 summarizes the results of the comparison. This analysis allowed us to assess whether the differences between the two methods were statistically significant for each of the variables evaluated.

Table 12: Obtained p-values and the hypotheses evaluated.

Parameter	p-value	Hypothesis evaluated
“Heart rate”	0.270	H ₀ : No significant difference
“SpO ₂ ”	1.28E-05	H ₀ : No significant difference
“Glucose”	0.429	H ₀ : No significant difference
“Temperature”	0.427	H ₀ : No significant difference

Source: Authors, (2026).

As shown in Table 13, only the “SpO₂” variable had a p-value below 0.05, indicating a statistically significant difference between the two methods. For “heart rate,” “glucose,” and “temperature,” the p-values were above the significance level, so the null hypothesis was retained. This indicates that, for these three variables, there was insufficient evidence to affirm a statistical difference between the prototype and the traditional method. This result suggests that, for most parameters, the system did not show significant statistical differences compared to the reference equipment. Based on the study’s findings, this implies that the prototype’s measurements remained within a range comparable to the traditional method. In the case of “SpO₂,” the difference found warrants further investigation into calibration and reading adjustment for that variable, since although the average error was low, the statistical comparison revealed a discrepancy between the two methods that warrants further review.

III.3 APPLICATION OF THE MACHINE LEARNING ALGORITHM FOR THE IDENTIFICATION OF PHYSIOLOGICAL PARAMETERS

III.3.1. Data Preprocessing and Handling

The predictive component of the system was trained using 1,500 physiological records collected by authorized clinical staff. Each record included the variables “BPM,” “SpO₂,” “Glucose,” and “Temperature.” Table 14 presents the structure of the variables used. This dataset formed the basis for the training, validation, and comparison of the machine learning models employed in the study.

Table 13: Description of the dataset obtained by the clinic.

Variable name	Range or value	Description	Type
“BPM”	50–140	Heart rate in beats per minute	Numeric
“SpO ₂ ”	70–100	Blood oxygen saturation (%)	Numeric
“Glucose”	70–200	Blood glucose level (mg/dL)	Numeric
“Temperature”	35–40	Body temperature (°C)	Numeric
“BPM_Category”	1, 2, 3	1 = normal, 2 = moderate risk, 3 = high	Numeric
“SpO ₂ _Category”	1, 2, 3	1 = normal, 2 = moderate risk, 3 = high	Numeric
“Glucose_Category”	1, 2, 3	1 = normal, 2 = moderate risk, 3 = high	Numeric
“Temperature_Category”	1, 2, 3	1 = normal, 2 = moderate risk, 3 = high	Numeric

Source: Authors, (2026).

Table 14 shows that the dataset included numerical and categorical variables useful for clinical classification. Initial processing included double validation, cleaning of inconsistencies, and Min-Max normalization, with the aim of improving training stability. This step was important because a cleaned dataset reduces analytical noise and improves the models’ generalization ability.

III.3.1.1. Target variable and oversampling technique

The target variable corresponded to the “clinical risk level,” coded into three classes. Before balancing, the dataset showed an imbalance between classes. Table 15 summarizes the original distribution. This behavior made it necessary to apply a strategy to reduce bias toward the majority classes.

Table 14: Data set for training.

Parameter	Classes before SMOTE	Majority class
“BPM”	1: 676; 2: 328; 3: 496	676
“SpO ₂ ”	1: 412; 2: 485; 3: 603	603
“Glucose”	1: 717; 2: 414; 3: 369	717
“Temperature”	1: 477; 2: 282; 3: 741	741

Source: Authors, (2026).

Table 15 shows an imbalance between categories, particularly in “Temperature” and “Glucose.” To reduce bias in the models, SMOTE was applied. This procedure allowed for the generation of new synthetic instances for the underrepresented classes, thereby better balancing the learning process.

Table 15: Oversampling with SMOTE.

Parameter	Class 1: Normal risk	Class 2: Moderate risk	Class 3: High risk	Total	IR
“Heart rate (BPM)”	676	328	496	1500	2.06
“Oxygen saturation (SpO ₂)”	412	485	603	1500	1.46
“Glucose”	717	414	369	1500	1.94
“Temperature”	477	282	741	1500	2.63

Source: Authors, (2026).

Table 16 allows us to identify the degree of imbalance using the IR index. The highest values were recorded for “Temperature” and “Heart Rate (BPM),” which justified the need to generate new synthetic instances for minority classes. This adjustment was important to prevent the models from unduly favoring the most frequent categories and, at the same time, to improve classification sensitivity at the less-represented risk levels.

III.3.2. Evaluation of Machine Learning Models

The performance of the algorithms was evaluated using stratified validation on the complete set of records. The comparison included a multilayer neural network, linear regression, SVM, and decision tree. The purpose of this phase was to determine which model offered the best predictive and classification capabilities for the monitored physiological parameters.

III.3.2.1. Multilayer Neural Network with Levenberg–Marquardt



Figure 15: Training process of the multilayer neural network.

Source: Authors, (2026).

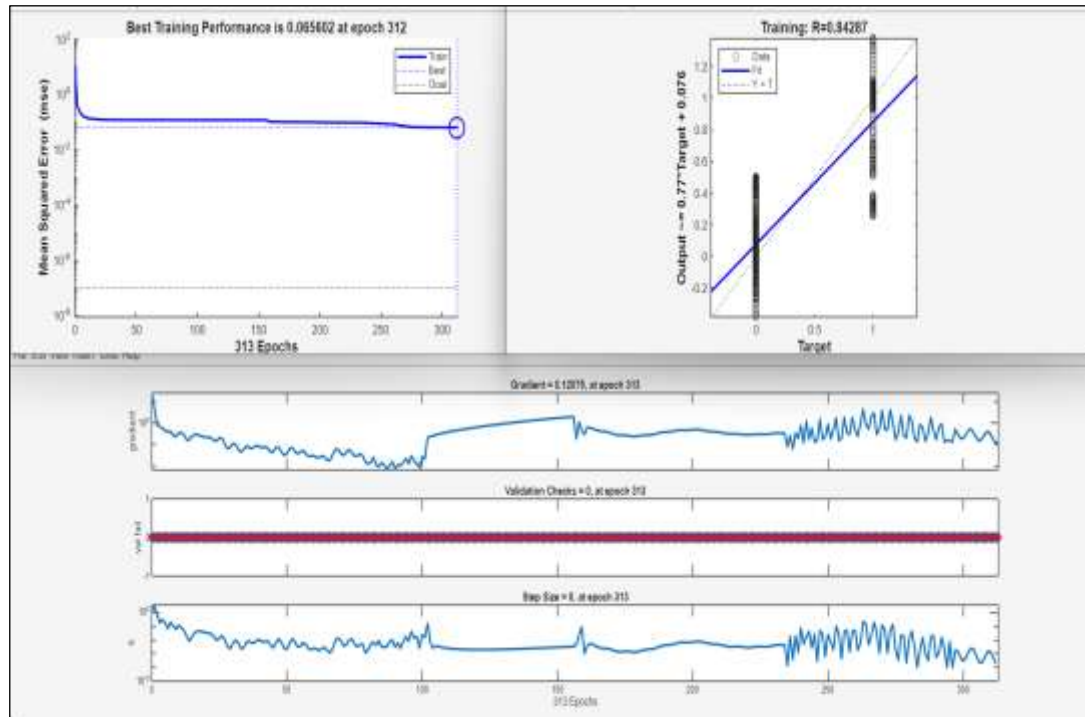


Figure 16: Results of training using Backpropagation.

Source: Authors, (2026).

Figure 15 and Figure 16 show the fitting process of the selected model. The multilayer perceptron achieved a coefficient of determination of 0.843, an MSE of 0.0042, and an RMSE of 0.1621. These values indicate a high fitting capacity and an adequate response to the variability of the physiological data. Furthermore, the training behavior indicates that the model successfully captured useful patterns within the dataset without losing stability during the learning process.

III.3.2.2. Linear Regression

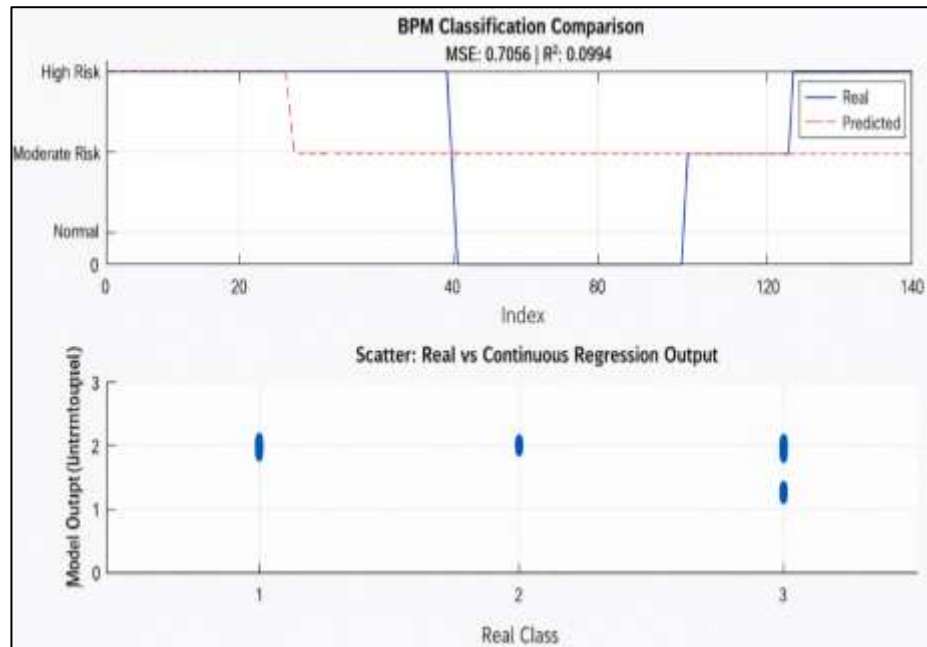


Figure 17: Results of the linear regression model in predicting physiological parameters.

Source: Authors, (2026).

Figure 17 reflects limited ability to capture nonlinear relationships. The model obtained an R^2 of 0.0986, an MSE of 0.7056, and an RMSE of 0.8470, values that indicate low predictive power compared to more complex models. This result suggests that the relationship between physiological variables and risk level cannot be adequately explained by a simple linear structure.

III.3.2.3 Support Vector Machines (SVM)

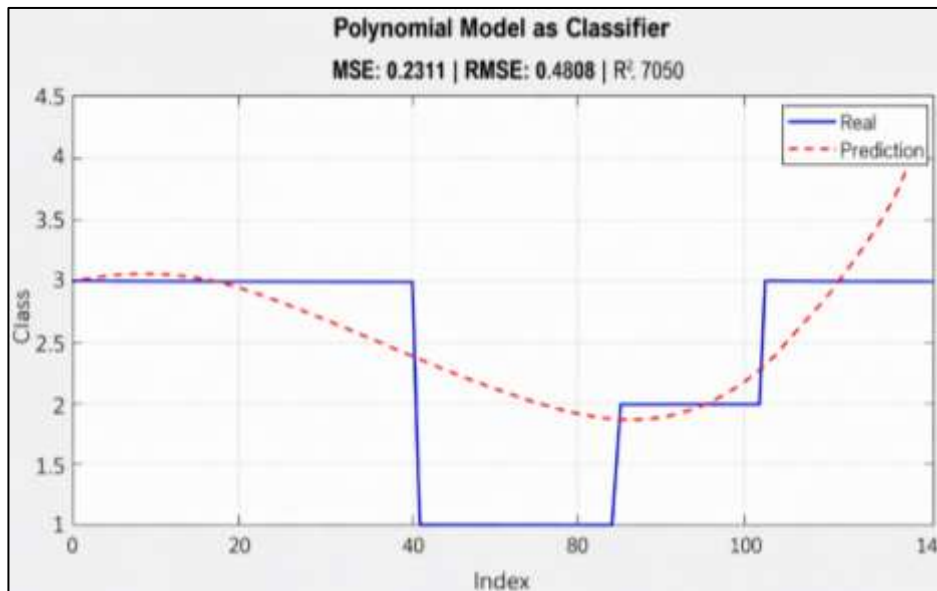


Figure 18: Performance of the SVM model in predicting physiological signals.
Source: Authors, (2026).

Figure 18 shows that the model achieved an R^2 of 0.7050, with an MSE of 0.2311 and an RMSE of 0.4808. These results outperformed linear regression, indicating a better ability to handle complex patterns in the data. Although it was not the strongest model in the analysis, it did demonstrate solid performance and better adaptation to the problem's nonlinear structure.

III.3.2.4 Decision Tree

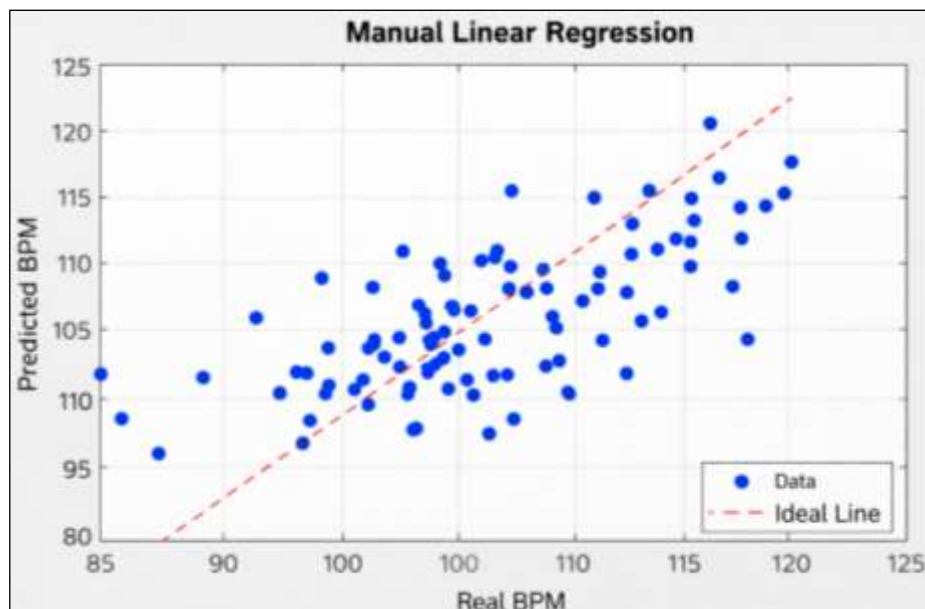


Figure 19: Comparison between actual and predicted values using a decision tree.
Source: Authors, (2026).

Figure 19 shows intermediate performance. The algorithm achieved an R^2 of 0.4174, an MSE of 33.16, and an RMSE of 5.76. Although its logic is interpretable, the fit was lower than that achieved by the MLP and the SVM. This finding indicates that the tree's interpretability was not sufficient to compensate for its lower generalization ability when faced with a physiological problem involving more complex relationships.

Table 16: Performance comparison among machine learning models.

Algorithm	Algorithm	R^2 score	MSE	RMSE	Accuracy (%)	F1-score (%)
SMOTE	Linear regression	0.0994	0.7056	0.8447	49.07	43.14
SMOTE	SVM (regression)	0.8450	0.2311	0.4808	91.30	89.80
SMOTE	Decision tree	0.7174	33.1646	5.7589	85.40	82.30
SMOTE	Levenberg–Marquardt	0.8430	0.0232	0.1621	95.42	98.13

Source: Authors, (2026).

Table 17 shows that the neural network with Levenberg–Marquardt achieved the best overall values for “Accuracy” and “F1-score,” while SVM also performed well. Linear regression was the least favorable option, confirming that the relationships between physiological variables and risk levels have a nonlinear structure. Overall, the results indicate that algorithms with a greater capacity to capture complex patterns offered better performance in clinical classification.

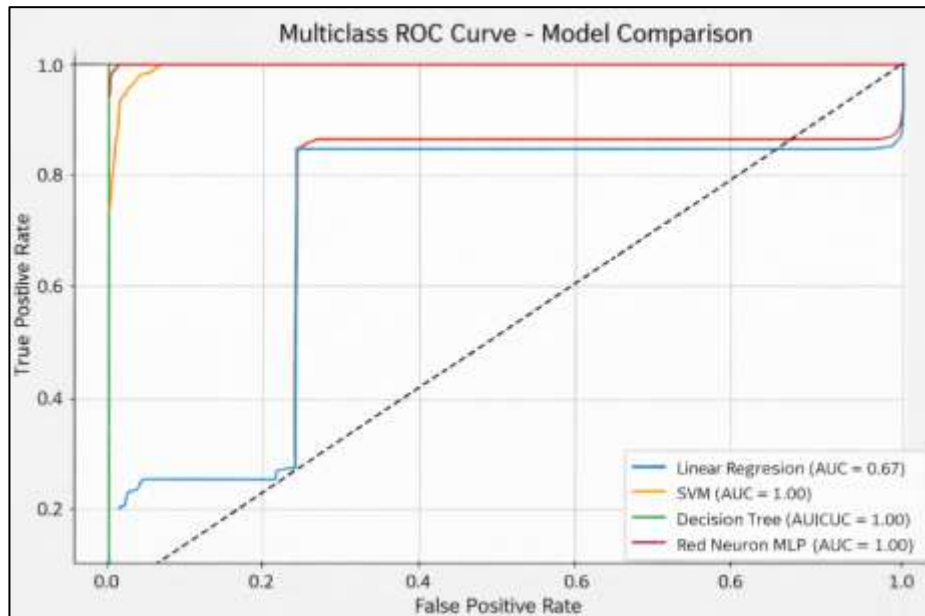


Figure 20: Multiclass ROC curve for the comparison of classification algorithms.

Source: Authors, (2026).

Figure 20 shows that the MLP, decision tree, and SVM achieved an AUC of 1.00, while linear regression obtained a value of 0.67. This result confirms that nonlinear algorithms provide better discrimination. The curve also shows that classification performance was stronger in the models that were able to distinguish risk categories more clearly.

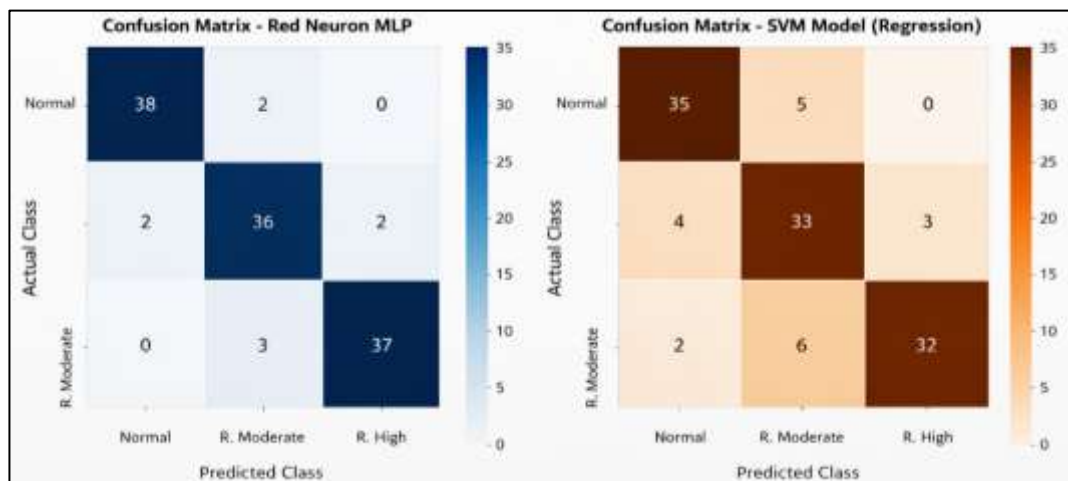


Figure 21: Confusion matrices of the best-performing models.

Source: Authors, (2026).

Figure 21 shows that the MLP had a high accuracy rate across all three classes: normal, moderate risk, and high risk. In contrast, the SVM recorded more errors in closely related classes, indicating a lower ability to distinguish between certain clinical categories. This difference is significant because better discrimination between intermediate and high-risk classes can enhance the system’s utility during clinical monitoring.

III.3.3. Neural Network Architecture

The definition of the optimal architecture involved testing with a single hidden layer and between 5 and 25 neurons. Figure 31 illustrates the organization of the selected algorithm. This phase allowed us to identify the configuration that offered the best balance between fit, generalization, and computational stability.

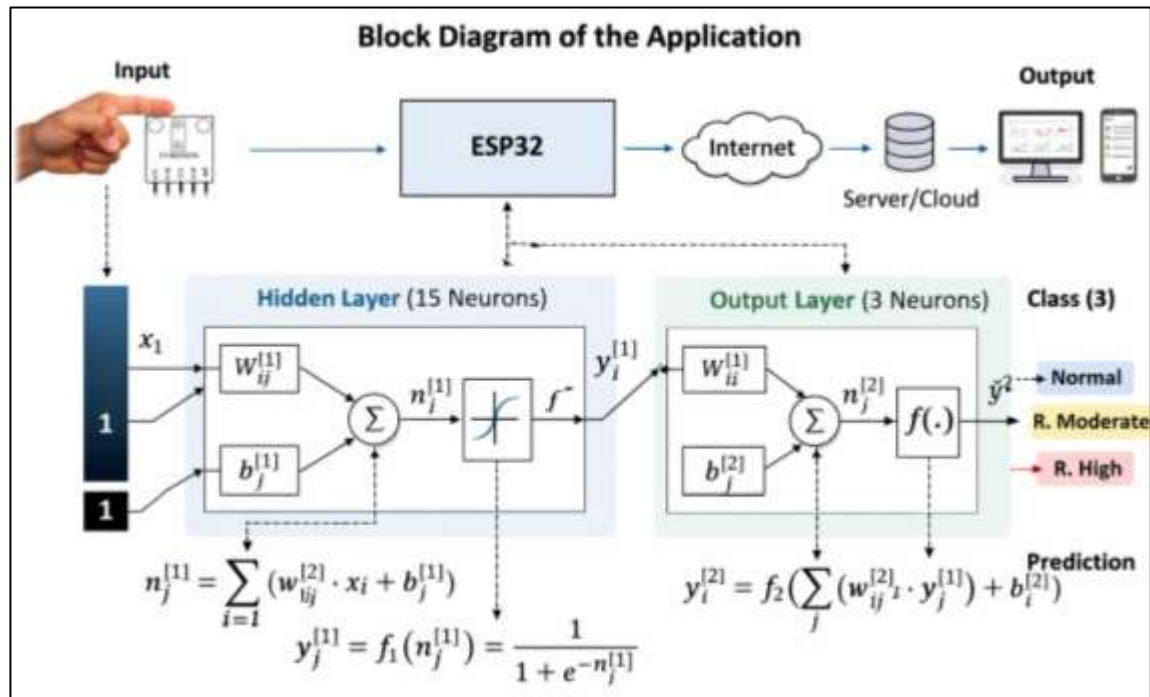


Figure 22: Architecture of the system's training and prediction algorithm.

Source: Authors, (2026).

Figure 22 shows the general configuration of the model. The architecture with 15 neurons in the hidden layer offered the best balance between accuracy and generalization, achieving an R^2 of 0.843 and an MSE of 0.0042. This result allowed us to identify the MLP as the most appropriate model for identifying clinical risk levels. The selection of this architecture also avoided unnecessary increases in complexity, maintaining high performance without overburdening the training process.

III.3.3.1. Discussion of the Machine Learning Component

The comparative analysis indicated that the MLP was the model with the best overall performance. Its F1-score of 98.13% and accuracy of 95.42% show that the system achieved accurate classification of clinical states. Previous studies in digital health have reported high results with deep architectures, including convolutional networks with attention mechanisms. In this work, a simpler architecture achieved comparable results for the set of physiological variables used, demonstrating that a well-tuned configuration can perform competitively without the need for more complex structures. The superiority of the MLP over linear regression, decision trees, and some of the SVM results suggests that the relationship between “heart rate,” “SpO₂,” “body temperature,” and “glucose” and the “clinical risk level” does not follow a strictly linear pattern. Therefore, the MLP’s ability to model nonlinear relationships was decisive in the observed performance. This point is important, as it confirms that the physiological information contained in the system requires analytical methods with greater mathematical flexibility. The confusion matrices also show that the MLP performed better in distinguishing between moderate and high risk. This is important from a clinical perspective, as more accurate classification at intermediate and high levels can contribute to the early detection of physiological abnormalities. Overall, the results support the use of the MLP as the system’s primary analytical component and suggest that its integration into the IoT architecture provides a solid foundation for machine learning-assisted physiological monitoring.

IV. CONCLUSIONS

This study examined the development and validation of a non-invasive physiological monitoring system that integrates Internet of Things technologies and machine learning techniques for real-time health observation. The research approach centered on analyzing how biomedical sensors, wireless communication, and predictive algorithms can support continuous monitoring of vital signs without requiring invasive procedures. Through experimental evaluation and model training, the system demonstrated the capacity to acquire, process, and interpret physiological signals obtained from human subjects. The results confirm that the integration of IoT hardware components with biomedical sensing technologies allows the reliable acquisition of physiological parameters such as heart rate, oxygen saturation (SpO₂), glucose estimation, and body temperature. The ESP-based microcontroller architecture enabled stable wireless communication and real-time data transmission to a web interface, allowing remote visualization and interpretation of physiological indicators. The selected sensors, including the MAX30100 optical sensor and temperature sensing elements, provided measurements with acceptable precision for continuous monitoring environments. Machine learning analysis conducted using MATLAB enabled the training of a predictive model based on a multilayer perceptron neural network. The trained model achieved a coefficient of determination of $R^2 = 0.99$, indicating strong predictive capacity when estimating physiological conditions from sensor signals. The low prediction error obtained during model validation confirms that the algorithm can classify physiological states with high accuracy. These results support the feasibility of integrating intelligent prediction models into biomedical monitoring systems aimed at preventive healthcare. The proposed system also demonstrates the feasibility of designing a portable and non-invasive biomedical device capable of monitoring multiple physiological parameters simultaneously. The integration of sensors, microcontroller processing, wireless connectivity, and machine learning analysis forms a unified architecture capable of collecting data continuously and transmitting it to digital platforms.

This architecture enables remote monitoring through web or mobile interfaces, supporting healthcare professionals and users in observing physiological changes in real time. From a practical perspective, the study contributes to the development of accessible technological solutions for remote health monitoring, particularly in environments where continuous clinical supervision is limited. The system architecture supports preventive healthcare strategies, facilitating early detection of abnormal physiological patterns and enabling timely decision-making. In addition, the integration of IoT and machine learning technologies provides a scalable framework that may support future biomedical monitoring applications in telemedicine, elderly care, and chronic disease management.

V. AUTHOR'S CONTRIBUTION

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