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Non-Contact Respiration Monitoring Using Bio-Radar Sensor Based on Linear Regression Classifier

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ABSTRACT Tuberculosis (TB) is an infectious disease that mainly attacks the lungs, caused by the bacterium Mycobacterium tuberculosis. To reduce its spread, hospitals use special rooms for TB patients and health workers follow strict Standard Operating Procedures (SOP). Recent advances in medical technology have led to the development of contactless respiratory monitoring techniques, such as bio-radar sensors that utilize the Doppler principle to detect lung movement. This research aims to explore the application of bio-radar sensors for contactless respiratory rate monitoring and then combine it with machine learning methods, specifically using linear regression algorithms, to translate bio-radar output into measurable respiratory rate values. By training a regression model using a processed raw data set to identify inspiration and expiration, where 1 is inspiration and 0 is expiration. To test the performance of the contactless breathing module, it was compared to a patient monitor. The module and comparison tool were run simultaneously with 10 measurement distance points for 10 patients or respondents with each distance point taken three times. The data that has been obtained from the results of comparisons between modules and comparison tools is entered into machine learning data analysis techniques, namely accuracy, precision and recall. The accuracy results were 74.9%, precision 71.4% and recall 83.3%. This research has proven that bio radar can be used to detect lung movement.

INDEX TERMS Respiration, Bio-Radar, Artificial Intelligence, Linear Regression

I. INTRODUCTION

Tubercolusis (TB) disease is a disease that attacks the lungs, TB is caused by mycobacterium tubercolusis bacteria, TB bacteria will attack the lungs and cause sufferers to experience shortness of breath accompanied by chronic cough [1] , in some cases it can lead to death [2]. TB is a dangerous disease that is easily transmitted, so in each hospital there is a special room for TB patients so as to reduce the risk of further transmission[2]. To avoid the transmission of the TB virus, nurses are required to follow standard procedure to minimize the risk of transmission of TB bacteria [3] [4] [5]. this review underscores the critical importance of point-of-care (POC) testing in the realm of infectious diseases, which pose significant threats to public health and the economy. POC tests act as a personal "radar," offering rapid and actionable results near the patient, thereby facilitating timely case identification, transmission disruption, and appropriate treatment administration [6].The statement on World TB Day 2021 compellingly underscores the urgent need for global leaders, community influencers, and funding agencies to prioritize the reduction of global inequities in the battle against tuberculosis. It emphasizes the critical importance of allocating resources for the implementation of existing TB diagnostic and management tools and highlights the potential adverse effects of the COVID-19 pandemic on TB control efforts[7]. It is planned that this bacterium can spread easily TB disease is a problem that exists throughout the world, especially in developing countries, while in 2019 Indonesia ranked third country with the most TB cases[8], Therefore, several approaches to be able to find out the patient's condition have been carried out by making a device that can help nurses know the patient's condition without making direct contact [9] . Among them is the development of module to find out the patient's respiration in a non-contact manner, one of which is a radar sensor / bio-radar that has been developed specifically for bio medical sensing aimed at knowing respiration[9] [10]. Bio radar is a sensor that uses the doppler principle as a medium to determine the movement made by an object. Bio radar sensor will emit ultrasonic waves and receive reflected waves, these waves will be detected and calculated by the sensor to obtain the respiration value [11] [12]. the increasing occurrence of foodborne disease outbreaks has prompted a critical need for advanced and efficient detection methods in the food industry. Traditional techniques, characterized by their time-consuming and labor-intensive nature, are being surpassed by innovative biosensing platforms. The giant magnetoresistance (GMR) biosensors, fueled by nanotechnological advancements, emerge as a promising solution for revolutionizing current food surveillance approaches [13]. Test results revealed the system's ability to detect stop breathing. However, the study still requires contact between the module and the patient, which potentially poses a risk of infection. In the same year, research was also carried out by Ruthvik Kukkapali et al, namely on wearable breathing monitors using micro-radar sensors [13]. The advantage of this study is that the prototype is used as a necklace with a portable system that can be worn on the chest because breathing movements can be detected very accurately. The system is also capable of penetrating walls, allowing respiratory detection up to a distance of 5 meters and also from behind walls. However, the study did not address the effect of distance on the object's sensor measurements due to the sensor's design as a necklace. Then in 2018 a study was conducted by Sherif Abdulatif, on real-time respiratory monitoring using FMCW radar sensors [14]. the transformative power of aligning with innovations in science and technology, with a specific focus on the significance of radar system technology. It eloquently argues that embracing these advancements not only eradicates ignorance but also amplifies our ability to understand, evaluate, and foresee possibilities in our society, environment, and the broader world[15]. examination of the evolution of radar technology post-World War II, highlighting its rapid development during the war and subsequent advancements. The historical context underscores the pivotal role of radar systems in providing a strategic edge to both Axis and Allied forces[16]. The results reveal that the three treatments administered to respondents did not significantly impact the outcomes of respiration rate measurements. Notably, the bioradar sensor exhibited effectiveness at various distances, with breaths per minute recorded at 40-43 for 10 cm and 25 cm, 33-36 for 50 cm and 75 cm, and 20-22 for 100 cm. However, at distances of 125 cm and 150 cm, respiration was not detected. The highest error value was observed at -100.00% for the more distant distances, and the lowest error value was 3.39% at 100 cm, signifying the effectiveness of the sensor at this distance[17]. The study demonstrates that respiration-induced changes in the dielectric constant of the paper, primarily influenced by breath humidity, result in variations in sensor capacitance. The chosen interdigitated electrodes configuration proves to have superior response time compared to resistive configurations. The integration of a simple phase-sensitive detector-based circuit and the MSP430 microcontroller for data acquisition, along with a user-friendly graphical interface, enhances the real-time monitoring experience[18]. the study underscores the significance of radar technology in healthcare, particularly for noncontact respiration monitoring. The proposed MFCW radar system stands out as a technologically efficient and viable solution, offering potential advancements in patient care through continuous and comfortable monitoring. The research contributes valuable insights to the field of healthcare technology, pointing towards a promising direction for the development of nonintrusive and effective respiration sensors[19]. The findings suggest that the BRL method is reliably implemented for the estimation of respiratory rhythm and respiratory rate variability during full-night sleep. This highlights the potential of bio-radiolocation as a non-invasive and promising method for continuous monitoring of respiratory parameters during sleep, offering valuable insights into respiratory patterns and variability over extended periods. The results contribute to the growing body of research supporting the utility of BRL in sleep monitoring and respiratory assessments[20]. this study emphasizes the importance of accurate respiratory rate (RR) measurement, especially in critically ill patients. Traditional methods relying on contact-based approaches may pose challenges, particularly with young children who may not tolerate such methods well, and the potential stress induced by contact-based measurements can impact the reliability of RR values [21]. This research contributes to the ongoing exploration of bioradar-based technologies for noncontact health monitoring, specifically in the context of breathing detection. The findings underscore the potential of forward scatter radar and mathematical modeling to enhance the accuracy and versatility of respiratory rate detection. As noncontact monitoring technologies continue to evolve, this work adds valuable insights to the field, paving the way for advancements in remote health monitoring systems [22].The 94 GHz module shows better performance than the 120 GHz module in terms of the maximum aspect angle and the distance at which the breathing signal can still be monitored. This can be justified by the apperture and higher output power of the 94 GHz module. However, the resolution aspect of the range does not show much influence on the results achieved. Furthermore, in 2020, a similar study was also conducted by Razak Mohd on respiratory monitoring, especially in children using IR-UWB radar sensors[23]. his paper has presented a survey outlining the diverse possibilities of radar technology in medical applications, emphasizing its potential without the need for direct instrumentation of the human body. While radar technology has historically been linked to military and defense applications, its evolution has paved the way for innovative and non-intrusive applications in the field of healthcare [24].This study presents a method for determining a child's respiratory status using a human motion detection method based on the IR-UWB radar sensor for non-contact detection of the child's respiratory status. The applied method can generate responses and distinguish different respiratory conditions in children. However, the study also still did not determine the optimal reading distance of the sensor. Then in 2022, research has also been carried out by Raden Duta Ikrar Abdi, about the development of patient respiration measurements with non-contact methods using thermal cameras and web cameras as sensors to detect patient respiration [25] , In this study, it was found that the use of a thermal camera can detect the respiration of patients with a temperature when inspiring 30.01, and when expirating of 30.05, with reference to this value, the calculation of the patient's respiration value can be carried out but in this study it has limitations when compared to patient monitors so that more than one thermal camera is needed to increase the accuracy of the respiration value. The contribution of this study is as follow:

a) Can monitor a person's breathing rate using a bio-radar sensor, making it easier to carry out examinations without having to touch the patient
b) Develop an algorithm to differentiate inspiratory and expiratory signals to provide more detailed respiratory information.
c) Create a data storage system so that it is easy to carry out further analysis using the Neuton AI system.

II. MATERIALS AND METHOD

The aim of this research is to create an integrated respiratory monitoring system and intelligent system that utilizes bio-radar sensor data. The research method applied is Pre-experimental with the After Only Design type. In this design, the researcher only involves one group of subjects and only pays attention to the final results without carrying out measurements or assessments of initial conditions, but includes a comparison group. The patient monitor is used as a comparison, namely the respiratory rate displayed by the module is compared with the respiratory rate displayed by the patient monitor.This research utilizes the MR60BHA1 bio-radar sensor to detect patient breathing by reading chest and stomach movements. The sensor is connected to an Arduino mega microcontroller to process data from the sensor. This module uses supervised machine learning programming with a linear regression algorithm.

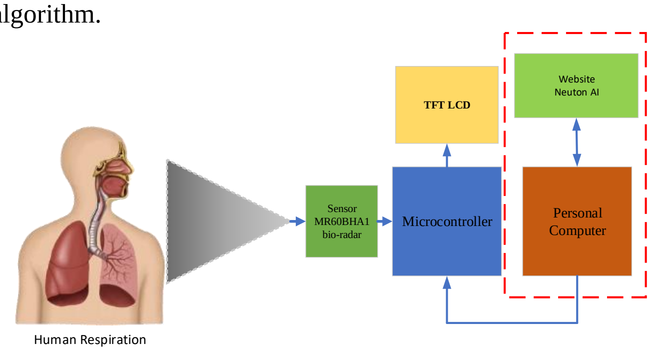

FIGURE 1. Block Diagram of The Module

In machine learning, it is known as the training data model process, the process is carried out through the Neuton AI website application. To display the respiratory rate value on this module, a TFT LCD is used. The circuit in this module is equipped with 2 18650 lithium batteries, each with a capacity of 3000 mAh 3.6 V arranged in a row. The MR60BHA1 sensor produces several data outputs, but this research only focuses on capturing breathing and distance data. Therefore, this research focuses on these two data which are processed using supervised machine learning programming to explore the optimal distance for the module to read respiratory rate values accurately and precisely after comparing them with respiratory rate values from a comparison device or patient monitor. Based on FIGURE 1 above, when the patient takes a breath or breathes out it will be detected by the MR60BHA1 bio-radar sensor which is connected to the Mega Arduino microcontroller.

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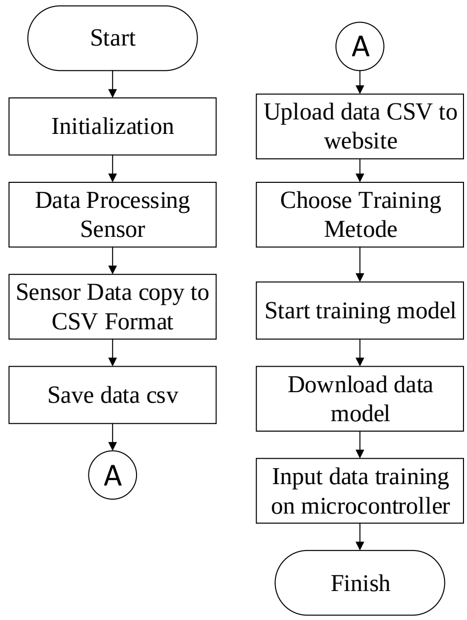

FIGURE 2. Flow Chart Training Process

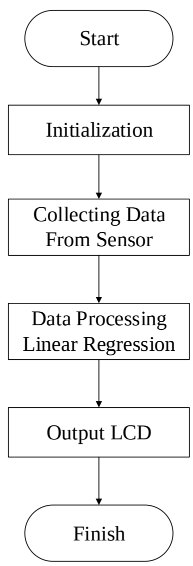

FIGURE 3. Flow Chart Program on Arduino

Based on FIGURE 2 data collection from the MR60BHA1 sensor by testing it using human respiration, the data obtained from this stage is processed using coding envelope programming so that it can be distinguished between inspiration and expiration from the sensor output. The data from the process is copied and stored in CSV form and then uploaded on the neuton AI website, then a linear regression algorithm is selected, then the model data training process is carried out on the neuton AI website. After the data has finished going through the training process, it can be downloaded again and entered into the microcontroller.

Based on FIGURE 3 when the button is ON, the module will turn on and perform the initialization process for a few seconds, then the process continues by taking the data detected from the sensor, after the sensor reading data is received then the microcontroller will work to process the data taken from the sensor to be displayed on the LCD output.

A. DATA ANALYSIS

In evaluating the performance of machine learning algorithms (especially supervised learning), it is necessary to use the Confusion Matrix reference. Confusion Matrix represents the prediction and the actual condition of the data generated by the machine learning algorithm. Based on Confusion Matrix, we can determine Accuracy, Precission and Recall.Accuracy is the ratio of correct predictions (positive and negative) to the overall data. Accuracy has

TABLE 1
Recapitulation of Module Error against Comparison Tool

Respondents	Distance 40 cm (Second)	Distance 60 cm (Second)
1	19	21
2	24	21
3	30	19
4	23	20
5	15	16
6	23	20
7	22	13
8	16	14
9	28	20
10	27	20

following equation (1)

$$\text{Accuracy} = (TP + TN) / (TP+FP+FN+TN) \quad (1)$$

where TP is True Positive, TN is True Negative, FP is False Positive, FN is False Negative. Precision is the ratio of true positive predictions compared to the overall positive predicted results. Precision has following equation (2).

$$\text{Precision} = (TP) / (TP+FP) \quad (2)$$

where TP is True Positive,FP is False Positive

Recall is the ratio of true positive predictions compared to the overall true positive data. Recall has the following equation (3).

$$\text{Recall} = (TP) / (TP + FN) \quad (3)$$

where TP is True Positive, FN is False Negative

Testing and data collection of module readings and comparison tools were carried out on 10 respondents who were standing with a total of 10 measurement distance points starting from a distance of 20 cm to 200 cm with multiples of 20 cm at each distance point. Each distance point was measured five times. At the time of testing and data collection, the position of the patient or respondent is standing perpendicular to this research module. At the same time, the ECG electrodes from the patient monitor as a comparison tool were attached to the respondent's body so that the readings from the module and patient monitor could be seen simultaneously. The distance between the module and the respondent is set according to the predetermined distance point.

III. RESULT

After measuring the respiration value between the module and the comparison tool or patient monitor at 10 distance points with 10 respondents and repeating the measurement 5 times at each distance point, a recapitulation of the SD and Error values is obtained as shown in table 1 below.

TABLE 2
Recapitulation of Module Time at 40 cm and 60 cm Distance

No	Distance (cm)	Average error (%)
1	20	100
2	40	4.7
3	60	5.1
4	80	19.9
5	100	47.6
6	120	32.5
7	140	42.8
8	160	43.9
9	180	62.8
10	200	86.8

TABLE 3
Actual Data and Prediction Data

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Actual(12)</td><td rowspan="2">Formula</td></tr>
<tr><td>P(6)</td><td>N(6)</td></tr>
<tr><td rowspan="4">Prediction (12)</td><td rowspan="2">P(7)</td><td>TP</td><td>FP</td><td rowspan="4">|
|
|
|</td></tr>
<tr><td>5</td><td>2</td></tr>
<tr><td rowspan="2">N(5)</td><td>FN</td><td>TN</td></tr>
<tr><td>1</td><td>4</td></tr>
<tr><td colspan="2">Accuracy</td><td colspan="2">74.9%</td><td>(TP + TN) / (TP+FP+FN+TN)</td></tr>
<tr><td colspan="2">Precission</td><td colspan="2">71.4%</td><td>(TP) / (TP+FP)</td></tr>
<tr><td colspan="2">Recall</td><td colspan="2">83.3%</td><td>(TP) / (TP + FN)</td></tr>
</table>

Based on TABLE 1 above, It is known that the lowest error value or optimal point of measurement is at a distance of 40 cm and 60 cm. To find out the performance of the module more specifically, time calculations have been carried out at both distances in seconds between the module and the comparison tool so that it can be seen how long it takes for the module to first display the respiration value the same as that displayed by the comparison tool which can be seen in TABLE 2. Furthermore, discussion of the results of data analysis based on accuracy, precession and recall parameters. TABLE 3 above is raw data S1, S2, S3 and S4 obtained from the model training process through the Neuton AI website application so that it can produce prediction data in the form of numbers 1 and 0 where 1 is interpreted as inspiration and 0 is interpreted as expiration. The resulting prediction data is compared with the actual data before the model training process. S1 Represents key evaluation metrics, such as accuracy, precision, recall. This metric is typically used to measure the overall performance of a classification model. S2 Representing secondary evaluation metrics may include metrics such as mean squared error (MSE). S3 Customized custom metrics. S4 Represents the threshold value or decision-making cutoff point.

TABLE 4
Accuracy, Precission and Recall Calculation Data

S1	S2	S3	S4	*Actual*	*Prediction*
0.10	0.49	0.69	0.45	1	1
0.11	0.19	0.24	0.12	0	0
0	0	0.63	0.58	1	1
0.21	0.66	0.25	0	0	1
0.03	0.38	0.52	0.04	1	1
0.02	0.01	0.09	0.32	0	0
0.8	0.59	0.03	0.01	1	1
0.38	0.01	0.1	0.11	0	0
0.02	0	0.91	0.83	1	1
0.12	0.15	0.12	0.04	0	0
0.04	0.04	0.08	0.06	1	0
0.32	0.04	0.76	0.5	0	1

TABLE 4 above is a confusion matrix table and has obtained the results of the calculation of 3 parameters, namely accuracy of 74.9%, precession of 71.4% and recall of 83.3%.

IV. DISCUSSION

The respiration value reading is unstable if the object or patient is not in a stable position, if there is a moving object behind or around the patient it can also affect the sensor reading, and the use of thick clothing can affect the sensor reading response. This sensor also requires a time ranging from 15 - 30 seconds to get the same respiratory rate value as the comparison tool or patient monitor.

The application used in the data training process is a website called Neuton A1. In running the data training process, it depends or relies on the performance of the server on the web so that in several trials it had experienced problems with upload failures, failed training processes or training processes that were too long. The microcontroller used in this research module is Arduino Mega. With the limited memory capacity of Arduino mega, it causes the limited code that can be accommodated, so that when various models are entered, the module often lags or hangs. This also causes the module to be unable to read respiration with accuracy and precision even at an optimal distance when dealing with patients or respondents with postures that differ significantly from the posture of the model used in the module. Certainly Let's compare the current project with some aspects research traditional or existing respiratory monitoring systems.Current Project (Non-Contact) Utilizes a bio-radar sensor for non-contact monitoring, minimizing the risk of bacterial or viral transmission. Traditional Systems (Contact) Many traditional systems involve sensors or probes that require physical contact with the patient, potentially increasing the risk of infections, especially in settings with contagious diseases. Optimal Measurement Distance, Current Project: Emphasizes the exploration of the distance between the sensor and the patient to achieve optimal measurement, addressing accuracy concerns. Traditional Systems, May not focus explicitly on optimizing measurement distance, potentially leading to variations in readings based on the sensor's proximity to the patient. By training a regression model using a processed raw data set to identify inspiration and expiration, where 1 is inspiration and 0 is expiration. To test the performance of the contactless breathing module, it was compared to a patient monitor. The module and comparison tool were run simultaneously with 10 measurement distance points for 10 patients or respondents with each distance point taken three times. The data that has been obtained from the results of comparisons between modules and comparison tools is entered into machine learning data analysis techniques, namely accuracy, precision and recall. The accuracy results were 74.9%, precision 71.4% and recall 83.3%. Even though the results are still not good, this research proves that bio radar can be used to detect breathing with a system that is simpler than that [25][17].

V. CONCLUSION

This study has demonstrated the feasibility of using bio-radar sensors for contactless respiratory rate monitoring, especially in tuberculosis (TB) patients. By combining these sensors with machine learning techniques, specifically linear regression algorithms, this research succeeded in translating bio-radar output into measurable respiratory rate values. The methodology involves training a regression model using processed raw data to differentiate between inspiratory and expiration phases. Through comparative evaluation of patient monitors, the performance of the contactless breathing module was assessed at multiple measurement distance points and patient samples.

The results showed promising results, with the contactless breathing module achieving 74.9% accuracy, 71.4% precision, and 83.3% recall when compared to the patient monitor. These metrics underscore the reliability and effectiveness of bio-radar sensor-based approaches in monitoring respiratory rate in TB patients. Overall, these findings suggest that bio-radar sensors, coupled with machine learning algorithms, offer a viable solution for non-invasive and efficient respiratory monitoring in healthcare settings, particularly for infectious diseases such as tuberculosis. Further research and development in this area could improve diagnostic and monitoring capabilities, ultimately improving patient care and management.

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