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# Communications Integration of 5G-WSN towards Healthcare Monitoring System Based on Deep Learning Techniques

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**ABSTRACT**

Healthcare monitoring-based systems are experiencing a surge in conventional methods with the integration of cutting-edge technologies such as the Internet of Things (IoT) and deep learning. This paper suggests a Wireless Sensor Network (WSN) with IoT architecture to monitor patients in real-time using the 5G networks. The system can effectively process the data that the wearable sensors capture regarding the heart rate, blood pressure, oxygen levels, and body temperature, and use deep learning models such as CNN-LSTM to process that data and convey the results to the user. It is created to update patients, especially the elderly, about their health promptly and to be able to contact healthcare providers remotely. The experimental results show that the system is effective as the accuracy of the system reaches 0.988 with a Maximum relative error of “heart rate” (2.19), “body temperature” (3.06), “systolic blood pressure” (3.3), “diastolic blood pressure” (3.4), and “SpO2” (1.03). The solution enhances access and offers a strong health monitoring system that is real-time and supports timely intervention and better patient care, particularly in remote locations.

**Keywords**: Deep learning, Internet of Things (IoT), health monitoring, WSN, cloud server

## 1. INTRODUCTION

The senior population is growing worldwide because of medical progress like vaccination, increased healthcare facilities, and easier access to medicines, particularly in industrialized nations [1]. As a result, there has been a rise in the need for doctors and other medical professionals. Pacemakers, medical glucose monitors, medical heart rate monitors, sphygmomanometers, and electronic stethoscopes are just a few examples of life-supporting equipment made possible by advancements in electronics. To better disseminate and gather information on human health [2]. Pulse rate and blood oxygen saturation levels are measurable, and useful for continuous monitoring if clinical conditions such as dyspnea due to pneumonia or acute cardiac events need to be managed. By keeping tabs on their oxygen levels, doctors can provide medication and teach them how to breathe correctly to raise their patients' saturation levels to as high as 93% [3]. Home healthcare applications that use onboard health monitoring sensors have much promise. However, many developing nations need more resources to take advantage of this potential because typical mobile devices cost between $399 and $550. The U.S. has a total of about 20% of its population that is rural and yet only around 9% of the nation’s physician workforce practices in rural areas, home healthcare monitors may solve the problem of patient access [4]. One intriguing answer is embedded technologies, which enable people to keep tabs on their health remotely or at medical facilities without requiring continual attention from medical staff [5]. Home healthcare is a fast-growing field of concern, with many advantages for individuals and society. Remote monitoring systems reduce the inconvenience of traveling to doctors’ offices and waiting to be attended to [6]. These innovations can improve healthcare's diagnostics, treatments, and affordability and make it more flexible to manage. Previous research has demonstrated the promise of ICT-based technology in A wearable wristband device for monitoring (self-) health at home and work using artificial intelligence deep learning Sergiu Stelian Ilie, John AhrendsMurthy Yenkatesh

Preis EUR 69,99. Erscheinung Sterne von Xaver Ozog Die Freeware Waiter Informational (less) More from my site Metric Alert: Keep An Automatic Eye on Your Financial Stats Next PVR IS of continuous Lives.. Improved health literacy and lower healthcare expenditures are two of the main goals of these innovations [7, 8]. This addresses the need for a low-cost, portable, and trustworthy health monitor system in light of mobile technology's monetary benefits and expanding capabilities. The suggested system uses Arduino-made sensors for measuring SpO2 levels, pulse rates, and temperatures. Low-cost data transmission to the internet or mobile phones makes the collected information readily available to the elderly at home, in clinics, and even in developing nations [9]. The percentage of hemoglobin bonded to oxygen is measured by a pulse oximeter known as the oxygen saturation level in the blood or SpO2. The normal range for SpO2 is 95–100%. Non-invasive medical sensors called pulse oximeters measure blood oxygen saturation [10]. Providing a non-invasive evaluation of patient oxygen concentration is crucial in medical intensive care units (ICUs), labor and recovery rooms, and operating rooms [11].CaszOxiSys is a real-time health monitoring system that measures oxygen saturation and heart rate with photodiodes and light-emitting diodes (LEDs). This bio signal data is subsequently transmitted over Bluetooth to a computer for analysis. This study aims to design a low-cost system with an accurate pulse oximeter, heart rate monitor, and other health monitoring sensors despite the wide availability of such devices on the market [12], pulse rate, and temperature sensors to monitor such vital signs in real-time. The devices are for use in the comfort of one's own home, medical settings, or areas with limited access to technology. The measurement of blood oxygen saturation levels relies on the fact that oxygenated hemoglobin Oxyhemoglobin ($HbO_2$) and deoxyhemoglobin (Hb) have differing light-absorption properties that are wavelength dependent. The relative absorption of red ( 640 nm) and infrared (950 nm) light transmitted through vascular tissues can, when projected though the tissue to be measured, estimate oxygen saturation in blood (SpO 2) [13]. Pulse oximeters accomplish this by using a pair of LEDs which are modulated with red and infrared light, usually transmitted through the thin tissue like the fingertip or ear lobe for instance. Deoxygenated hemoglobin has a much greater degree of absorbance in the red band than oxygenated hemoglobin and displays greater transparency in the infrared range compared to oxygenated hemoglobin [14]. To ensure the signal extraction is correct, high-pass filters and low-pass filters are used for removal of the DC component of blood signal as well as the type-low-frequency noise and other high-frequency noise generated by power supply interference and not ideal characteristics of operational amplifier [15]. This allows for more precise measurements of blood saturation. This method also filters a phototransistor's output to eliminate noise. Rail-to-rail shifts between 0 and 5V are generated by another circuit from the resultant signal, representing the contraction and dilation of the heart. The microcontroller records the duration of these changes to derive an average, which yields a more accurate readout [16]. The maxima and minima of the AC/DC for each signal after the red and infrared wavelengths traverse human tissue are then used to compute $SpO_2$. The saturation is typically calculated according to the Mendelson and Kent relation [17, 18], derived from the Beer-Lambert law. The pulse-oximeter sensor uses the AC components of the LEDs light emitted for representing the minute changes created by contraction and dilation of heart. The absorption of the - signal and therefore blood oxygen saturation is approximately proportional to the reciprocal square of its DC component (such as LED intensity at a given wavelength) [19]. There are several significant contributions in this paper to the research field of health monitoring. Firstly, it describes a low-cost, portable, and credible health monitoring system that measures both SpO2 levels. The device features a reliable on a microcontroller board that produces accurate readings for these key health indicators. The system is also an affordable and accessible solution using inexpensive data transmission to the Internet or mobile phones for home and clinic use, as well as potentially outside first-world nations. It also presents an alternative to enhance the reading reliability, using the microcontroller for the average time calculation of shifts between rail-rail (0-5 V). This method improves the precision and reliability of this system. SpO2 is computed using an established Mendelson and Kent equation through analysis. The system's high performance is validated through the experimental results, which show a maximum error of 2% when compared with commercially available pulse oximeters such as Choice Med. Further, the proposed system has flexible wearability through a wireless sensor. It can be directly connected to the microcontroller, and the results can be viewed through various platforms such as mobile phones, computers, LCD monitors or even on a computer monitor--a plug-and-play design for monitoring these health conditions in an individual. These works are contributing towards health monitoring and they can open the door to low cost, accessible healthcare for a larger part of the population.

## 2. Materials and Methods

The IOT and deep learning (DL) technology-based patient monitoring system was designed as an integrated system including software. Data collected on patients at the bedside were through IoT devices (wearable sensors and emerging health care devices). It enabled fast and accurate analyses of data through the use of DL techniques. The model was based on different data and health attributes. The data were normalized and CNN and RNN structures, as well as computing paradigms, were tuned to optimize for real-time performance. Through extensive testing in real-world medical care scenarios, the system demonstrated its capacity to re-engineer how patients were managed and patient outcomes improved thorough stability and reliability.

### 2.1 WSN and IoT Integrating Challenges

Wireless Sensor Networks (WSN) integration with Internet of Things (IoT) comprises several challenges [20]:

- Security: Enabling the IoT on WSNs will require IP addressing functionalities to be introduced even on sensor nodes, which in general have a basic role of sensing. This makes the system more vulnerable and a potential attack to which require high level of security for all the system.
- Quality of Service (QoS): Sensors need to optimize resources to provide quality service, particularly because the IoT devices are diverse gadgets with varying resource requirements. There might be a need to do protocol translation and repeaters at the gateways, and the collaboration resources achieved through collaborative effort often aid in sustaining high quality of service even when the resources are heavily loaded or when the security measures are such that they demand many resources.
- Configuration: WNSs should be programmed to grow their network, modify their architecture, and scale themselves. Users must also be prepared to install software updates and recover the system in case of a network outage or faults.
- Node Compromise: The sheer size of the nodes in a typical WSN increases the potential for physical attacks or node compromise. Such vulnerabilities can potentially result in unauthorized access to or manipulation of data in the network.
- Unauthorized Data Access: The share size of the nodes in a typical WSN increases the potential for physical attacks or compromising the nodes. Such vulnerabilities can result in unauthorized access to or manipulation of data in the network.
- Denial of Service (DoS) Attacks: WSNs that are not well secured in the IoT networks can suffer from DoS attacks, which makes it possible to flood the network and cause the services failure or prevent data traffic.
- Data Privacy: is also a problem to be protected as WSN based IoT can spread sensitive data over many levels of communication. So, good encryption and efficient data transmission protocols are important against unauthorized access to and corruption of the encrypted data.

### 2.2 Proposed Model

Figure 1 depicts a 5G-enabled healthcare monitoring system that integrates the wireless sensor networks (WSN) and the Internet of Things (IoT) to facilitate real-time monitoring of patients' health conditions. Under this system, wearable sensors measure and track vital signs such as blood pressure, heart beat rate, oxygen levels, and body temperature. These sensors are linked to a Raspberry Pi with a 5G system antenna that broadcasts the recognized information in the IoT cloud via the high-speed 5G network. Convolutional Neural Networks (CNNs) and Long-Short-Term Memory (LSTM) networks are deep learning models that can be combined to improve the system's functionality. Such sophisticated models would interpret the data the sensors were receiving and ensure that the measurements were correct and that an abnormal pattern or a potential health risk was presented in real time. The CNN would end up discarding key information about the data, like the heart rate or level of oxygen in the blood. Simultaneously, the LSTM was processing the time-sequenced data in order to predict future health patterns and identify high-risk instances sooner. After processing, the data is safely stored in the cloud database and is available to medical professionals. If a serious health incident is identified, the system will trigger an emergency activation, which will notify the ambulance team and send an emergency alarm to the medical personnel. With this integration of IoT connectivity, 5G technology, and deep learning, patients will be guaranteed to be attended to instantly, even when not present. It will make healthcare more accessible and efficient.

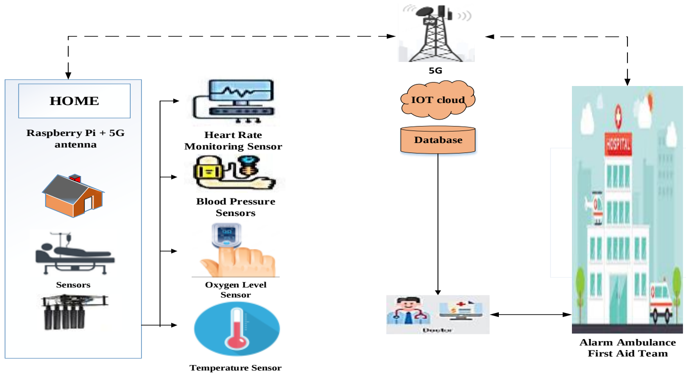


Figure 1. Integration Of WSN And IOT In 5G System Architecture for Patient Monitoring

The system will be programmed to continuously check the vital signs of a patient using a number of special sensors that will give meaningful health information. The MAX30100 Pulse Oximeter is a device that is a combination of a SpO2 and a heartbeat rate sensor, which detects the change in blood flow beneath the skin using light thus enabling it to accurately monitor the pulse of the patient and oxygen saturation. GY-906 contactless temperature sensor is a device which measures body temperature by infrared technology and thus it offers a speedy and non-invasive method of monitoring the presence of a fever. The “digital wrist blood pressure” and “heart rate monitor” measures “systolic and diastolic” blood pressure as it detects the force of blood being pumped through the arteries and assists the doctors in knowing the way the heart is pumping blood in the body. The AD8232 ECG monitoring Sensor measures the activity of the heart electrically, and this allows information about the rhythm of the heart and assists in identifying any irregularities. Such sensors collaborate to gather important data transmitted via a 5G system to a cloud data repository. The data is accessible to the healthcare professionals in real-time using a web application, which allows them to be able to respond to any health-related emergencies, including sending medical help when it is needed. This unification of the IoT technology will make sure that the patients get the care at the right time, making healthcare more convenient and efficient. The proposed system shown if figure 2

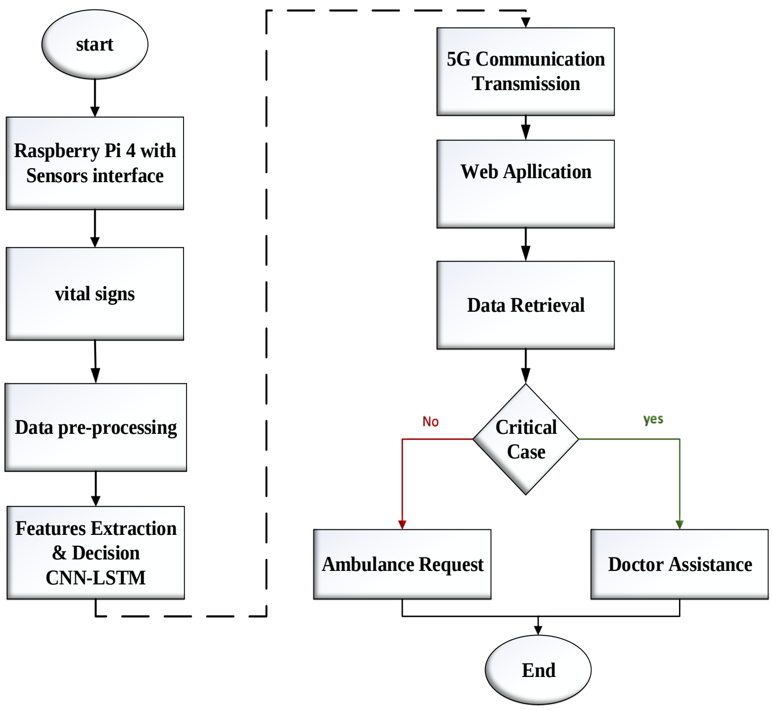


Figure .2 Flowchart of The Proposed System.

## 3. Results and Discussions

Here, we are going to talk about the findings of our work, including the process of gathering data and processing it, and the measurements of precision that we applied to assess the work of our models. Lastly, we will examine the findings.

### 3.1 Data Collection and Preprocessing

The data in the article is a subset of the COVID-19 Data Sharing/BR initiative, an initiative to hasten research on the pandemic on a worldwide level. It consists of 177000 Brazilian people tested on COVID-19 [17]. The information contains various essential data, including clinical documents, which follow up on disease development and medical status, and laboratory test outcomes, and there are more than 750 types of tests. It also includes the diagnostic data, such as PCR test results and demographic data, such as age, gender, and location. All the data is pseudonymized to adhere to the privacy regulations and be confidential, but it allows researchers to gain significant information. It was an FAPESP-USP is the **primary funding agency** for academic research in São Paulo state project together with the main Brazilian hospitals such as Fleury Institute, Sírio-Libanês, Albert Einstein Hospital. The project attempts to make this data publicly accessible to help the world understand and respond to COVID-19, with the repository updating in real time as new information is acquired.

Before examining the emerging DR models themselves, like any Glioblastoma-orientated MDR approach, data extracted from the Data Sharing/BR project needs to undergo an important preprocessing process to assure accuracy and privacy principles. To begin with, the data undergoes cleaning to remove inconsistencies, nonexistent data, and duplication, so that the data is precise and can be analyzed. Next, patient confidentiality is preserved by pseudonymizing all personal identifiers to ensure that the Brazilian and international privacy laws are adhered to. It also makes the data standardized across various sources so that the test results, demographics, and medical records are uniform. However, the data is collected in multiple health institutions with different reporting practices. Figure 3 and 4 show training loss and accuracy for best classifier

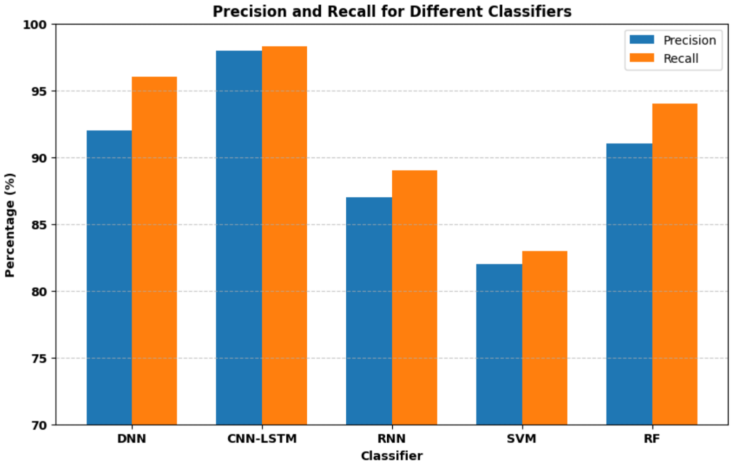


Figure .3 Comparison Of the Classifiers on All Focal Effects.

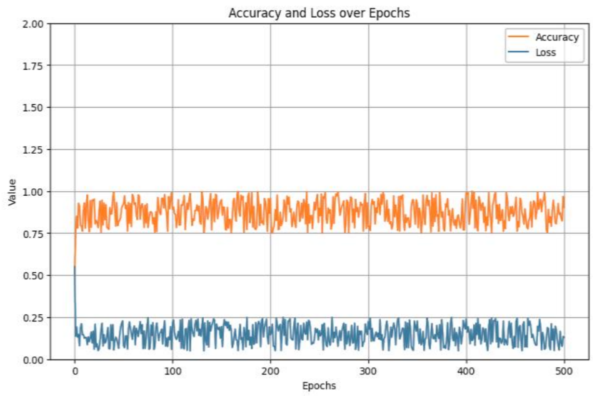


Figure 4. Training Loss and Accuracy for CNN-LSTM.

### 3.1.1 Deep Learning (CNN-LSTM)

Figure 3 shows the actual classification results of the proposed model. Several classifier models (deep neural networks (DNNs), convolutional neural networks with long short-term memory cells (CNN-LSTM), “recurrent neural network (RNN)”, “support vector machine (SVM)” and “random forest (RF))” are compared in this paper, to find the most effective approach in detecting cyberattacks and anomaly detection in IoT networks. To have a complete testing and training set, 100 subjects performed 10 different actions and movements, and the set lasted 60 seconds. The CNN-LSTM method is uniquely different because it can process both spatial and temporal data at the same time. Therefore, it is beneficial in time series data used in IoT applications. These findings indicate that CNN-LSTM is always better than the traditional models, such as ANN and RNN, and has better precision and recall. This is especially so in places where dynamic behaviors and actions cannot be detected in advance. The CNN-LSTM model is successful only when updated and adapted to new data. The higher the level of training examples, the greater the model's generalization power, resulting in a better prediction. Nevertheless, constant data collection is a significant challenge in that it is time-consuming and resource-intensive. Nonetheless, the CNN-LSTM approach can significantly improve the work of the traditional models and is highly robust at detecting anomalies in IoT.

### 3.2 Evaluation Metrics

We have used some standard evaluation measures to evaluate the output of the system, including accuracy, precision, recall, and F1-score. Accuracy denotes the rate of correctly categorized cases among the number of cases in the dataset [21].

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

TP is the count of actual positive samples, TN is the count of true negative samples, FP is the count of false positive samples, and FN is the count of false negative samples. The precision refers to the proportion of the actual positive samples to the number of overall positive samples the model has predicted.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

Recall is the ratio of actual positive samples to the total number of positive samples in the dataset.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

F1-score is the harmonic mean of precision and recall which provides a balanced score of model performance since it goes by both accuracy of optimistic predictions and the capacity of the model to identify all positive samples that are relevant.

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

### 3.3 Results Analysis

The prototype developed is tested with different patients or subjects to determine the effectiveness and working capability of the health monitoring system. There are four vital physiological parameters, “heart rate, body temperature, blood pressure and oxygen saturation (SPO2)”, which are used to assess their performance. The effectiveness of the system is subsequently tested by comparing the gathered data on measurements with the output of the known commercial sensors presently in the market. This comparative analysis would provide a solid test of the accuracy and reliability of the system in a real-life medical use.

Table 1 and Figure 5 illustrate the relative error of body temperature measurement (compared with a commercial non-contact thermometer) for the five patients compared to a GY-906 temperature sensor. For most samples, errors are minor relative errors in P1 and P3 or null, which means that the determinations have been adequately done. P4, however, has a greater error at 6.061%, indicating matters related to sensor calibration or environmental conditions. Generally, the GY-906 sensor works well but needs enhancement to provide constant, accurate results under all conditions.

Table 1. Body temperature collected with the GY-906 temperature sensor and its comparison with a commercial non-contact thermometer

| No of patient samples | Room Temperature | Actual body temperature | Body temperature observed | Relative error (%ϵr) |
|---|---|---|---|---|
| P1 | 34°C | 35°C | 35°C | 0.000% |
| P2 | 35°C | 36°C | 35°C | 2.778% |
| P3 | 33°C | 35°C | 35°C | 0.000% |
| P4 | 34°C | 33°C | 35°C | 6.061% |
| P5 | 35°C | 34°C | 35°C | 2.941% |

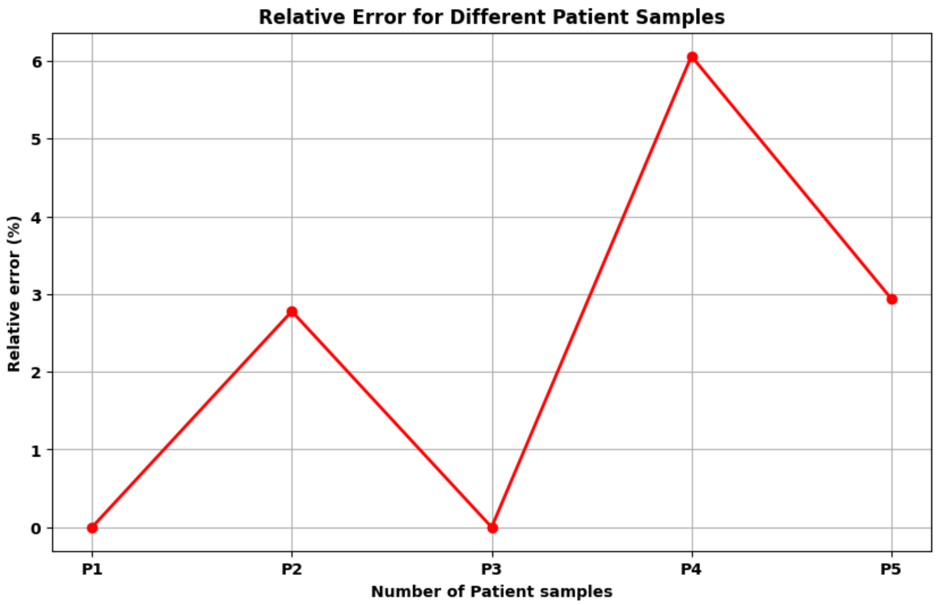


Figure 5. Relative Error as A Function of Number Of Patient Readings for Body Temperature.

The data in Table 2 and Figure 6 compare the relative errors in systolic and diastolic blood pressure measurements across five patient samples using the developed IoT system. The results show that the relative error fluctuates between 2.4% and 3.4% for both systolic and diastolic measurements. Sample P3 exhibits the lowest error, while P4 shows the highest for systolic measurements. Overall, the IoT system performs well but could benefit from optimization to reduce discrepancies, especially in higher blood pressure readings.

Table 2. Blood Pressure data collected with the developed IOT system

| Number of samples | Systolic | Diastolic |
|---|---|---|
| P1 | 110 | 60 |
| P2 | 103 | 65 |
| P3 | 111 | 69 |
| P4 | 120 | 88 |
| P5 | 140 | 90 |

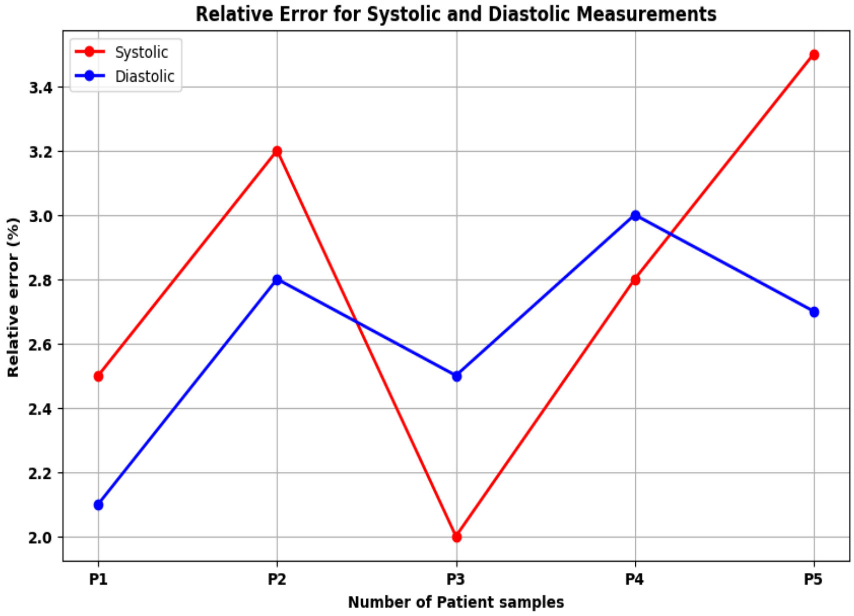


Figure 6. Relative Error Vs. Number of Subjects in BP Measurement

Table 3 and Figure 7 data compare the SpO2 measurements from the developed SpO2 sensor and a commercial oximeter. It can be seen from the results that the relative error is 0.000% for most of patient samples (P1, P2, and P4), which demonstrates high precision. However, there are some small differences in P3 and P5, with relative error values of 1.031% and 1.020%. With this minor non uniformity, the used sensor works very well and closely follows the commercial oximeter and thereby it proves to be successful for health monitoring applications. The results in table 4 show Previous Works *with* Our Method.

Table 3. Comparison Between the Spo2 System Measured and The Commercial Oximeter.

| Number of samples | SpO2 (our sensor) (in %) | SpO2 (commercial sensor) (in %) | Relative error (%ϵr) |
|---|---|---|---|
| P1 | 99 | 99 | 0.000% |
| P2 | 97 | 97 | 0.000% |
| P3 | 96 | 97 | 1.031% |
| P4 | 99 | 99 | 0.000% |
| P5 | 97 | 98 | 1.020% |


Figure 7. Relative Error of the Measured Spo2 to the Retail Oximeter.

Table 4. Comparison some of the Previous Works with Our Method.

| Ref | Method | Accuracy |
|---|---|---|
| [18] | Deep CNN | 0.913 |
| [19] | CNN with attention layers | 0.982 |
| [22] | ANN | 0.987 |
| Proposed method | CNN -LSTM | 0.988 |

**Conclusion**

This paper focuses on transforming healthcare to incorporate IoT and WSN into a 5G network that operates at high-speed data rate. Our proposal was employed a Raspberry Pi device for collecting patient data using “wearable sensors”, such as “body temperature” monitoring, “blood pressure” monitoring, oxygen monitoring, and heart rate sensors. Deep learning models like CNN-LSTM were included in the system to analyze real-time data. The information is transmitted to the 5G network, where it is stored and accessed using web applications. Raspberry Pi manages to merge the decision-making process, and when provided with deep learning to extract simple features, the accuracy is 0.988. The max relative errors are “heart rate” (2.19), “body temperature” (3.06), SBP (3.3), DBP (3.4), and “SpO2” (1.03). This possible system will be set to exercise priority in cases where the patient or victims demand urgent medical care or emergency service.

**Conflicts of interest**

The authors declare no conflict of interest.

**Author contributions**

Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, supervision, project administration, and funding acquisition: Mohammed Younus Mohammed

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