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DIAGNOSTIC RISK PERCENTAGE BASED ON VITAL SIGNS READINGS ON HEALTH MONITORING DEVICES

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Abstract

The development of the field of health technology has progressed rapidly - especially in the aspect of being connected to the Internet and also allowing the storage and monitoring of vital signs data utilizing IoT features. However, there is no health monitoring that contains advanced check-up analysis referring to the acquisition of vital signs data that has been stored in the health data record. This is exactly where additional parameters beyond the vital signs have not been integrated in health monitoring. The purpose of this independent research is to find a gap between industry and academia in the form of additional parameters that are not yet available in the industrial world. The additional parameter is the percentage value of health diagnostic risk. The selection of this parameter is based on the need to analyze the level of diagnostic risk through the acquisition of vital signs that have available readings in health monitoring device equipment. The algorithm mechanism itself revolves around mapping for the diagnosis of health conditions referring to the normal limits of vital signs utilizing the decision tree algorithm. The goal is none other than to simplify the flow in determining the patient's advanced health diagnosis. Regarding the diagnostic risk percentage parameter, the diagnosis and calculation include five vital signs that are the main indicators: heart rate, oxygen saturation (SPO_2), body temperature (T_{Body}) supplemented with skin temperature (T_{Skin}), and respiratory rate.

Keywords: check-up analysis, diagnostic risk, diagnostic risk percentage, health monitoring, medical check-up, vital signs

Introduction

In the current era of development, the field of health technology has experienced a lot of progress. This includes the aspect of monitoring a person's/patient's health (health monitoring). Now, health data record storage is connected to the Internet (Da Costa et al., 2018). It can even allow storing and monitoring vital signs data using IoT features (Swaroop et al., 2019; Chennam et al., 2021; Lourenço, 2021). However, there is no health monitoring that includes advanced check-up analysis referring to the acquisition of vital signs data that has been stored in the health data record. To be precise, here it is in the form of a diagnostic risk percentage value based on the results of vital sign readings which have not been integrated into health monitoring.

The diagnostic risk percentage itself is a statistical measure in percent units used in the medical world to assess the possibility or risk of someone developing a disease or certain health condition based on the results of a diagnostic examination referring to the acquisition of vital sign values during a health examination (Castiglione et al., 2022). Its main role is to make it easier for medical personnel to make appropriate clinical decisions referring to obtaining vital signs during health examinations (Shreffler, Genova, & Huecker, 2023).

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Regarding the percentage of diagnostic risk, the role of smartwatches has only reached the stage of providing various health indicators - including vital signs - such as heart rate, sleep patterns and physical movements (Masoumian et al., 2023; Kabe et al., 2020). For example, on the Xiaomi Mi Band 2 smartwatch equipment which is integrated with the Mi Fit application, apart from checking vital signs such as heart rate, both on the smartwatch and the application screen, it can display several additional parameters, including the following: number of steps (step counter), total distance walked (step length/ distance), calories burned, and sleep quality (Kang et al., 2020; Youssef et al., 2020). Also, the Viatom CheckMe Pro equipment, apart from monitoring sleep quality, also has analysis of crucial additional parameters in the form of perfusion index (PI) in peripheral tissue through the reading of two basic vital signs like oximetry equipment: heart rate and oxygen saturation (Weenk et al., 2018; Sahu et al., 2022).

The aim of this research is to find the gap between industry and academics in the form of additional parameters that do not yet exist in the industrial world. The context in this case leads to a practical gap in the industrial world where these additional parameters are not yet available in many patient monitoring equipment in hospitals, as well as portable monitoring equipment and smartwatches.

Research Methods

Diagnosis of Health Conditions

In order to be able to know the patient's health condition when carrying out a diagnosis at the advanced check-up stage, which is able to map the symptoms of abnormalities/ diseases if they are present in the patient's body, it is necessary to set normal limits for each vital sign (Michaud et al., 2021) in carrying out decision making using algorithm. And this diagnosis also includes advanced check-up analysis that combines analysis of all vital signs on health monitoring equipment: a clear explanation of the meaning of the results, an overall summary, and a more in-depth analysis. Even if necessary, directions for consultation or further examination are also included (Leite, Gruber & Hodgkinson, 2020).

Vital Signs Risk Scoring Mechanism

Referring to the early detection scoring system, equipped with reading limit values for mapping abnormalities for each vital sign in Table 1, along with the overall risk scoring mechanism for each vital sign, as well as markings for the overall total diagnostic risk score (RD).

Table 1. Overall Mechanism of Vital Sign Risk Score Scoring and Final Diagnostic Risk (RD) Percentage Scale

Risk score scale (R)	3	2	1	0	1	2	3
heart rate (BPM)	<40	40-50	51-59	60-100	101-110	111-130	<130
respiratory frequency (RR)		<9	9-11	12-20	21-30	31-39	≤40
Body Temperature (°C)	≤ 34	34.1-35	35-35.9	36-37.4	37.5-37.9	38-39.9	≤40
oxygen saturation (%)	<90	90-92	92-94	95-100			
Diagnostic risk score scale (R_D)	0-20%	21-40%	41-60%	61-80%	81-100%		

Research Methodology Flow

The research began by conducting a literature study to determine the most significant vital signs in measuring diagnostic risk. After analyzing various scientific sources to identify the main vital signs in order to determine the percentage of diagnostic risk, four vital signs were finally selected sequentially according to the priority scale as a reference regarding diagnostic risk: BPM (heart rate), RR (respiratory frequency), and TBody (Body Temperature), and SPO_2 (oxygen saturation).

The next step is to understand the value limits and the scoring calculation mechanism for each vital sign that has been identified. This is done through in-depth literature study to ensure that each vital sign is assigned an appropriate value based on the clinical condition at hand.

The research then continued by studying various existing regression and classification algorithms. The goal is to find the most suitable and effective algorithm for predicting diagnostic risk based on the vital signs that have been collected.

After evaluating various algorithms, the decision tree became the preferred algorithm used in this research. This is because the decision tree approach refers to the limits of obtaining values for each vital sign.

The next step is to prepare a dataset consisting of the vital signs that have been identified. This dataset includes input in the form of four vital signs, namely BPM, SPO_2, TSkin, and TBody, as well as output in the form of the RR vital sign that you want to predict.

*Datasets*that has been prepared is then used for the training, validation and testing processes with the regression algorithm available in MATLAB R2021b software. The goal is to produce a model that is able to predict RR with high accuracy based on vital signs input.

The prediction model that has been successfully validated is then implemented in coding form on the Arduino IDE platform. This allows RR predictions to be carried out in real-time into health monitoring device equipment.

The final step is to create coding for the Decision Tree classification which can determine the percentage of diagnostic risk. This coding is also implemented in the Arduino IDE to enable automatic diagnostic risk assessment based on vital signs contained in the health monitoring device equipment.

When summarized, this research follows a systematic methodological flow starting from literature study to determine important vital signs, understanding the scoring mechanism, choosing the right algorithm, to implementing coding on the Arduino IEE platform for prediction and classification using health monitoring device equipment. With these steps, the study aims to produce a system that can accurately predict RR and assess diagnostic risk based on patient vital signs.

Combination of Regression and Classification

In general, this research combines regression and classification approaches in the use of its algorithm. A regression approach was used to obtain predictions of respiratory frequency (RR) vital sign readings. Meanwhile, a classification approach, using a decision tree algorithm, is used to obtain a diagnostic risk percentage.

Data retrieval

The following data is collected on patients, namely as follows:

1) Collecting data on vital signs on patients who have previously been taken by health monitoring devices made by researchers (Juan Karnadi et al, 2021) where all vital signs (Juan Karnadi et al, 2020) have been validated against a tool that is trusted to be a validator (Juan Karnadi et al, 2024) as input.

2) Using a special respiratory frequency sensor which is not part of the health monitoring device equipment) as an output reference base in predicting RR vital sign values.
3) Requires training on overall vital sign data at points 1 and 2 with MATLAB R2021b software to then obtain predicted results for RR vital sign values.
4) Perform vital sign scoring calculations and diagnostic risk percentages using the vital sign data that has been obtained.

Results and Discussion

Comparison of Vital Signs Availability and Diagnostic Risk Percentage Parameter Output

The following is a comparison table between smartwatch equipment, portable monitoring, and health monitoring devices made by researchers (see Table 2) regarding the availability of vital signs, efforts to add new vital signs, and additional parameters that exist or are the target output/goal of this research.

Table 2. Comparison of Vital Signs Availability, Efforts to Add New Vital Signs, and Additional Parameters in Equipment

Tool/Device Name	Availability of Vital Signs	Efforts to Add New Vital Signs	Additional Parameters
Xiaomi Mi Band 2 Smart Watch	Heart Rate & Oxygen Saturation	-	Sleep Quality
Viatom CheckMe Pro	Heart Rate, Oxygen Saturation & Temperature	-	Perfusion Index
Health Monitoring Heart Rate, Saturation Device (Made by Researchers)	Heart Rate, Oxygen Saturation, Body Temperature & Skin Temperature	Respiratory Frequency	Diagnostic Risk Percentage (Research Objective))

Based on the table above, the diagnostic risk percentage parameter output is not yet available on the comparable smartwatch or portable monitoring equipment. So, in this study, it is necessary to include a diagnostic risk percentage. The purpose of efforts to complete diagnostic risk percentages into health monitoring device equipment is to make it easier for medical parties to make decisions based on the condition of the patient's vital signs.

Basis for Establishing the Diagnostic Risk Percentage Formula

The main consideration that is the basis for forming a diagnostic risk percentage formula - apart from continuous and non-continuous monitoring which has been mentioned in the literature review - is the high cost and mortality caused by one non-communicable disease: cardiovascular disease. Another consideration is also looking at the prevalence of sufferers of non-communicable diseases in Indonesia - specifically cardiovascular diseases. The two cardiovascular diseases that are priority attention here are stroke and heart disease.

Stroke is closely related to the vital sign of respiratory frequency. Meanwhile, diseases that lead to heart disease are closely related to the vital sign heart rate. Based on data on the prevalence of non-communicable diseases from Riskesdas (2018), 109 out of 1000 people suffer from stroke; while 15 out of 1000 people suffer from heart disease.

Then other non-communicable diseases, namely asthma, correlate with the vital signs of respiratory frequency and oxygen saturation. 24 out of 1000 people suffer from asthma (Indonesian Ministry of Health, 2018).

Priority Determination of Vital Signs in Diagnostic Risk

From a medical/clinical aspect, the vital signs mentioned in the literature review section are able to provide an actual picture of a person's physical health condition and are considered to have the most essential information in mapping a patient's health for medical parties - especially health workers. This was confirmed after thoroughly observing the medical needs. There was also a post-observation discussion with medical personnel who were skilled in using patient monitoring equipment at the hospital.

On the other hand, regarding the availability of vital signs, health monitoring devices made by researchers with available vital signs which have been discussed in Table 2 previously, are the preference in determining the priority of vital signs in diagnostic risk. Heart rate, oxygen saturation, skin temperature and available body temperature - as well as the addition of the vital sign respiratory frequency - have covered almost all the most crucial vital signs in medical personnel. Only the vital sign blood pressure - because it is included in the most crucial vital sign - is not included in this health monitoring device (Levental et al., 2018; Kumar & Krishnamoorthi, 2021).

Regarding the implementation of health checks, the health monitoring device used - with reading results that can also be accounted for - makes it easy to carry out short assessments. This convenience is another factor when determining the priority of vital signs which are closely related to diagnostic risk. The three aspects mentioned in this subchapter are taken into consideration in determining the priority of vital signs regarding diagnostic risk using health monitoring devices made by researchers in research regarding the percentage of diagnostic risk.

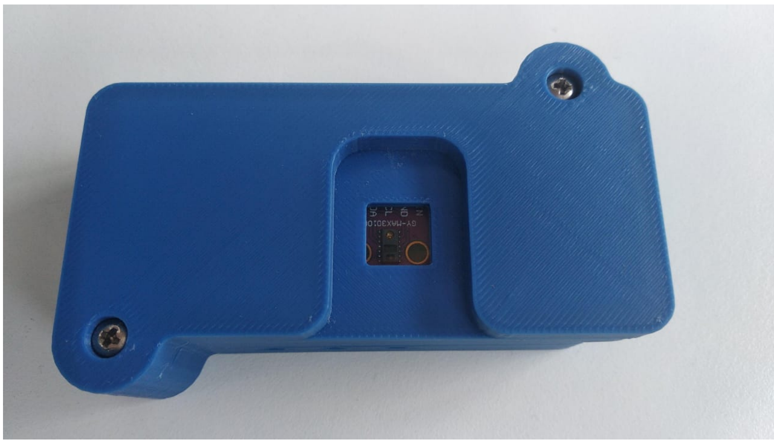

Figure 1. Health Monitoring Device Equipment Made by Researchers

Establishment of Scoring Mechanism and Diagnostic Risk Percentage

The formation of the scoring mechanism and diagnostic risk percentage combines existing domain knowledge in health scientific aspects, as well as aspects of algorithm design and use. The health scientific aspects referred to here include vital sign diagnostic risk mapping and early detection systems - through early warning scores. Meanwhile, aspects of design and use of the algorithm utilize a classification algorithm approach where the decision tree is the main reference and reference algorithm.

*Outputs*from the formation of a mechanism which then becomes a framework, it is called a framework because it can comprehensively summarize the mapping of a person's health condition and the potential diagnostic risks he or she experiences simply by referring to the limits of the output values of existing vital signs. Even further, from this quantitative approach, the health condition of each vital sign that has been mapped earlier, is summarized again through the classification of the range of diagnostic risk percentage values, which provides a comprehensive picture of the overall health condition of the person/patient being examined.

Data Collection Approach

Regarding data collection on patient signs that was carried out, with a total of 100 respondents obtained, the data collection technique was carried out using an experimental approach using health monitoring devices made by researchers. Meanwhile, conceptually, the method used is the volunteer lab test method. To be precise, this was carried out for 3 months starting from February to April 2024 at the FT UI Manufacturing Research Center (MRC) Building.

Prediction of Respiratory Frequency Readings

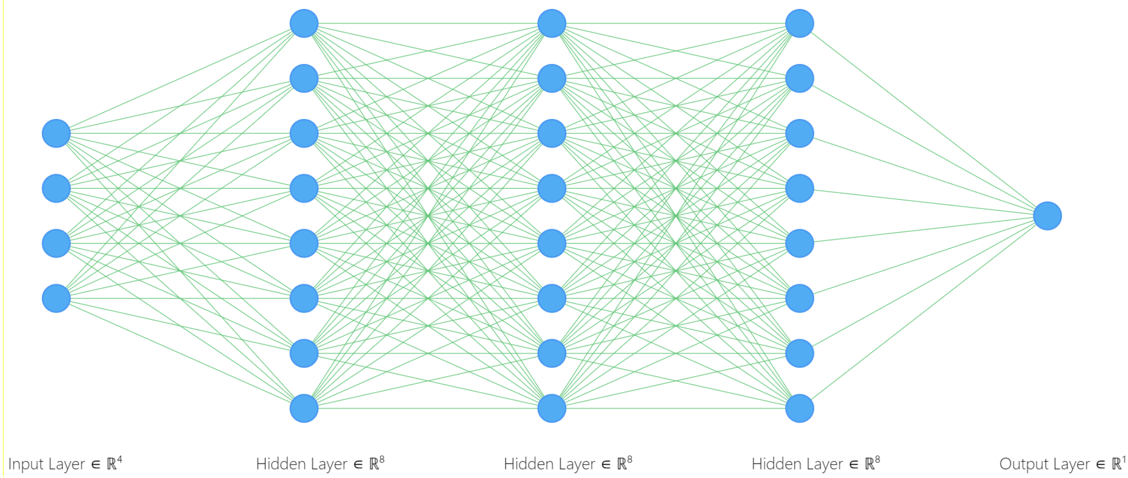

Figure 2. MATLAB Neural Network Software Architecture for Predicting Respiratory Frequency Readings

Utilizing the neural network feature contained in MATLAB R2021b software, crucial steps to obtain respiratory frequency reading values are taken so that they can be implemented into health monitoring device equipment. The input uses the readings of the following four vital signs: heart rate, oxygen saturation, skin temperature and body temperature. And there are 8 layers used (see Figure 2) to carry out predictions of respiratory frequency readings. What has been executed by MATLAB, will be converted into the Arduino IDE programming language.

As a result, the prediction of respiratory frequency readings obtained from MATLAB software is highly correlated with the respiratory frequency values obtained from other sensor tests where data collection is carried out with separate equipment outside the health monitoring device and this is the output target in training. The error obtained in the respiratory frequency prediction results obtained during training, validation, and testing for the respiratory frequency value used as the output reference is close to 0 as in Figure 4.2 below. However, the range of input values for heart rate and oxygen saturation still does not vary: heart rate is in the range of 62 to 77 BPM; oxygen saturation in the range of 95 to 97%.

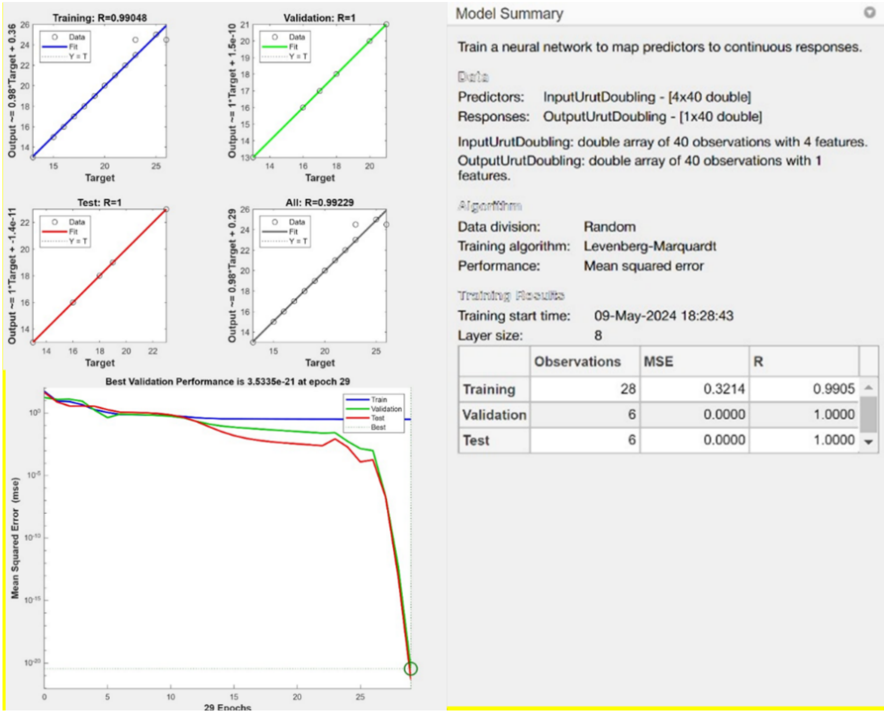

Figure 3. Results of Training, Validation, and Testing with MATLAB Software for Predicting Respiratory Frequency Readings

Interpretation of the Diagnostic Risk Percentage Scale

From the diagnostic risk percentage value scale that has been described, the following is an explanation of the classification. A value of 0-20% describes the condition of the patient who is still in a normal/healthy condition. Meanwhile, a value of 21-40% indicates that the patient's health condition is starting to require attention. Then a value of 41-60% means that the patient/person needs to undergo further examination. Meanwhile, a value of 61-80% means that the person has begun to need to have their health monitored regularly. And a value in the range of 81-100% gives an interpretation that the patient is in a very critical condition.

From a total of 100 respondents/patients whose data were taken, the values obtained for heart rate, oxygen saturation or body temperature did not indicate any significant risk (R = 0). Meanwhile, for respiratory frequency risk scoring, 48 of them had no risk related to respiratory frequency. The remaining 52 people showed a mild risk level for experiencing non-communicable diseases involving respiratory problems. Even so, the overall RD percentage value gives an idea that all respondents/patients whose data were taken are in a healthy condition. The summary can be seen in Table 3 below.

Table 3. Summary of Scoring Results and Percentage of Health Diagnosis Risk

Number of subjects	R_{BPM}	R_{SPO2}	R_{TBODY}	R_{RR}	RD
48 peoples	0 (healthy)	0 (healthy)	0 (healthy)	0 (healthy)	0% (Normal)
52 peoples				1 (low risk)	10% (Normal)

Results and Analysis of Obtaining Diagnostic Risk Percentage Values

Table 4. Diagnostic Risk Percentage Results Based on Obtaining Vital Signs, Heart Rate (BPM), Oxygen Saturation (SPO2), and Body Temperature (TBODY)

BPM	SPO2 (%)	TBODY (°C)	RR/min	Diagnostic Risk
69	97	36.3	19	0%
62	97	36.3	13	0%
77	97	36.2	25	10%
67	97	36.1	18	0%
70	96	36.4	15	0%
74	96	36.4	22	10%
67	97	36.3	13	0%
73	97	36.1	23	10%
73	97	36.2	19	0%
71	97	36.2	20	0%
64	97	36.3	13	0%
67	96	36.1	15	0%
68	96	36.1	16	0%
72	96	36.5	18	0%
76	95	36.4	21	10%
72	97	36.2	20	0%
77	97	36.2	25	10%
73	96	36.3	25	10%
71	97	36.3	17	0%
71	95	36.3	16	0%
78	96	36.1	27	10%
75	96	36.3	28	10%
81	96	36.2	29	10%
70	96	36.2	18	0%
78	96	36.2	25	10%
80	96	36.2	26	10%
70	96	36.1	18	0%
77	96	36.3	27	10%
72	96	36.5	18	0%
73	96	36.2	21	10%
76	97	36.1	27	10%
81	96	36.1	28	10%
72	96	36.4	16	0%
73	96	36.3	29	10%
72	96	36.3	28	10%
74	96	36.4	22	10%
68	96	36.3	10	0%
75	97	36.2	21	10%
78	96	36.1	26	10%
73	96	36.5	18	0%
76	96	36.1	24	10%
67	97	36.4	16	0%
81	96	36.1	28	10%
77	96	36	24	10%
78	96	36.3	26	10%
79	97	36.1	28	10%
75	97	36.2	22	10%

BPM	SPO2 (%)	TBODY (°C)	RR/min	Diagnostic Risk
73	97	36.3	23	10%
66	97	36.1	18	0%
80	95	36.3	21	10%
73	97	36.5	21	10%
71	97	36.4	17	0%
78	96	36.2	26	10%
67	96	36.1	15	0%
75	97	36.2	21	10%
78	96	36.1	26	10%
68	97	36.5	20	0%
69	96	36.5	17	0%
69	96	36.8	13	0%
69	96	36	22	10%
73	96	36.7	16	0%
72	96	36.5	18	0%
70	96	36	23	10%
71	96	36.3	25	10%
69	96	36.3	15	0%
69	96	36.3	15	0%
69	96	36.3	15	0%
69	97	36.2	19	0%
72	96	36.3	28	10%
69	97	36.2	19	0%
69	96	36.2	17	0%
70	96	36.4	16	0%
69	96	36.1	17	0%
69	96	36.3	15	0%
69	96	36.3	15	0%
74	96	36.2	21	10%
68	96	36.4	16	0%
69	97	36.1	17	0%
69	96	36.2	17	0%
69	96	36.6	17	0%
69	96	36.6	17	0%
69	96	36.3	15	0%
70	96	36.5	18	0%
72	96	36.3	28	10%
73	96	36.3	29	10%
75	97	36.8	21	10%
72	96	36.6	18	0%
77	96	36.3	27	10%
72	96	36.2	19	0%
72	97	36.3	21	10%
73	96	36.2	21	10%
78	96	36.2	26	10%
77	97	36.2	25	10%
74	97	36.2	20	0%
72	96	36.2	20	0%
73	97	36.1	23	10%
70	97	36.3	24	10%
70	97	36.2	19	0%
82	96	36.3	26	10%

BPM	SPO2 (%)	TBODY (°C)	RR/min	Diagnostic Risk
71	96	36.2	19	0%

From the obtained diagnostic risk percentage values, there is one similar pattern. The similarity is that all the values obtained for heart rate, oxygen saturation and body temperature are still within normal limits and the risk scale is zero (R = 0). As a result, the data obtained along with the diagnostic risk percentage value is less able to describe the sensitivity of the health monitoring device to at least those who have abnormalities or indeed one of whose vital signs is slightly outside the normal range other than healthy people. Apart from that, for dozens of respondents, the respiratory frequency reading values obtained on the health monitoring device also tended to be inaccurate. In other words, obtaining normal values for other vital signs is not followed by normal respiratory frequency readings. This is because it is influenced by the range of vital sign values which is not that large. So, more data collection is needed, with a greater range of values for vital signs than before - including for body temperature and skin temperature, the largest range of which can only reach 0.6 °C. So that later when training is carried out, up to the validation and testing stages, predictions of respiratory frequency readings can also be included when vital sign values are obtained which are currently not within the range, so that the sensitivity of the equipment readings can be better described.

Conclusion

The most crucial aspect that influences the diagnostic risk percentage value obtained in this study is the sensitivity of the health monitoring device made by researchers - this is most visible in the prediction of respiratory frequency vital sign readings. This means that there is still a need for data collection with a more diverse range of acquisition and range of vital sign values. So that it can further increase the accuracy and precision of vital sign readings from health monitoring devices - especially respiratory frequency vital signs. So that later the diagnostic risk percentage results obtained can be accounted for and reflect the mapping of health diagnoses based on vital conditions in the entire human body. Regarding the questions and objectives of this research, the following conclusions can be outlined; (1) the diagnostic risk percentage parameter covers the need for parameters that do not yet exist in smartwatches - as well as portable monitoring equipment. In diagnostic risk analysis, the biggest role of this parameter lies in the selection of vital signs which are considered to play an essential role in the medical world, (2) the development of a diagnostic risk percentage framework in the form of a combination of a regression approach for predicting respiratory frequency readings and classification using a decision tree algorithm in a diagnostic risk scoring and scaling mechanism is able to provide an actual picture of a person's physical health condition, (3) the existence of a diagnostic risk percentage parameter can fill the practical gap in health monitoring in the form of a comprehensive summary of health diagnosis mapping which is not yet available on patient monitoring equipment in hospitals, as well as portable monitoring equipment and smartwatches, and (4) in this research, the interpretation results have not been accommodated in the implementation of algorithm programming with the Arduino IDE.

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