GIRIJANANDA CHOWDHURY INSTITUTE OF MANAGEMENT AND TECHNOLOGY

"DESIGN AND DEVELOPMENT OF A STANDALONE BIOMEDICAL SYSTEM TO DETERMINE PATIENT'S HEALTH CONDITION USING MACHINE LEARNING"

This Dissertation Project is submitted in Partial fulfillment for the requirements for the degree of

MASTER OF TECHNOLOGY
in
ELECTRONICS AND COMMUNICATION ENGINEERING

ASSAM SCIENCE AND TECHNOLOGY UNIVERSITY, GUWAHATI

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DECLARATION

I hereby declare that this dissertation project work **"DESIGN AND DEVELOPMENT OF A STANDALONE BIOMEDICAL SYSTEM TO DETERMINE PATIENT'S HEALTH CONDITION USING MACHINE LEARNING"** was carried out by me under the guidance and supervision of Mr. Alokojjwal Das (Assistant Professor), Department of Electronics and Communication Engineering, Girijananda Chowdhury Institute of Management and Technology, Guwahati and Dr. Sandip Bordoloi (Associate Professor and HOD(i/c)), Department of Electrical Engineering, Girijananda Chowdhury Institute of Management and Technology, Guwahati. This project is submitted to Department of Electronics and Communication Engineering during the academic year August 2023 - June 2024. This work is never produced before any authority except Assam Science and Technical University for evaluation.

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ABSTRACT

The modern patient monitoring system is the integration of biomedical parameters and machine learning algorithms. This paper presents a biomedical device integrating sensors like Heart Rate/SpO_2 sensor with machine learning for health monitoring. Multiple linear regression and ANOVA identified relations between significant parameters like age, weight, gender, medical history, blood pressure, pulse pressure, SpO_2 and heart rate for predicting health status. Decision tree algorithms categorized subjects into different health levels based on vital parameters. The objectives of this project work is to monitor vital patient's health parameters using sensors and asserting the deviation percentage from a normal person of that age group using machine learning and also to develop it as a standalone application device. The second objective of this project work is to predict the health status of a patient by applying Multiple Regression, Logistic Regression and Decision tree using determinant parameters SpO_2, Heart Rate, Age, Weight, Gender and Medical History reading. Additionally, it aims to analyze the relation between blood pressure (Systolic and Diastolic) with SpO_2, Heart Rate, Age, Weight, Gender and Medical History. The system demonstrated quite accurate prediction with low error rates, highlighting its potential for reliable, personalized healthcare monitoring.

Keywords: Health Status, Multiple Regression, Logistic Regression, Decision Tree, Heart Rate, SpO_2

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LIST OF ABBREVIATIONS, SYMBOLS AND NOTATIONS

°C	:	Degree Centigrade
°F	:	Degree Fahrenheit
&	:	And
Fig.	:	Figure
RTC	:	Real Time Clock
%	:	Percentage
µA	:	Microampere
LCD	:	Liquid Crystal Display
MLR	:	Multiple linear regression
IR	:	Infra-Red
LED	:	Light Emitted Diode
MHz	:	Mega Hertz
KHz	:	Kilo Hertz
Ω	:	Ohm
V_{CC} or V	:	Voltage
GND	:	Ground
A	:	Ampere
I2C	:	Inter-integrated Circuit
IDE	:	Integrated Development Environment
PPR	:	Pulse Pressure
SpO_2	:	Oxygen Saturation
BMI	:	Body Mass Index
BPM	:	Beats per Minute
Pa	:	Pascal
P-value	:	Probability under the assumption of no effect or no difference
Q-Q Plot	:	Quantile-Quantile Plot
ANOVA	:	Analysis of Variance
mmHg	:	Millimeter of Mercury
Kg	:	Kilogram

CHAPTER 1
INTRODUCTION

1.1 Introduction

The "Design and Development of a Standalone Biomedical System to Determine a Patient's Health Condition Using Machine Learning" is a self-ideation project that aims to revolutionize healthcare by leveraging the power of artificial intelligence and machine learning. This ambitious endeavor combines the fields of biomedicine, data science, and technology to create a sophisticated system that can assist in the early diagnosis, continuous monitoring, and personalized management of a patient's health.

In an era of rapid technological advancement, the integration of machine learning into healthcare has emerged as a promising solution to enhance the accuracy, efficiency, and accessibility of medical diagnostics and care. This project represents a significant step forward in the realm of biomedical engineering, where we endeavor to design, develop, and deploy a self-contained, intelligent biomedical system capable of assessing a patient's health condition with remarkable precision.

Traditionally, healthcare has been heavily reliant on the expertise of healthcare professionals, which, while invaluable, can be limited by human constraints and the potential for diagnostic errors. The incorporation of machine learning into healthcare is poised to augment these capabilities by offering data-driven insights, predictive analytics, and real-time monitoring, thus transforming the way we approach patient care.

The significance of this project cannot be overstated. It has the potential to transform the healthcare landscape by improving early detection, enhancing patient outcomes, and optimizing resource utilization. By harnessing the power of machine learning, this standalone biomedical system bridges the gap between data-driven decision-making and healthcare delivery, ushering in a new era of medical care characterized by precision, accessibility, and personalized attention.

1.2 Brief History and Background

The integration of machine learning in healthcare has roots dating back to the late 20th century. Early applications were primarily focused on medical imaging and diagnostic tasks. In the 2000s, researchers began exploring the potential of machine learning for predictive modeling, clinical decision support systems, and personalized medicine. Increased computational power and the availability of large datasets started influencing the development of more sophisticated machine learning algorithms. The 2010s witnessed a surge in healthcare-related machine learning research and applications. Deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), gained popularity for tasks like image analysis and natural language processing. Electronic health record (EHR) data became more accessible, allowing for more comprehensive analysis and predictive modeling.

Several milestones marked the progress of machine learning in healthcare, including IBM Watson's victory on Jeopardy in 2011, showcasing the potential of artificial intelligence in processing and understanding natural language. Breakthroughs in image recognition, particularly in medical imaging, paved the way for applications like tumor detection and classification.

Alongside advancements, the field faced challenges such as the interpretability of machine learning models, concerns about bias in algorithms, and the need for robust validation and regulatory frameworks.

Towards the late 2010s, there was an increasing focus on developing systems for personalized medicine, considering individual genetic variations, lifestyle factors, and real-time monitoring.

The 2020s saw a continued expansion of machine learning applications in healthcare. The COVID-19 pandemic further emphasized the importance of data-driven approaches in epidemiology, diagnostics, and vaccine development.

Ongoing research and development continue to explore the potential of machine learning for early diagnosis, predictive modeling, and personalized treatment plans.

It's important to note that specific projects, like the one we described, might have unique histories and timelines depending on the organizations or research teams involved. The evolution of machine learning in healthcare reflects a dynamic and ongoing process, shaped by technological advancements, research breakthroughs, and the evolving needs of the healthcare industry.

1.3 Motivation for doing this project

The motivation to do this project has come from the digitization and remote access of patient monitoring system applications and tools. This project will allow us to take a step towards the remote monitoring and controlling of health parameters, analyse the data without the physical presence of doctor. The biomedical domain was chosen with machine learning because new technological things are emerging in the field of the medical sector which increment the scope of its efficiency with respect to artificial intelligence and its compatibilities with many other things.

1.4 Objective of this project

The objectives of the Project work are

1. To monitor vital patient's health parameters using sensors and asserting the deviation percentage from a normal person of that age group using machine learning and also to develop it as a standalone application device.
2. To predict the health status of a patient by applying Multiple Regression and Decision tree using determinant parameters SpO_2, Heart Rate, Age, Weight, Gender and Medical History reading. To determine relation between blood pressure (Systolic and Diastolic) with SpO_2, Heart Rate, Age, Weight, Gender and Medical History.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

The review of literature is a pre-requisite aspect of every well-defined research which not only strengthens the breadth of our knowledge but also helps in identifying gaps of our understanding on the research topic. The relevant scientific literature helps us in selecting the research problems and conducting the research to its future heights.

2.2 Literature review

1. **"Healthcare monitoring system using IoT" by S. Shaikh, et al. [1]**

   The paper by S. Shaikh and V. Chitre (2017) presents a healthcare monitoring system that utilizes IoT technology to enhance patient care. The authors contribute to the field by developing a system that integrates various sensors and IoT devices to continuously monitor critical health parameters such as heart rate, temperature, and blood pressure. The study's results reveal that the system provides real-time health data, which significantly improves the accuracy and responsiveness of medical interventions. The authors conclude that their IoT-based healthcare monitoring system has the potential to revolutionize patient care by offering continuous monitoring and early detection of health anomalies, thereby reducing hospital readmissions and improving overall patient outcomes.

2. **"Patient health monitoring system using IoT" by Sangeethalakshmi K, et al. [2]**

   The paper by Sangeethalakshmi K et al. (2023) presents a comprehensive study on the development and implementation of an IoT-based patient health monitoring system. This system leverages various sensors to continuously collect and transmit vital health data, which is then processed and analyzed to provide real-time monitoring and early detection of health issues. The results demonstrated that this IoT-based approach significantly enhances the accuracy and timeliness of health monitoring compared to traditional methods, leading to more proactive healthcare management. The authors concluded that such systems hold great potential for improving patient outcomes, particularly for those with chronic conditions, by enabling continuous monitoring and timely medical interventions.

3. **"A Wireless Patient Monitoring System using Integrated ECG module, Pulse Oximeter, Blood Pressure and Temperature Sensor" by S. Marathe, et al. [3]**

The paper by S. Marathe et al. (2019) details the development of a wireless patient monitoring system that integrates an ECG module, pulse oximeter, blood pressure, and temperature sensors. The authors' contribution lies in creating a comprehensive and efficient system capable of continuously monitoring multiple vital parameters, facilitating better patient management. The results indicate that the integrated system reliably transmits accurate health data in real-time, significantly enhancing the capability for early detection and timely intervention of potential health issues. The authors conclude that this wireless monitoring system offers substantial improvements over traditional monitoring methods, particularly in providing continuous and remote healthcare, which is critical for managing patients with chronic conditions and in emergency scenarios.

4. **"Portable and Centralised E-Health Record System for Patient Monitoring Using Internet of Things(IoT)" by F. Shanin, et al. [4]**

The paper by F. Shanin et al. (2018) introduces a portable and centralized e-health record system leveraging IoT for enhanced patient monitoring. The authors' significant contribution is the development of a system that consolidates patient health data from various IoT devices into a centralized platform, facilitating seamless access and management of health records. The study's results demonstrate that this system improves the efficiency and accuracy of patient monitoring by enabling real-time data collection and analysis, which supports timely medical decision-making. The authors conclude that their IoT-based e-health record system offers a substantial advancement in healthcare, providing a scalable solution that enhances patient care by ensuring continuous and integrated health monitoring across different healthcare settings.

5. **"Smart healthcare in smart cities: wireless patient monitoring system using IoT" by M. Poongodi, et al. [5]**

The paper by M. Poongodi et al. (2021) explores the integration of IoT-based wireless patient monitoring systems within the context of smart cities. The authors contributed to the field by developing a comprehensive framework that leverages IoT technologies to enable continuous, real-time monitoring of patient's health metrics. The study's results indicate that the proposed system significantly improves the efficiency and effectiveness of healthcare delivery, particularly in urban settings where scalability and accessibility are crucial. The authors concluded that implementing such smart healthcare solutions in smart cities can lead to better health outcomes, reduced healthcare costs, and enhanced patient satisfaction, emphasizing the system's potential for widespread adoption and impact.

6. **"IoT Based Remote Patient Monitoring System" by S. Maqbool, et al. [6]**

The paper by S. Maqbool et al. (2020) presents an innovative IoT-based remote patient monitoring system designed to enhance healthcare delivery by enabling continuous, real-time tracking of patients' vital signs. The authors contributed to the field by developing a system that integrates various sensors and communication technologies to collect, transmit, and analyze health data remotely. The results of the study demonstrate that this system effectively improves the accuracy and timeliness of health monitoring, leading to better management of chronic diseases and reduced hospital visits. The authors concluded that IoT-based remote monitoring systems have significant potential to transform healthcare by providing patients with more personalized and proactive care, ultimately improving health outcomes and reducing healthcare costs.

7. **"Patient Health Monitoring System Development using ESP8266 and Arduino with IoT Platform" by J. A. J. Alsayaydeh, et al. [7]**

The paper by J. A. J. Alsayaydeh et al. (2023) details the development of a patient health monitoring system utilizing ESP8266 and Arduino integrated with an IoT platform. The authors contribute significantly by creating an affordable and efficient system that continuously monitors vital health parameters and transmits the data in real-time for remote analysis. The results indicate that this system effectively tracks key health metrics such as heart rate, temperature, and oxygen levels, providing accurate and timely health information. The authors conclude that their IoT-based health monitoring solution, leveraging cost-effective hardware like ESP8266 and Arduino, holds substantial promise for improving patient care, especially in remote and resource-limited settings, by enabling continuous health surveillance and prompt medical interventions.

8. **"Predictis: an IoT and machine learning-based system to predict risk level of cardiovascular diseases" by M. N. Islam et al. [8]**

The paper by M. N. Islam et al., titled "Predictis: an IoT and machine learning-based system to predict risk level of cardiovascular diseases," introduces an advanced system named Predictis that leverages IoT and machine learning to assess the risk of cardiovascular diseases.

The authors contribute by developing a comprehensive framework that integrates wearable sensors and a machine learning algorithm to continuously monitor and analyze patients' vital signs and lifestyle data. The results indicate that Predictis is highly effective in predicting cardiovascular risk with significant accuracy, outperforming traditional risk assessment methods. The study concludes that the implementation of Predictis can revolutionize preventive healthcare by providing early warnings and personalized health recommendations, ultimately reducing the incidence and severity of cardiovascular diseases.

9. "A survey on medical and diseases prediction using machine learning" by N. Anubhama et al. [9]

The paper by N. Anubhama and N. Ms. M Parvathi (2023) provides a comprehensive survey on the application of machine learning techniques for medical and disease prediction. The authors contribute to the field by systematically reviewing and analyzing various machine learning algorithms and their effectiveness in predicting a range of diseases, from chronic conditions to acute illnesses. The results of the survey highlight that machine learning models, particularly those utilizing deep learning and ensemble methods, show significant promise in achieving high accuracy and reliability in medical diagnostics. The authors conclude that the integration of machine learning in healthcare can greatly enhance disease prediction, facilitating early diagnosis and personalized treatment plans, ultimately improving patient outcomes and reducing healthcare costs.

10. "Human Disease Prediction using Machine Learning Techniques and Real-life Parameters" by K. Gaurav et al. [10]

The paper by K. Gaurav et al. (2023) explores the use of machine learning techniques combined with real-life parameters to predict human diseases. The authors contribute to the medical field by developing and evaluating models that incorporate diverse health indicators, such as lifestyle habits and clinical measurements, to enhance the accuracy of disease prediction. The results demonstrate that integrating real-life parameters significantly improves the predictive power of machine learning models, allowing for more precise and personalized health risk assessments. The authors conclude that their approach can potentially revolutionize disease prediction, enabling earlier interventions and tailored healthcare strategies, which can lead to better patient outcomes and more efficient healthcare delivery.

11. “Simulation of a machine learning enabled learning health system for risk prediction using synthetic patient data” by A. Chen et al. [11]

The paper by A. Chen and D. O. Chen, titled "Simulation of a machine learning enabled learning health system for risk prediction using synthetic patient data," presents a significant advancement in the application of machine learning for healthcare risk prediction. The authors developed a learning health system (LHS) that employs machine learning algorithms to predict patient risk profiles using synthetic patient data, which preserves patient privacy while providing a robust dataset for training. The results indicated that the LHS could accurately predict various health risks, demonstrating its potential to improve early intervention and personalized treatment plans. In conclusion, the study highlights the effectiveness of using synthetic data to develop and validate predictive models in healthcare, offering a promising approach to enhance clinical decision-making and patient outcomes while safeguarding patient privacy.

12. “Retracted: A System of Remote Patients’ Monitoring and Alerting Using the Machine Learning Technique” by M. Dhinakaran et al. [12]

The paper originally published by M. Dhinakaran et al. (2024) proposed a novel system for remote patient monitoring and alerting utilizing machine learning techniques. The contribution of this work was the development of a sophisticated ML-based system designed to continuously monitor patients' health metrics and provide timely alerts for potential health issues, thus enabling proactive medical intervention. The results indicated that the system was effective in early detection and alerting, improving patient outcomes by ensuring timely medical responses. However, the paper was subsequently retracted, suggesting that the findings and conclusions might be unreliable or invalid. This retraction underscores the importance of rigorous validation and peer review in the development of healthcare technologies.

13. “Healthcare Monitoring using Machine Learning Based Data Analytics” by N. S. R. Janani et al. [13]

The paper by N. S. R. Janani et al. (2023) presents a comprehensive study on healthcare monitoring through machine learning-based data analytics. The authors contribute to the healthcare field by developing a system that utilizes advanced machine learning algorithms to analyze health data, enabling the continuous and precise monitoring of patient health. The results indicate that this approach significantly enhances the ability to detect anomalies and predict potential health issues in real-time, leading to timely and more effective medical interventions. The authors conclude that machine learning-based data analytics can revolutionize healthcare monitoring by providing a robust, scalable, and accurate method for health surveillance, ultimately improving patient outcomes and optimizing healthcare resources.

14. "An Intelligent Whole-Process Medical System Based on Cloud Platform" by H. Wang et al. [14]

The paper by H. Wang and S. Tao, titled "An Intelligent Whole-Process Medical System Based on Cloud Platform," presents a significant contribution to the integration of artificial intelligence (AI) and cloud technology in healthcare. The authors developed an intelligent medical system that leverages cloud platforms to manage the entire medical process, from patient registration to post-treatment follow-up. The results demonstrated that the system could efficiently handle large-scale medical data, improving the accuracy and speed of medical diagnostics and treatment plans. Additionally, the system enhanced patient management by providing real-time data access and analysis, leading to more personalized and effective healthcare services. In conclusion, Wang and Tao emphasized that their cloud-based AI system represents a substantial advancement in medical technology, offering a scalable and efficient solution to modernize healthcare delivery and improve patient outcomes.

15. "Machine learning-based clinical decision support system" by C. K. Gomathy et al. [15]

In the paper "Machine learning-based clinical decision support system" by C. K. Gomathy, the author contributes to the field of healthcare by developing a clinical decision support system (CDSS) that utilizes machine learning algorithms to assist medical professionals in making informed decisions. The results of the study show that the machine learning-based CDSS significantly enhances diagnostic accuracy and treatment efficacy by analyzing patient data and predicting potential health outcomes with high precision. Additionally, the system is designed to integrate seamlessly with existing electronic health records, providing real-time support and reducing the cognitive load on healthcare providers. In conclusion, Gomathy highlights the potential of machine learning in revolutionizing clinical decision-making processes, leading to improved patient care and optimized healthcare resource utilization.

16. **“Non-invasive health prediction from visually observable features” by F. Y. Khong et al. [16]**

The paper by F. Y. Khong et al., titled "Non-invasive health prediction from visually observable features," makes a notable contribution to the field of health diagnostics by developing a method for predicting health conditions based on non-invasive, visually observable features. The authors utilized advanced image processing and machine learning techniques to analyze visual data such as facial features, skin conditions, and other observable indicators to predict various health metrics. The results demonstrated that their system could accurately predict health conditions with a high degree of reliability, offering a promising alternative to more invasive diagnostic methods. In conclusion, Khong and colleagues emphasized that their non-invasive approach could significantly enhance early detection and monitoring of health conditions, making healthcare more accessible and less discomforting for patients, thus paving the way for broader applications in remote health monitoring and telemedicine.

17. **“Analysis of patient health condition based on hybrid machine learning algorithm” by A. N. Kumar et al. [17]**

The paper by A. N. Kumar et al. (2022) investigates the analysis of patient health conditions using a hybrid machine learning algorithm. The authors contribute to the healthcare analytics field by developing a sophisticated algorithm that combines multiple machine learning techniques to enhance the accuracy and reliability of health condition predictions. The study's results show that the hybrid algorithm outperforms traditional methods in diagnosing various health conditions, offering improved precision in health assessments. The authors conclude that the application of hybrid machine learning algorithms in patient health analysis can significantly advance medical diagnostics, providing more accurate and timely insights that can improve patient care and treatment outcomes.

18. **“Optimizing Patient Record Linkage in a Master Patient Index Using Machine Learning: Algorithm Development and Validation” by W. Nelson et al. [18]**

The paper by W. Nelson et al. (2023) focuses on optimizing patient record linkage in a Master Patient Index (MPI) using advanced machine learning algorithms. The authors contribute by developing and validating a novel machine learning-based algorithm designed to improve the accuracy and efficiency of linking patient records across different healthcare systems. The study's results demonstrate that their algorithm significantly enhances the accuracy of patient record matching, reducing errors and ensuring more reliable integration of patient data. The authors conclude that implementing machine learning techniques in MPI systems can greatly improve the consistency and reliability of patient records, leading to better coordinated care and more informed medical decision-making.

19. "MedAi: A Smartwatch-Based Application Framework for the Prediction of Common Diseases Using Machine Learning" by S. T. Himi et al. [19]

The paper by S. T. Himi et al. (2023) introduces "MedAi," a smartwatch-based application framework designed for the prediction of common diseases using machine learning. The authors contribute to the healthcare field by developing an innovative framework that leverages the data collected from smartwatches to predict health conditions accurately and efficiently. The results of their study demonstrate that MedAi significantly enhances the predictive accuracy for common diseases, outperforming traditional methods by integrating machine learning algorithms with real-time health data. The study concludes that MedAi offers a promising solution for continuous health monitoring and early disease detection, potentially revolutionizing how health issues are managed by providing timely and personalized medical interventions.

20. "Patient Monitor for SpO2 and Temperature Parameters" by M. S. T. P. Sahrul et al. [20]

In their paper titled "Patient Monitor for SpO2 and Temperature Parameters," M. S. T. P. Sahrul, T. Triwiyanto, and T. Hamzah contribute to the field of biomedical engineering by developing a patient monitoring system designed to continuously measure blood oxygen saturation (SpO2) and body temperature. The system integrates sensors for SpO2 and temperature monitoring with real-time data processing capabilities, ensuring accurate and timely health status updates. The results from their study showed that the monitoring system provided reliable readings comparable to standard medical devices, demonstrating its potential effectiveness in clinical settings. In conclusion, the authors assert that their patient monitoring system can significantly enhance patient care by providing continuous, real-time health monitoring, thus enabling prompt medical interventions and improving overall health outcomes.

21. “Assistive Blood Pressure Monitor for Senile Population” by M. P. Kumar et al. [21]

The paper by M. P. Kumar, R. N. Reddy, S. Deekshitha, and D. S. Reddy, titled "Assistive Blood Pressure Monitor for Senile Population," presents an innovative solution aimed at improving healthcare for the elderly. The authors developed an assistive blood pressure monitoring device specifically designed for the senior population, incorporating features to accommodate age-related challenges such as diminished dexterity and cognitive decline. The results demonstrated that the device is user-friendly and provides accurate blood pressure readings, thereby validating its efficacy and reliability for elderly users. In conclusion, the study underscores the potential of this assistive technology to enhance the quality of life and health management among the elderly, promoting greater independence and timely medical intervention.

CHAPTER 3
THEORETICAL CONSIDERATION

3.1 Data acquisition

Data acquisition is the process of sampling signals that measure real-world physical conditions and converting the resulting samples into digital numeric values that can be manipulated by a computer. Data acquisition systems, abbreviated by the acronyms DAS, DAQ, or DAU, typically convert analog waveforms into digital values for processing. The components of data acquisition systems include:

1. Sensors, to convert physical parameters to electrical signals.
2. Signal conditioning circuitry, to convert sensor signals into a form that can be converted to digital values.
3. Analog-to-digital converters, to convert conditioned sensor signals to digital values.

3.2 Multiple Linear Regression

3.2.1 Brief Introduction

Multiple linear regression (MLR), also known simply as multiple regression, is a statistical technique that uses several explanatory variables to predict the outcome of a response variable. The goal of multiple linear regression is to model the linear relationship between the explanatory (independent) variables and response (dependent) variables. In essence, multiple regression is the extension of ordinary least-squares (OLS) regression because it involves more than one explanatory variable.

3.2.2 Brief Description

Simple linear regression is a function that allows an analyst or statistician to make predictions about one variable based on the information that is known about another variable. Linear regression can only be used when one has two continuous variables—an independent variable and a dependent variable. The independent variable is the parameter that is used to calculate the dependent variable or outcome. A multiple regression model extends to several explanatory variables.

The multiple regression model is based on the following assumptions:

1. There is a linear relationship between the dependent variables and the independent variables
2. The independent variables are not too highly correlated with each other
3. y_i observations are selected independently and randomly from the population
4. Residuals should be normally distributed with a mean of 0 and variance σ

The Formula is given by:

$$y_i=\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\ldots+\beta_p x_{ip}+\epsilon$$

where, for $i=n$ observations:
y_i = dependent variable
x_i = explanatory variables
β_0 = y-intercept (constant term)
β_p = slope coefficients for each explanatory variable
ϵ = the model's error term (also known as the residuals)
The coefficient of determination (R-squared) is a statistical metric that is used to measure how much of the variation in outcome can be explained by the variation in the independent variables. R^2 always increases as more predictors are added to the MLR model, even though the predictors may not be related to the outcome variable.
R^2 by itself can't thus be used to identify which predictors should be included in a model and which should be excluded. R^2 can only be between 0 and 1, where 0 indicates that the outcome cannot be predicted by any of the independent variables and 1 indicates that the outcome can be predicted without error from the independent variables.
When interpreting the results of multiple regression, beta coefficients are valid while holding all other variables constant ("all else equal"). The output from a multiple regression can be displayed horizontally as an equation, or vertically in table form.

3.3 Logistic Regression

Logistic regression is a supervised machine learning algorithm used for classification tasks where the goal is to predict the probability that an instance belongs to a given class or not. Logistic

regression is a statistical algorithm which analyze the relationship between two data factors. The article explores the fundamentals of logistic regression, it's types and implementations.
Logistic regression is used for binary classification which takes input as independent variables and produces a probability value between 0 and 1.

3.4 Heart Rate

Heart rate is the number of times the heart beats in 1 minute. It is different from pulse rate which is the number of times your arteries create a noticeable "pulse" due to increase in blood pressure as a result of your heart contracting. Heart rates vary from person to person. It is lower when anyone is at rest and higher when anyone exercises. A healthy heart rate for adults over 18 is usually between 60 and 100 beats per minute (bpm).
The maximum heart rate is, on average, the highest the pulse one can get. One way to get a rough estimate of the predicted maximum is to subtract one's age from the number 220.
Another term is the Target heart rate zone, which is usually the heart rate with 60% - 80% of one's maximum heart rate.

Table 3.1 Relation between Age and Heart Rate (Source [29])

Age	Target Heart Rate (HR) Zone (60%-80%)	Predicted Maximum Heart Rate
20	120-170	200
25	117-166	195
30	114-162	190
35	111-157	185
40	108-153	180
45	105-149	175
50	102-145	170
55	99-140	165
60	96-136	160
65	93-132	155
70	90-128	150

3.5 Oxygen Saturation (SpO_2)

Oxygen saturation (SpO_2) is a measure of the amount of oxygen-carrying hemoglobin in the blood compared to the amount of hemoglobin that is not carrying oxygen.

Essentially, this abbreviation indicates the oxygen amount being carried by red blood cells in the body. SpO_2 is measured by a percentage amount. A normal level of oxygen (SpO_2) is usually 95% or higher. Some people with chronic lung disease or sleep apnea can have normal levels around 90%.

Table 3.2 SpO_2 level status (Source [26])

SpO_2 value	**Status**
89	Chronic lung disease or sleep apnea
88	Chronic lung disease or sleep apnea
87	Chronic lung disease or sleep apnea
92	Chronic lung disease or sleep apnea
95	Normal
96	Normal
98	Normal
99	Normal
99	Normal

3.6 Body Mass Index (BMI)

Body Mass Index (BMI) is a person’s weight in kilograms divided by the square of height in meters. A high BMI can indicate high body fatness. BMI screens for weight categories that may lead to health problems, but it does not diagnose an individual's body fatness or health.

Table 3.3 Hight weight relationship (Source [27])

Height		**Females**		**Males**	
(in cm)	**(in inches)**	**(in kg)**	**(in lb)**	**(in kg)**	**(in lb)**
137 cm	4'6"	28.5-34.9	63-77	28.5-34.9	63-77
140 cm	4' 7"	30.8-37.6	68-83	30.8-38.1	68-84
142 cm	4' 8"	32.6-39.9	72-88	33.5-40.8	74-90

145 cm	4'9"	34.9-42.6	77-94	35.8-43.9	79-97
147 cm	4'10"	36.4-44.9	81-99	38.5-46.7	85-103
150 cm	4'11"	39-47.6	86-105	40.8-49.9	90-110
152 cm	5' 0"	40.8-49.9	90-110	43.1-53	95-117
155 cm	5' 1"	43.1-52.6	95-116	45.8-55.8	101-123
157 cm	5' 2"	44.9-54.9	99-121	48.1-58.9	106-130
160 cm	5' 3"	47.2-57.6	104-127	50.8-61.6	112-136
163 cm	5' 4"	49-59.9	108-132	53-64.8	117-143
165 cm	5' 5"	51.2-62.6	113-138	55.3-68	122-150
168 cm	5' 6"	53-64.8	117-143	58-70.7	128-156
170 cm	5' 7"	55.3-67.6	122-149	60.3-73.9	133-163
173 cm	5'8"	57.1-69.8	126-154	63-76.6	139-169
175 cm	5' 9"	59.4-72.6	131-160	65.3-79.8	144-176
178 cm	5'10"	61.2-74.8	135-165	67.6-83	149-183
180 cm	5' 11"	63.5-77.5	140-171	70.3-85.7	155-189
183 cm	6'0"	65.3-79.8	144-176	72.6-88.9	160-196
185 cm	6' 1'	67.6-82.5	149-182	75.3-91.6	166-202
188 cm	6'2"	69.4-84.8	153-187	77.5-94.8	171-209
191 cm	6' 3'	71.6-87.5	158-193	79.8-98	176-216

The Formula of Weight are given by:

Weight (in pounds) = 5 x BMI + (BMI/5) x (Height (in inches) - 60)

Weight (in kilograms) = 2.2 x BMI + (3.5 x BMI) x (Height (in meters) - 1.5)

Table 3.4 BMI (Source [27])

BMI	**Inference**
BMI below 18.5	Indicates being underweight
BMI between 18.5 and 24.9	Falls within the normal/healthy weight range.
BMI between 25.0 and 29.9	Suggests overweight status
A BMI of 30.0 or higher	Indicates obesity

3.7 Blood Pressure

Blood pressure is the measurement of the pressure or force of blood inside your arteries. Each time one's heart beats, it pumps blood into arteries that carry blood throughout the body. This happens 60 to 100 times a minute, 24 hours a day. Arteries deliver oxygen and nutrients to your whole body so it can function.

3.7.1 Blood Pressure vs. Heart Rate

Both of these have to do with the heart, but they're two different things. Blood pressure is how powerfully the blood travels through the blood vessels. Heart rate is the number of times the heart beats in one minute.

An increase in heart rate doesn't mean that blood pressure is going up, too.

Table 3.5 Blood pressure relationship with age and gender (Source [30])

Gender	Age	Systolic Blood Pressure (mm Hg)	Diastolic Blood Pressure (mm Hg)
Male	21-25	120.5	78.5
	26-30	119.5	76.5
	31-35	114.5	75.5
	36-40	120.5	75.5
	41-45	115.5	78.5
	46-50	119.5	80.5
	51-55	125.5	80.5
	56-60	129.5	79.5
	61-65	143.5	76.5
Female	21-25	115.5	70.5
	26-30	113.5	71.5
	31-35	110.5	72.5
	36-40	112.5	74.5
	41-45	116.5	73.5
	46-50	124	78.5
	51-55	122.55	74.5
	56-60	132.5	78.5
	61-65	130.5	77.5

Table 3.6 Category of blood pressure (Source [30])

Category	Systolic Blood Pressure (mm Hg)	Diastolic Blood Pressure (mm Hg)	Management
Dangerously low	50 or lower	33 or lower	A critical condition that requires emergency medical attention with IV fluids
Very low	60 or lower	40 or lower	Lifestyle modifications with medications
Low	Less than 90	Less than 60	Lifestyle modifications and regular checkups
Normal	Less than 120	Less than 80	Active lifestyle
Elevated	120-129	80 or more	Doctors may recommend lifestyle changes at this stage
Hypertension stage I	130-139	80-89	Doctors may prescribe blood pressure medications and some lifestyle changes to reduce the risk of heart disease and stroke.
Hypertension stage II	140-159	90-99	Doctors may prescribe a combination of medications and lifestyle changes; they may treat complications that may have increased due to high blood pressure.
Hypertensive crisis	180 or higher	120 or higher	A critical condition that requires emergency medical attention

3.8 Pulse Pressure

Pulse pressure is the difference between the systolic and diastolic values of blood pressure. Pulse pressure tends to increase as the body ages, and this value can also indicate health problems before you develop symptoms.

The Formula is given by:

Pulse Pressure = Systolic Blood Pressure – Diastolic Blood Pressure

3.8.1 Why does pulse pressure matter?

The arteries that carry the blood are naturally stretchy and flexible, but they can only hold so much blood at any time. This is called arterial compliance. The arteries also get less flexible and stretchy as the body grows older, which is natural and expected. This is sometimes referred to as arterial stiffness. Arteries also tend to be stiffer in people with diabetes and chronic kidney disease.

Blood pressure and pulse pressure can be valuable information for the healthcare provider, helping the patient spot a wide variety of heart and circulatory problems.

3.9 Brief Overview of MAX30100

3.9.1 Introduction

Whenever we breathe in oxygen, the oxygen enters our lungs and passes into our blood. The blood carries oxygen to various organs of our body. Blood carries oxygen to our body, by means of hemoglobin. During a pulse oximetry reading, a small clam-like device is attached to our finger.

A small bean of light is passed through the finger. This light passes the finger and is used to measure the content of oxygenated or deoxygenated blood.

3.9.2 Working of MAX30100 pulse oximeter sensor

The sensor has two light-emitting diodes and one photodiode. The LEDs are used to emit the light and the photodiode is used to detect and measure the intensity of the received light. In MAX30100 one LED emits monochromatic light and the other LED emits infrared light.

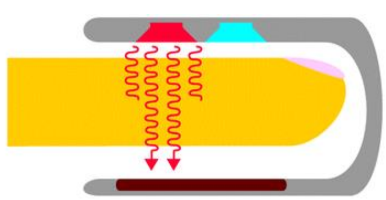

Fig. 3.1 LED and IR configuration inside pulse oximeter (Source [22])

The MAX30100 pulse oximeter can measure both the heart pulse rate and the oxygen level in the blood. The Red light that the red LED emits is used to measure the pulse rate and for measuring the oxygen level, both the LEDs are used.

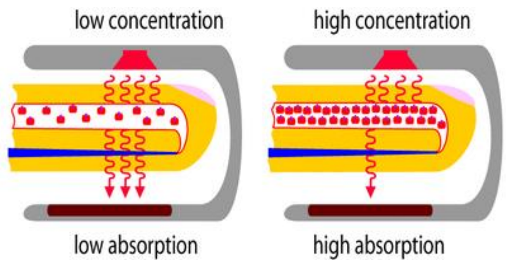

Fig. 3.2 Working of pulse oximeter (Source [22])

When the heart pumps the blood, the oxygenated blood is increased in the body and when the heart relaxes the volume of the oxygenated blood is decreased in the body. As a result, the time variation in the change of the volume of the oxygenated blood, the pulse rate is calculated (One variation = one pump of the heart). This whole change in the light is detected and measured by the photodiode. The oxygen content is measured by using both the Light-emitting diodes. The oxygenated blood in our body absorbs more infrared light and allows red light to pass through it and the deoxygenated blood absorbs more red light and allows infrared light to pass through it. The photodiode in the MAX30100 sensor is used to measure the change in the intensity of the light. Using this photodiode, the intensity of the light which is passed into the finger and the through the blood is measured by the photodiode and passes the signal to the analog to digital converter and gives the output data in form of I2C serial communication protocol and using a microcontroller the pulse rate and the blood oxygen measurement are monitored.

3.10 Working Principle of DS18B20 Temperature Sensor

The working principle of this DS18B20 temperature sensor is like a temperature sensor. The resolution of this sensor ranges from 9-bits to 12-bits. But the default resolution which is used to power-up is 12-bit. This sensor gets power within a low-power inactive condition. The temperature measurement, as well as the conversion of A-to-D, can be done with a convert-T command. The resulting temperature information can be stored within the 2-byte register in the sensor, and after that, this sensor returns to its inactive state. If the sensor is power-driven by an exterior power supply, then the master can provide read time slots next to the Convert T command. The sensor will react by supplying 0 though the temperature change is in the improvement and reacts by supplying 1 though the temperature change is done.

3.11 Working Principle of DHT11 Temperature and Humidity Sensor

DHT11 sensor consists of a capacitive humidity sensing element and a thermistor for sensing temperature. The humidity sensing capacitor has two electrodes with a moisture holding substrate as a dielectric between them. Change in the capacitance value occurs with the change in humidity levels. The IC measure, process this changed resistance values and change them into digital form. For measuring temperature this sensor uses a Negative Temperature coefficient thermistor, which causes a decrease in its resistance value with increase in temperature. To get larger resistance value even for the smallest change in temperature, this sensor is usually made up of semiconductor ceramics or polymers.

3.12 Basics of LCD

Character LCDs can come with or without backlights. Backlights can be LED, fluorescent or electroluminescent.

Character LCDs use a standard 14-pin interface. If the screen has a backlight, it will have 16 pins. Character LCDs can operate in 4-bit or 8-bit mode. In 4-bit mode, pins 7 through 10 are unused and the entire byte is sent to the screen using pins 11 through 14 by sending a nibble at a time.

Types of LCD:

1 Graphical LCD

2 Dot Matrix LCD

Graphical LCD: Graphical LCD work on Pixel. It is mostly seen in LCD Television, Computers, Laptops, Mobile Phones, etc.

Dot Matrix LCD: Dot Matrix LCD work on Dots (in an Array) which is easy to operate as compare to Graphical LCD. It is mostly seen in Calculators.

3.13 Working Principle of RTC DS1307 Module

In the simple circuit the two inputs X_1 and X_2 are connected to a 32.768 kHz crystal oscillator as the source for the chip. V_{BAT} is connected to positive culture of a 3V battery chip. V_{CC} power to the I2C interface is 5V and can be given using microcontrollers. If the power supply V_{CC} is not granted read and writes are inhibited.

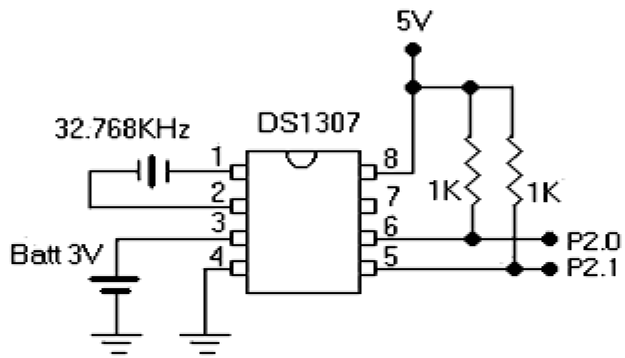

Fig. 3.3 Circuit Diagram of RTC DS1307 Module

3.14 Working Principle of 4x3 Keypad

There are 12 numbers and/or characters and 12 push-buttons (switch). Each push-button is associated with each number or character.

All the columns are set to HIGH i.e. + 5V and rows to LOW i.e. ground (It can be interchanging columns to LOW and rows to HIGH according, but then it need to change the programming model accordingly).

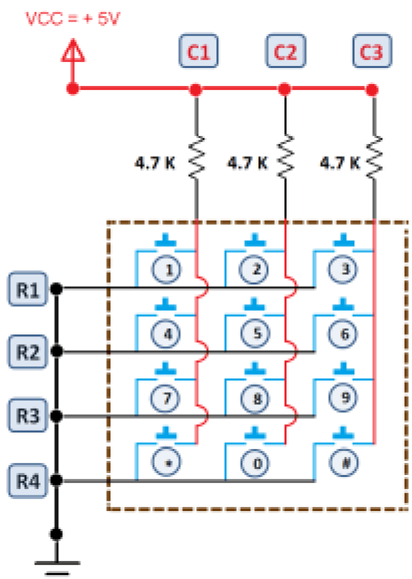

Fig. 3.4 Internal circuit of 4x3 Keypad

If no key has been pressed then all columns will remain HIGH and if the key has been pressed then its corresponding column will give a LOW signal (because it shorted to ground via row).

CHAPTER 4
SYSTEM DEVELOPMENT

4.1 Phase 1

4.1.1 Patient Record

The proposed project is based on the different kinds of patient, therefore patient data is collected from GNRC Medical, North Guwahati with due permission, consisting of patient's SpO_2 level, Body Temperature, Blood Pressure readings.

The collected data contains 50 indoor patient's data and total of 663 samples. The age of patient ranges from 20 to 50.

Statistics of collected patient's data are as follows:

Table 4.1 Statistics of collected patient's data from GNRC Medical, North Guwahati

Gender	20-30 Age	31-40 Age	41-50 Age	With Operation	Without Operation	ICU Case
Male	9	4	11	1	23	1
Female	7	10	9	2	24	0

The above data is further tested with machine learning algorithm for analyse and prediction.

4.2 Phase 2

4.2.1 Normal Person Data

A small hardware was made with different sensors like the MAX30100 sensor (pulse oximeter and heart sensor), and DS18B20 (temperature sensor). In this phase, the readings of normal human beings are taken where the subjects are of the category 1 (Fit) and 2 (Suffering from any disease or under medication).

4.2.2 Block Diagram of Constructed Hardware

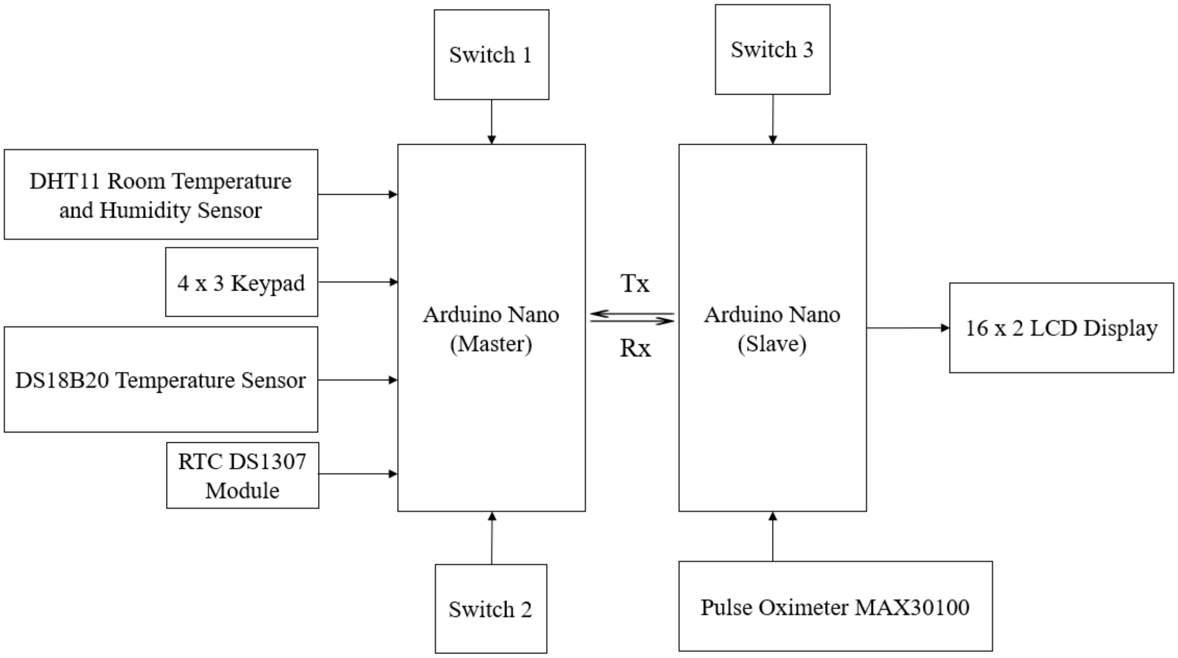

Fig. 4.1 Block diagram of the constructed hardware in phase 2

4.2.3 Working Principle of Constructed Hardware

There are two Arduino nano boards. Both the Arduino boards are serially connected. One Arduino nano board act as Master and other one act as Slave.

The Master Arduino Nano takes the data from 4x3 Keypad and transmits the data to Slave Arduino Nano which shows the data in LCD. While pressing Switch 1, the Master Arduino Nano takes the reading of DHT11 and DS18B20 Temperature Sensors Data. When Switch 2 is pressed, it send the same data to Slave Arduino Nano which shows the reading in LCD. The RTC DS1307 Module record the date and time and sends to Master Arduino Nano which again transmit the same to Slave Arduino Nano.

The MAX30100 Pulse Oximeter Sensor is connected to Slave Arduino Nano. When Switch 3 is pressed, it takes the reading from Pulse Oximeter Sensor (Heart Rate and SpO_2 Level) and display it on LCD.

4.2.4 Circuit Diagram of Constructed Hardware

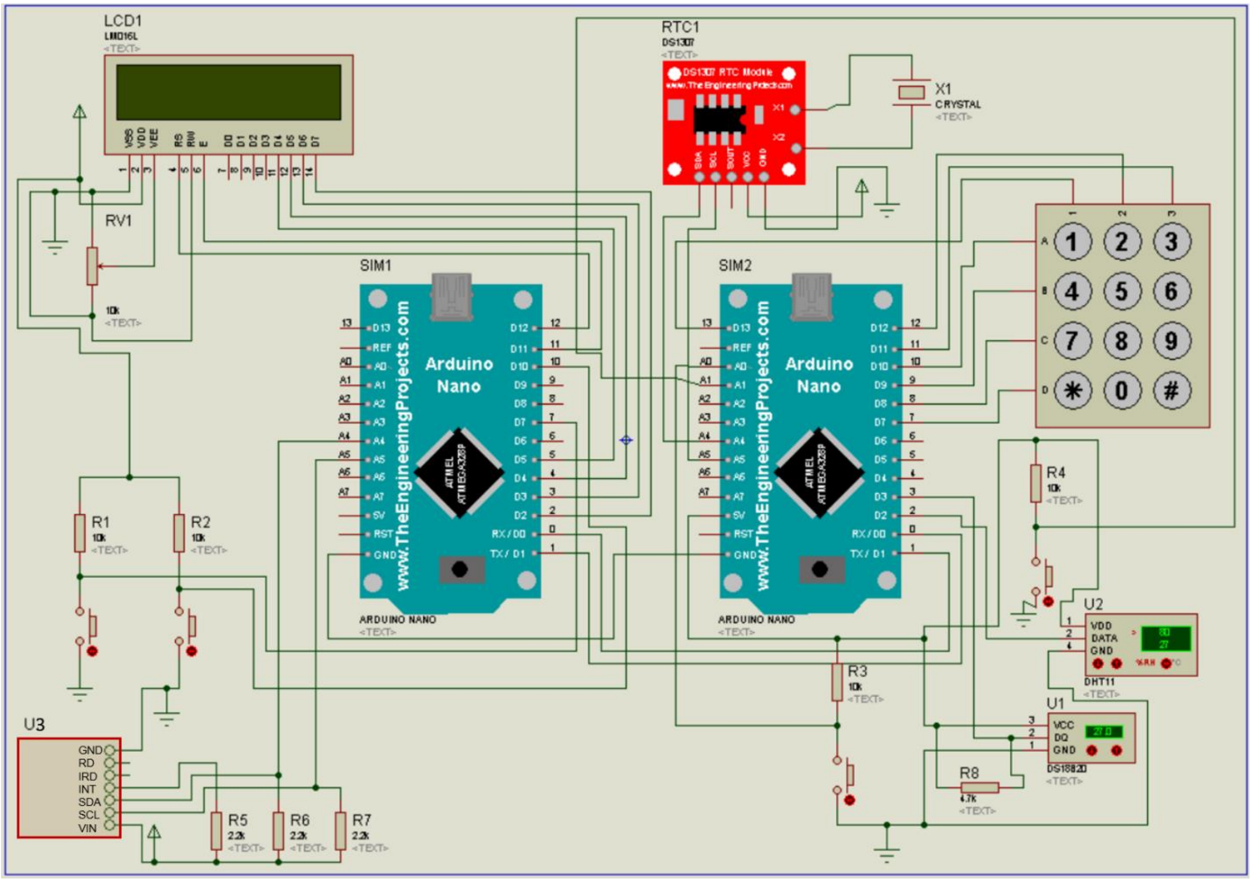

Fig 4.2 Circuit diagram of constructed hardware in phase 2

4.2.5 Circuit Description of Constructed Hardware

In the above circuit, SIM 1 is the Slave Arduino Nano Board and SIM 2 is the Master Arduino Nano.

The A, B, C, D Row Pins of Keyboard are connected to Master Arduino Nano at Pin Number D10, D9, D8 and D7. The 1, 2, 3 Column Pins of Keyboard are connected to Master Arduino Nano at Pin Number D13, D12 and D11.

The SCL and SDA pins of RTC DS1307 Module are connected to pins A5 and A4 of Master Arduino Nano. The V_{CC} and GND of RTC DS1307 Modules are connected with 5 V and Circuit Ground.

The Data Pin of DS18B20 Temperature Sensor is connected to the pin number D3 of Master Arduino Nano. The V_{CC} and GND of it are connected to 5V and Circuit Ground. There is a resistor of 4.7 KΩ connected between V_{CC} and Data Pins.

The Data Pin of DHT11 Temperature Sensor is connected to the pin number D2 of Master Arduino Nano. The V_{CC} and GND of it are connected to 5V and Circuit Ground.

There are two button switches along with 10 KΩ resister in series, connected with Master Arduino Nano at pin A0 and A1.

The LCD is connected to Slave Arduino Nano. The Data pins D0 to D7 of LD are connected to D5, D4, D3 and D2 pins of Slave Arduino Nano. The RS and EN pins of LCD are connected to D12 and D11 pins of Slave Arduino Nano. The V_{CC} and GND of it are connected to 5V and Circuit Ground. The V_O is connected with a 10 KΩ potentiometer which is use for contrast control. The RW pin of LCD is connected to Circuit Ground.

The SCL and SDA pins of MAX30100 are connected to A5 and A4 pins of Slave Arduino Nano. The VIN pin of MAX30100 is connected to 3.3 V and GND is connected to Circuit Ground. There are three pull-up resistors of 2.2 KΩ connected between V_{CC}, SCL, SDA and INT Pins of MAX30100.

There are two button switches along with 10 KΩ resister in series also connected to Slave Arduino Nano at pin D10 and D7.

4.2.6 Flowchart of the Constructed Hardware System

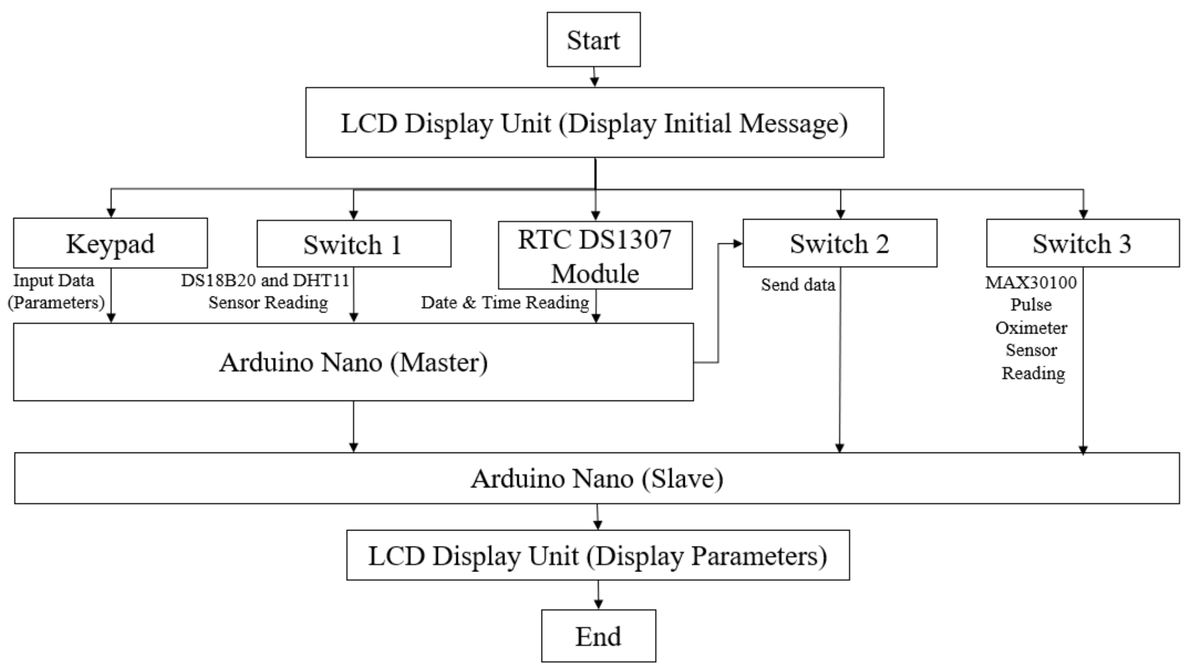

Fig 4.3 Flowchart of the Constructed Hardware in phase 2

The constructed hardware system follows the flowchart represented in Fig. 4.3. When the circuit is powered on, the LCD will show the initial message. As per the instructed message in LCD, the data is inserted by using keypad like age, weight, etc. The DS18B20, DHT11, RTC DS1307 Module and Keypad are connected to Master Arduino Nano. When the Switch 1 is pressed, Master Arduino Nano takes the reading of DS18B20 and DHT11 Sensors and keypad data. When the Switch 2 is pressed, it transmits the data to Slave Arduino Nano. Slave Arduino Nano further display the data on LCD. The Slave Arduino Nano is also connected to MAX30100 Pulse Oximeter Sensor. When Switch 3 is pressed, it reads the data coming from MAAX30100 and display it to LCD.

4.3 Phase 3

In this phase, measurements of 37 subjects (Male and Female) of 20-29, 30-39 and 40-50 age groups are taken and analysed using Multiple Linear Regression.

Table 4.2 Detail of the subjects under 20-29 Age Group

Subject Number	Age	Weight	Gender	Medical History
1	23	85	Male	No
2	21	70	Male	No
3	20	60	Male	No
4	24	60	Male	No
5	22	70	Male	No
6	23	70	Male	No
7	24	60	Male	No
8	24	82	Male	No
9	23	62	Male	No
10	22	63	Male	No
11	25	108	Male	No
12	21	65	Male	No
13	21	79	Male	No
14	21	52	Male	No

15	21	65	Female	No
16	23	49	Female	No
17	22	78	Male	No

Table 4.3 Detail of the subjects under 30-39 Age Group

Subject Number	Age	Weight	Gender	Medical History
1	33	120	Male	Yes
2	36	70	Male	No
3	39	73	Male	Yes
4	33	48	Female	No
5	39	80	Male	No
6	38	70	Male	No
7	37	85	Male	No
8	35	80	Male	No
9	37	70	Female	Yes

Table 4.4 Detail of the subjects under 40-50 Age Group

Subject Number	Age	Weight	Gender	Medical History
1	43	84	Male	No
2	43	53	Female	No
3	42	84	Male	Yes
4	40	67	Male	No
5	45	75	Female	No
6	48	66	Female	No
7	45	49	Female	Yes
8	45	49	Female	Yes
9	44	85	Female	No
10	43	53	Female	No
11	43	55	Male	No

Statistics of collected patient's data are as follows:

Table 4.5 Statistics of tested data of normal person via constructed hardware

Gender	20-29 Age	30-39 Age	40-50 Age	With Medical History	Without Medical History
Male	15	7	4	3	23
Female	2	2	7	3	8

For this, parameters - age, weight, gender, medical history, body temperature, room temperature, humidity, heart rate, SpO_2 level, systolic and diastolic blood pressure along with pulse rate (using a commercial blood pressure machine) and pulse pressure (calculated) are taken for consideration. For this, Medical History is categorized into two levels- 0 (Fit), 1(Suffering from diseases or under medication) and Gender is categorized into two levels- 1(Male) and 2(Female). A total of 3426 numbers of subject sample data were analysed using multiple linear regression. In machine learning, the data is split into 70% training data and 30% testing data.

4.3.1 Block Diagram of the System

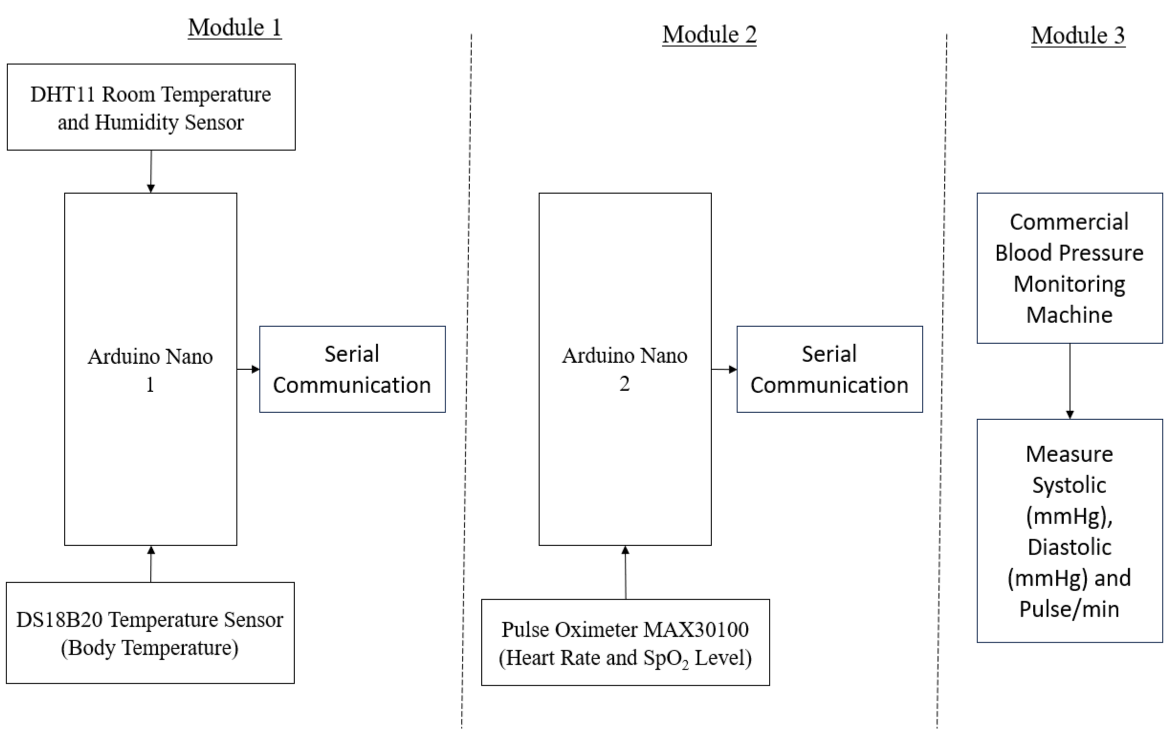

Fig. 4.4 Block diagram of the constructed hardware in phase 3

4.3.2 Working Principle of the System

The system is divided into three modules. The module 1 consist of DHT11 sensor for room temperature and humidity measurement and DS18BB20 sensor for body temperature measurement. These two sensors are connected with an Arduino nano which is named as Arduino Nano 1. By the Arduino, the data are taken serially and saved in excel.

The module 2 consist of MAX30100 sensor for measuring SpO_2 level and the Heart rate along with the Arduino Nano. This Arduino Nano names as Arduino Nano 2. In this section also, the data are taken serially and saved in excel.

The module 3 consist of a Blood Pressure Monitoring machine through which blood pressure and pulse/minute are measured and entered manually into excel.

4.3.3 Circuit Diagram of the System

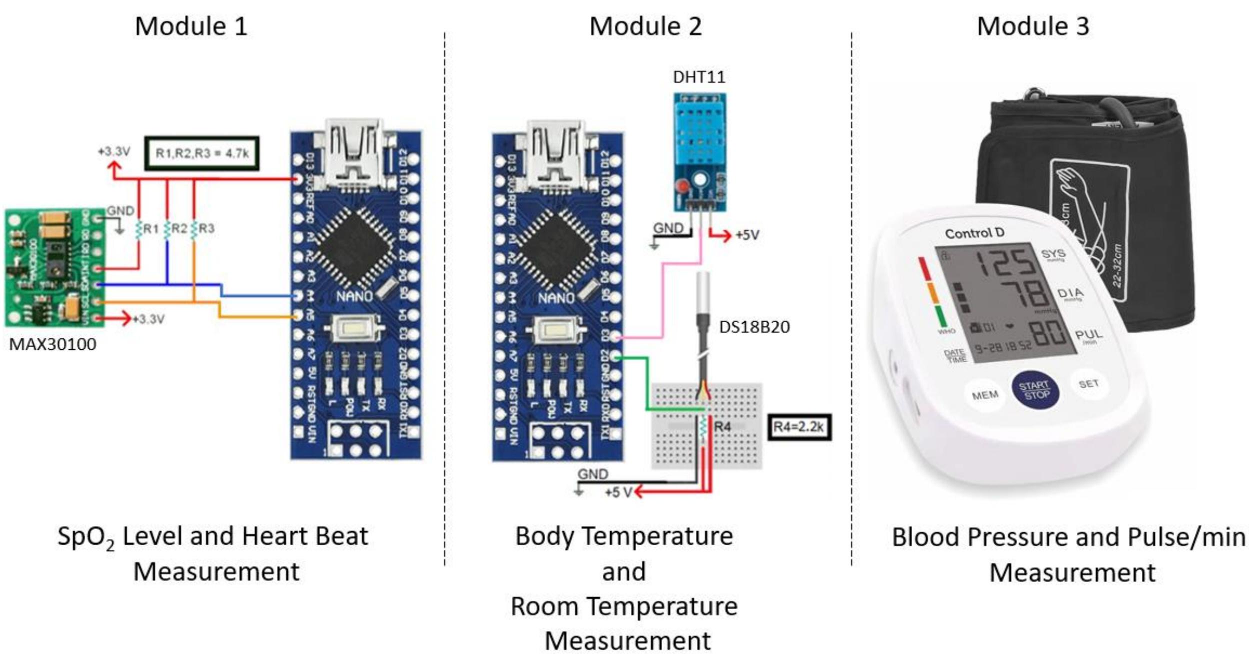

Fig 4.5 Circuit diagram of the system in phase 3

4.3.4 Circuit Description of the System

The system is divided into three modules. The module 1 consist of MAX30100 sensor for measuring SpO_2 level and the Heart rate along with the Arduino Nano. The V_{CC} and INT pin of MAX30100 are connected with 3.3 V of Arduino Nano. The SCL and SDA pins of MAX30100 are connected to A5 and A4 pins of Arduino Nano. There are three pull-up resistors of value 4.7 K which are connected with SCL, SDA and INT pins. The GND pin of MAX30100 connected with GND of Arduino Nano.

The module 2 consist of DHT11 sensor for room temperature and humidity measurement and DS18BB20 sensor for body temperature measurement. The V_{CC} pin of DHT11 and DS18B20 are connected with 5V of Arduino Nano. The GND pins of both the temperature sensors are connected with GND of Arduino Nano. The data pins of DS18B20 and DHT11 are connected to D2 and D3 pins of Arduino Nano. In DS18B20, a 2.2 K pull-up resistor is connected with the data pin.

The module 3 consist of a Blood Pressure Monitoring machine through which blood pressure and pulse/minute are measured.

4.3.5 Flowchart of the Constructed Hardware System

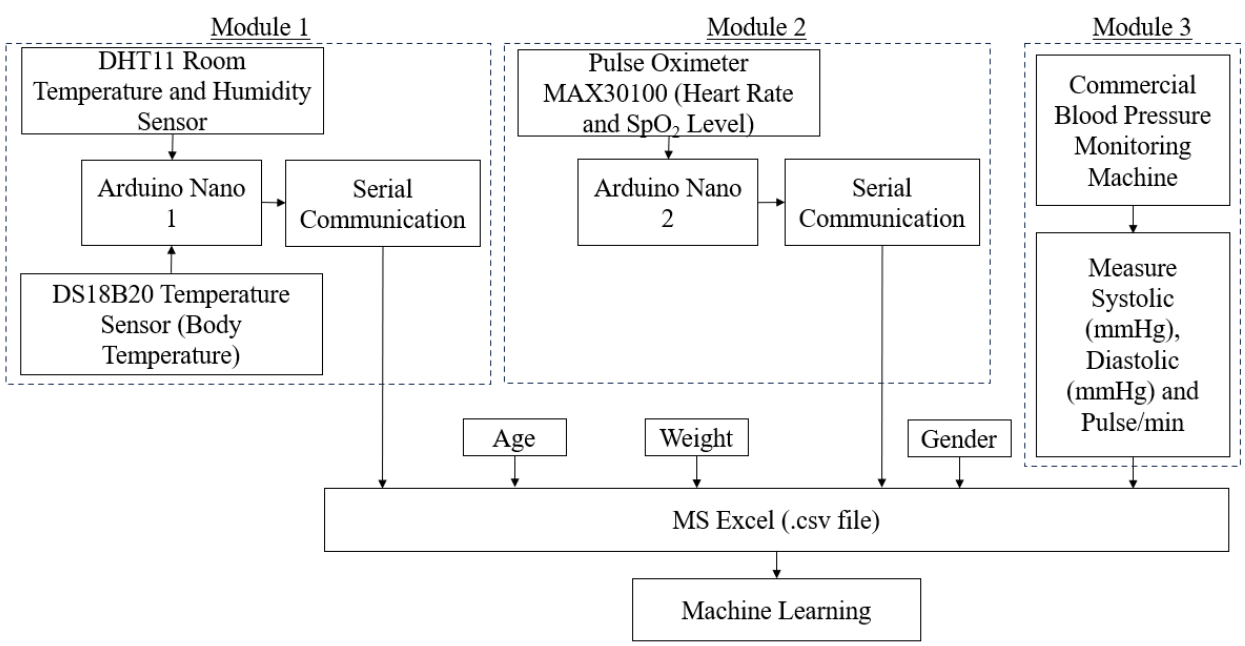

Fig 4.6 Flowchart of the Constructed Hardware in phase 3

When the power is on, the Arduino Nano 1 take the readings of room temperature, humidity and the body temperature with respect to the sensors. The Arduino Nano 2 takes the readings of heart rate and SpO_2 level. These readings are serial communicate and data are stored in the excel. Manually, the age, weight, gender and the readings of commercial blood pressure machine are feed to excel. The data is then processed using machine learning for the output.

4.4 Phase 4

4.4.1 Part 1

As in phase 3, the hardware is distinct, here in this phase, further multiple linear regression done with the same data used in phase 3 and new hardware is made.

For the analysis of the outcome after using regression the health status of a person is determined using decision tree algorithm and the normal range of the body parameters as found from literature are taken into consideration.

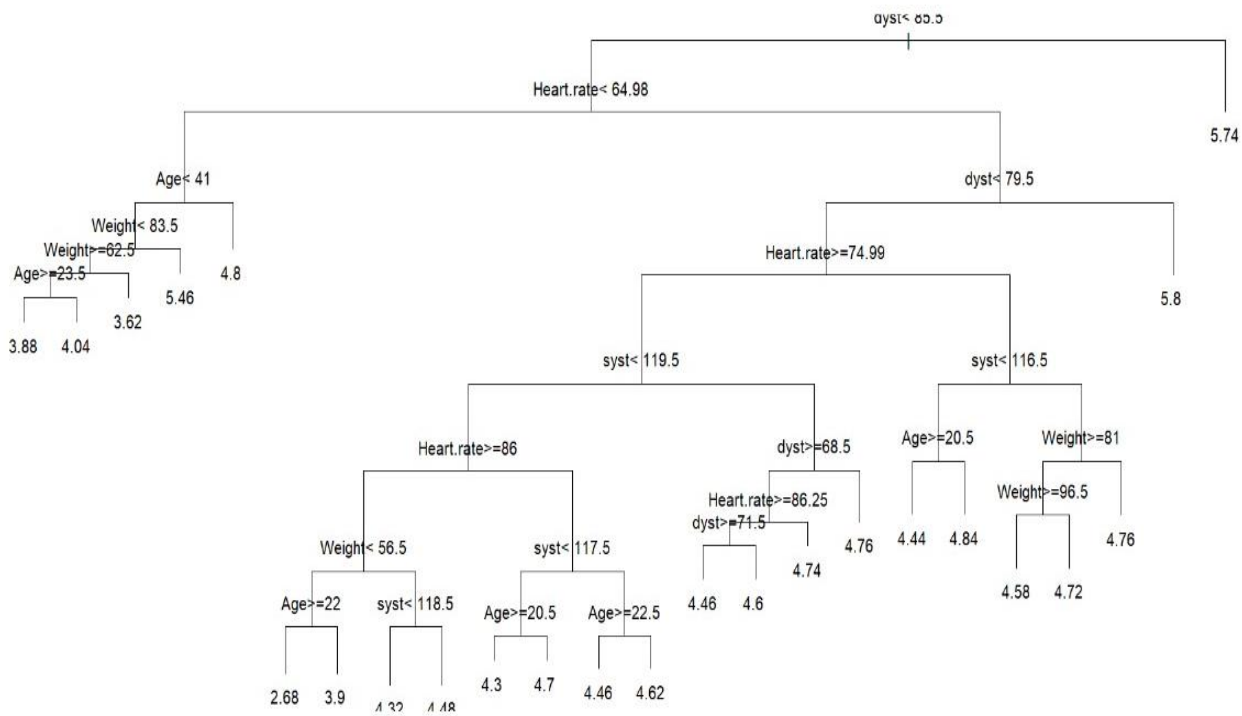

Fig. 4.7 Decision Tree for Phase 4 Part 1

Using the decision tree output, the health status of a subject is categorised as follows:

Category 1: If the Diastolic is greater than 86, Heart rate is greater than 65, Health Status is greater than 5.54 and Medical History is equal to 1 then the person is **"Not Healthy"**.

Category 2: If the Diastolic is less than 86, Heart rate is less than 75, Systolic is less than 117, Age is greater than or equal to 21, Health Status is in between 4.44 and 4.84 and Medical History is equal to 0 then the person is **"Healthy"**.

Category 3: If the Diastolic is less than 86, Heart rate is less than 75, Systolic is greater than 117, Weight is greater than 97, Health Status is in between 4.58 and 4.76 and Medical History is equal to 1 then the person is **"Moderate Healthy"**.

Category 4: If the Diastolic is less than 86, Heart rate is greater than and equal to 75, Systolic is less than 120, Health Status is in between 4.46 and 4.76 and Medical History is equal to 0 then the person is **"Healthy"**.

Category 5: If the Diastolic is less than 86, Heart rate is less than 86, Systolic is less than 120, Age is in between 21 and 23, Health Status is in between 4.3 and 4.62 and Medical History is equal to 0 then the person is **"Healthy"**.

Category 6: If the Diastolic is less than 86, Systolic is less than 120, Heart rate is greater than or equal to 86, Weight is less than 57, Age is greater than or equal to 22, Health Status is in between 3.9 and 4.48 and Medical History is equal to 1 then the person is **"Healthy"**.

Category 7: If the Diastolic is less than 86, Heart rate less than 65, Weight is less than 84, Age is in between 24 and 41, Health Status is in between 3.88 and 5.46 then the person is **"Moderate Healthy"**.

4.4.2 Part 2

In this phase, further literature review has been done and found the standard values of Heart rate, SpO_2, BMI, Systolic, Diastolic with respect to Age, Weight and Gender of the person.

For the analysis of the outcome, the multiple linear regression, logistic regression and decision tree are used. As machine learning required numeric value for prediction, scores are defined for parameters.

For this BMI is categorised is scores which are as follows:

Table 4.6 BMI Score

BMI	Inference	Score
BMI below 18.5	Indicates being underweight	0.6

BMI between 18.5 and 24.9	Falls within the normal/healthy weight range	1
BMI between 25.0 and 29.9	Suggests overweight status	0.4
BMI of 30.0 or higher	Indicates obesity	0.2

Medical History is categorised in scores which are as follows:

Table 4.7 Medical History Score

Medical History	**Inference**	**Score**
Fit	Normal	0
Normal being with Medication	Health Attention	1
Unfit/Patient	Medical Attention	2

Health Status is categorised in score which are as follows:

Table 4.8 Health Status score

Health Status	**Score**
Normal	1
Abnormal	0.8
Bad Health	0.6
Medical Care	0.4
Hospital Attend	0.2

For the given condition, a decision tree was made.

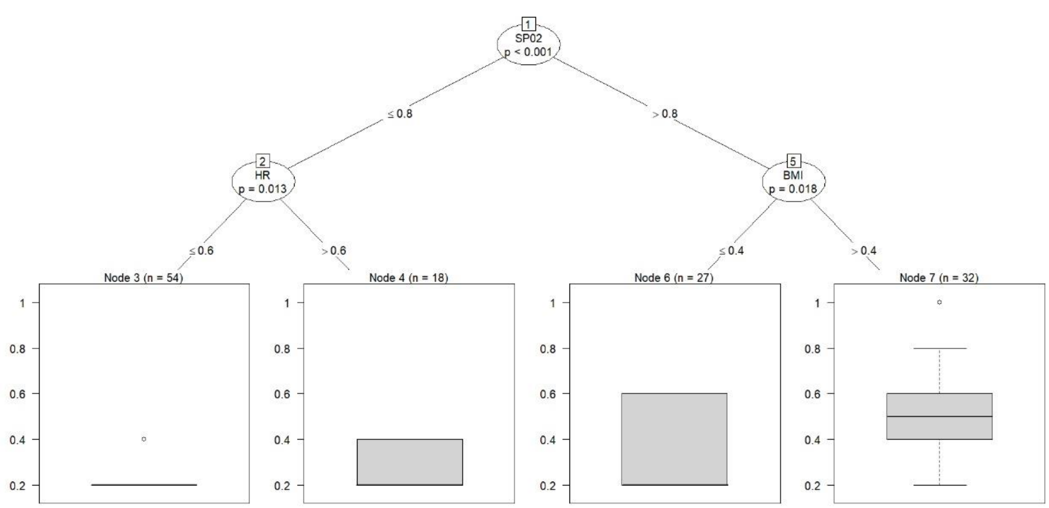

Fig. 4.8 Decision tree for phase 4 Part 2

The decision tree predicts that the P-value of SpO_2=0.001, Heart rate=0.013 and BMI=0.018. Using the decision tree, the health status is categorised in following categories:

Category 1: When score of SpO_2 is less than or equal to 0.8 and score of Heart rate is less than or equal to 0.6, then the health score is 0.2.

Category 2: When score of SpO_2 is less than or equal to 0.8 and score of Heart rate is greater than 0.6, then the health score is in between 0.2 and 0.4.

Category 3: When score of SpO_2 is greater than 0.8 and score of BMI is less than and equal to 0.4, then the health score is in between 0.2 and 0.6.

Category 4: When score of SpO_2 is greater than 0.8 and score of BMI is greater than and equal to 0.4, then the health score is in between 0.4 and 0.6.

4.4.3 Block Diagram of the System

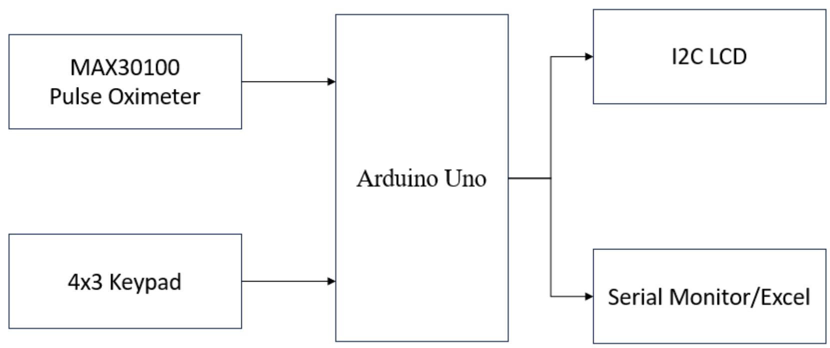

Fig. 4.9 Block diagram of the system

4.4.4 Working Principle of the System

First of all, LCD shows the initial message. Then by using 4x3 Keypad, the parameters like Age, Weight, Gender and Medical History are entered. The entered data are processed by Arduino and shown in LCD and Serial Monitor/Excel simultaneously. Then the Heart Rate and SpO_2 level readings are taken from MAX30100 Pulse oximeter. The entered data are processed by Arduino and shown in LCD and Serial Monitor/Excel simultaneously. Also, parameters like Systolic, Diastolic, Pulse Pressure, BMI, Medical History Status and Health Status shown in LCD and Serial Monitor/Excel simultaneously.

4.4.5 Circuit Diagram of the System

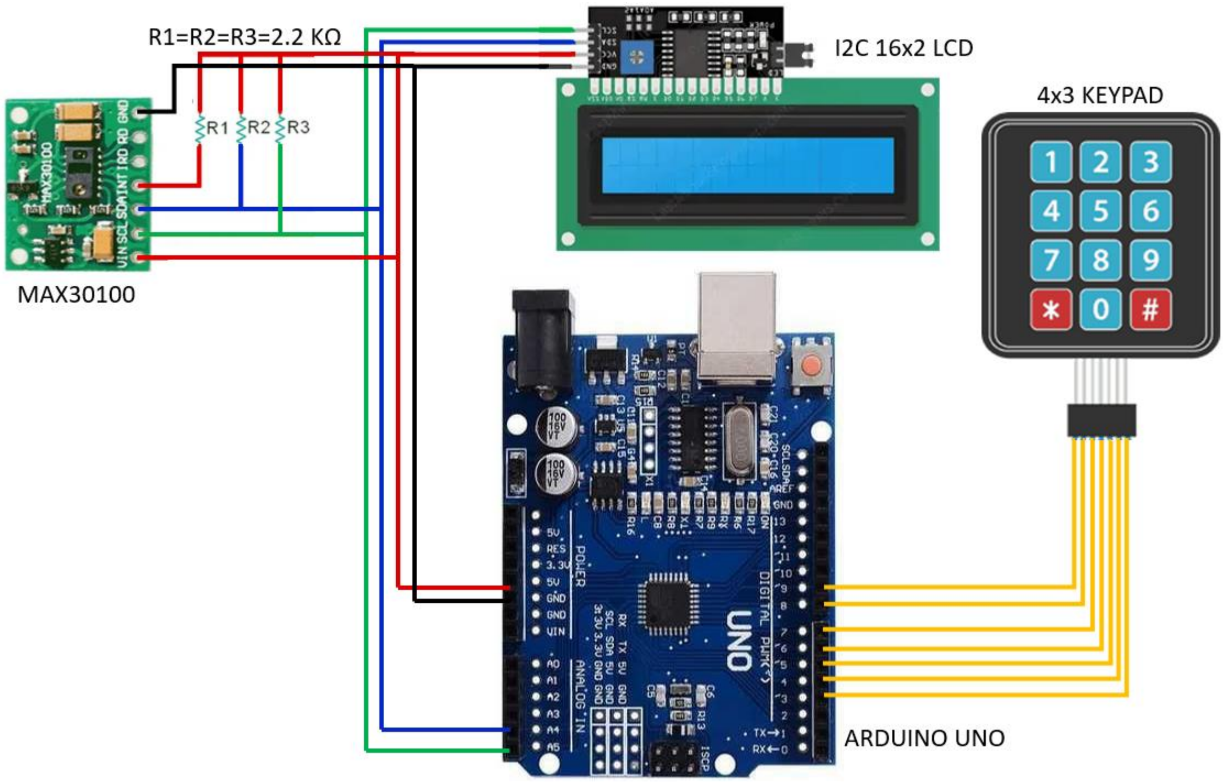

Fig. 4.10 Circuit diagram of the system

4.4.6 Circuit Description of the System

The circuit connection consists of Arduino Uno, 4x3 Keypad, I2C LCD Display and MAX30100 Pulse Oximeter. The 4x3 Keypad row pins are connected to D9, D8, D7 and D6 pins of Arduino Uno and column pins are connected to D5, D4 and D3 pins of Arduino Uno. The V_{CC} pin of I2C LCD and MAX30100 are connected to 5V pin of Arduino Uno. The Ground pins of I2C LCD and MAX30100 are connected to Ground pins of Arduino. The SCL pins of I2C LCD and MAX30100 are connected to A5 pin of Arduino Uno. The SDA pins of I2C LCD and MAX30100 are connected to A4 pin of Arduino Uno. The SCL, SDA and INT pins of MAX30100 are also connected with pull-up resistors of 2.2 KΩ where 5V supply is given.

4.4.7 Flowchart

4.4.7.1 Flowchart for Part 1

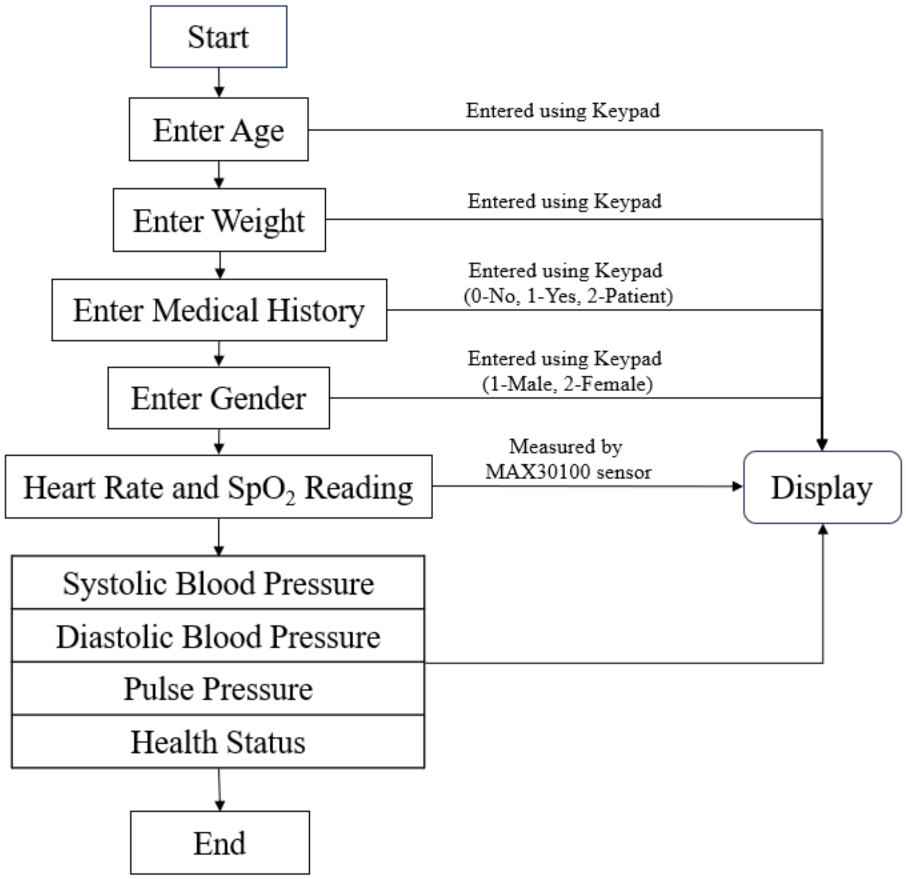

Fig 4.11 Flowchart of the System for Phase 4 Part 1

When the system is turned on, it asked for age, weight, medical history and gender one by one. Using 4x3 keypad, the respective data are entered. As 4x3 keypad have only numeric values, Medical history is categoried in 0-No, 1-Yes and 2-Patient. The gender is also categoried in 1-Male and 2-Female. The entered data is shown in LCD. After this, using MAX30100 sensor, Heart rate and SpO2 level is measured and it shows the data in LCD. Using these input data, system will shows values of Systolic blood pressure, Diastolic blood pressure, Pulse pressure and Health Status.

4.4.7.2 Flowchart for Part 2

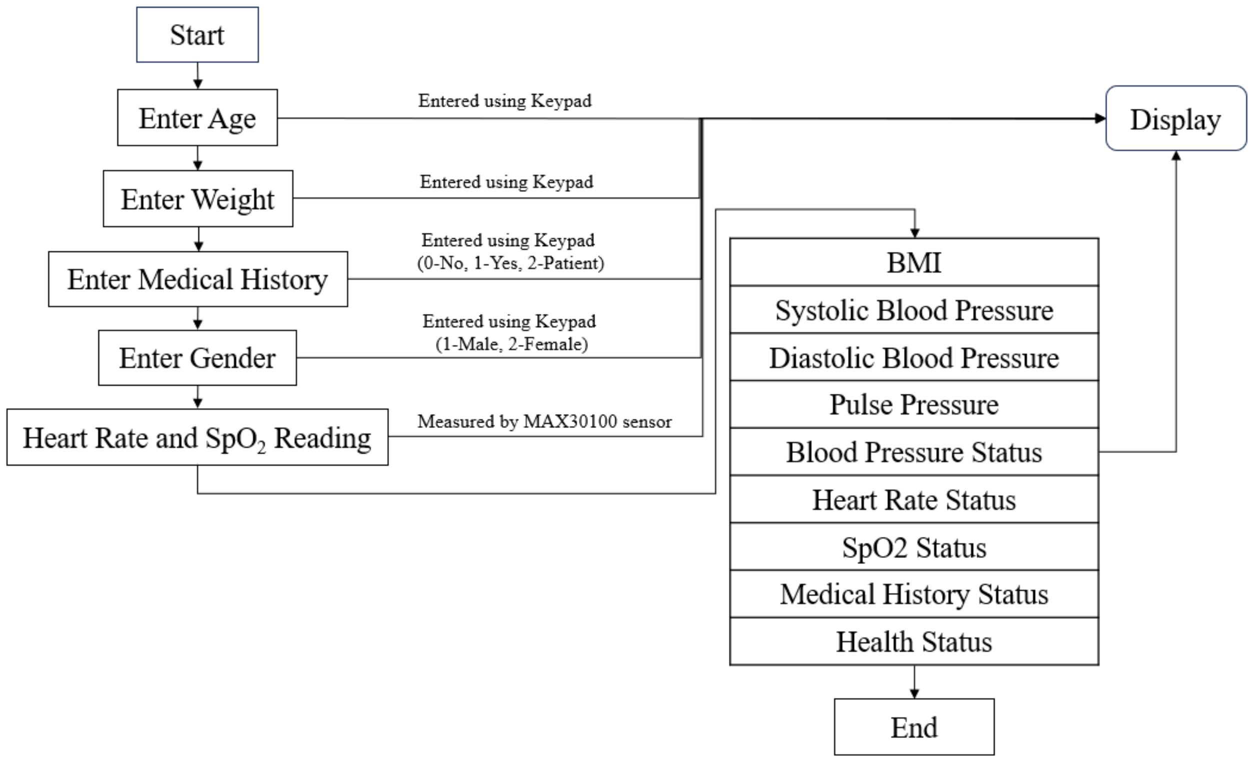

Fig 4.12 Flowchart of the System for Phase 4 Part 2

When the system is turned on, it asked for age, weight, medical history and gender one by one. Using 4x3 keypad, the respective data are entered. As 4x3 keypad have only numeric values, Medical history is categoried in 0-No, 1-Yes and 2-Patient. The gender is also categoried in 1-Male and 2-Female. The entered data is shown in LCD. After this, using MAX30100 sensor, Heart rate and SpO2 level is measured and it shows the data in LCD. Using these input data, system will shows values of BMI, Systolic blood pressure, Diastolic blood pressure, Pulse pressure and the status of Blood pressure, Heart rate, SpO_2, Medical history and Health Status.

4.4.7.3 Machine Learning Flowchart

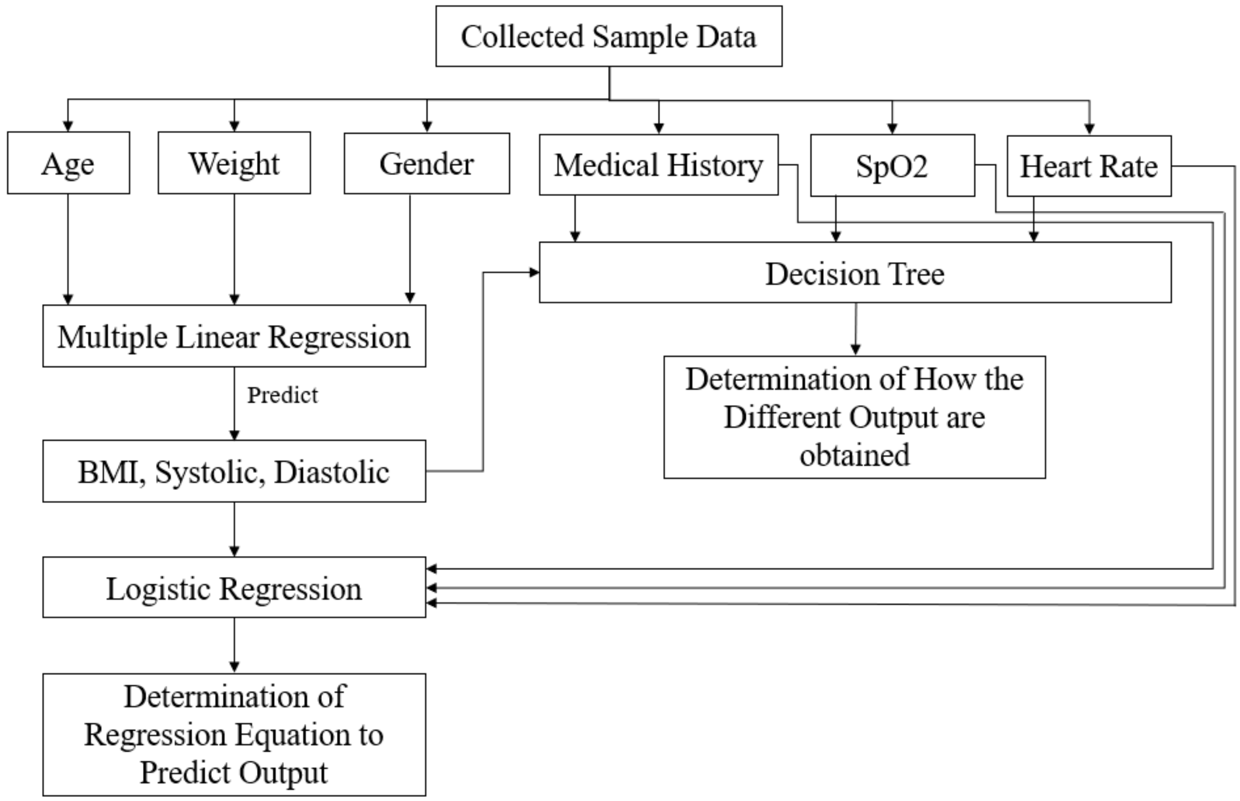

Fig 4.13 Machine Learning Flowchart

For the purpose of machine learning, the collected sample data are splint into two parts. The age, weight and gender are done multiple linear regression and using that the BMI, Systolic blood pressure and Diastolic blood pressure. The BMI, Systolic blood pressure, Diastolic blood pressure, Medical History, SpO_2 and Heart Rate are done Logistic regression and Decision tree. The Logistic regression determine the regression equation to predict the output and decision tree determine the how the different outputs are obtained.

CHAPTER 5

HARDWARE REQUIREMENT

5.1Arduino Uno

Fig 5.1 Arduino Uno Board

Arduino UNO is a microcontroller board based on the **ATmega328P.** It has 14 digital input/output pins (of which 6 can be used as PWM outputs), 6 analog inputs, a 16 MHz ceramic resonator, a USB connection, a power jack, an ICSP header and a reset button. It is part of the Arduino platform, which provides an open-source hardware and software ecosystem for building various electronic projects.

The board can be powered using a USB connection or an external power supply. It operates at 7-12 volts and can be powered by a USB cable, a 9V battery, or an external power adapter.

5.2 Arduino Nano

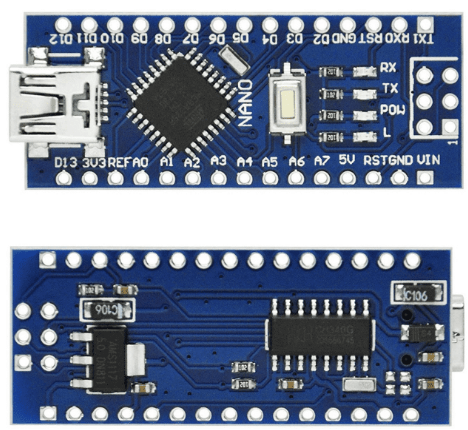

Fig. 5.2 Arduino Nano Board

The Arduino Nano is an open-source breadboard-friendly microcontroller board based on the Microchip ATmega328P microcontroller (MCU) and developed by Arduino.cc and initially released in 2008. It offers the same connectivity and specs of the Arduino Uno board in a smaller form factor.

The Arduino Nano is equipped with 30 male I/O headers, in a DIP-30-like configuration, which can be programmed using the Arduino Software integrated development environment (IDE), which is common to all Arduino boards and running both online and offline. The board can be powered through a type-B mini-USB cable or from a 9 V battery.

5.3 DHT11 Temperature and Humidity Sensor

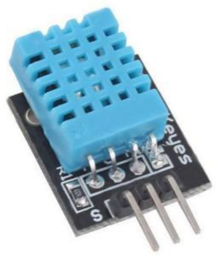

Fig. 5.3 DHT11 Temperature and Humidity Sensor

The DHT11 is a basic, ultra low-cost digital temperature and humidity sensor. It uses a capacitive humidity sensor and a thermistor to measure the surrounding air and spits out a digital signal on the data pin (no analog input pins needed).

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5.3.1 Pin Configuration of DHT11 Temperature and Humidity Sensor

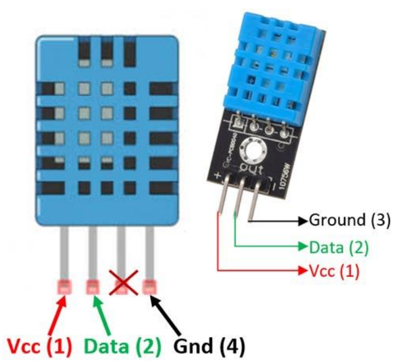


Fig. 5.4 Pin Detail of DHT11 sensor

Table 5.1 Pin Detail of DHT11 sensor

Pin Number	Pin Detail	Description
1	V_{CC}	Power Supply of 5 V DC
2	Data	Serial Data Communication
3	Ground	Ground connection

5.3.2 DHT11 Specification:

Operating Voltage	:	3.5 V to 5.5 V
Operating Current	:	0.3 mA (measuring) 60μ (standby)
Output	:	Serial Data
Temperature Range	:	0°C to 50°C
Humidity Range	:	20% to 90%
Resolution	:	Temperature and Humidity both are 16-bit
Accuracy	:	±1°C and ±1%

5.4 4 x 3 Keypad

Fig. 5.5 4x3 Keypad

A keypad is a block or pad of buttons set with an arrangement of digits, symbols, or alphabetical letters. Pads mostly containing numbers and used with microcontrollers are numeric keypads. Keypads are found on devices which require mainly numeric input such as calculators, television remotes, ATMs. Many devices follow the E.161 standard for their arrangement. E.161 is an ITU-T Recommendation that defines the arrangement of digits, letters, and symbols on telephone keypads and rotary dials.

5.4.1 4 x 3 Keypad Pin Detail

Fig. 5.6 Pin Detail of 4x3 Keypad

Table 5.2 Pin Detail of 4x3 Keypad.

Pin Number	Pin Detail	Description
1	R1	Row 1
2	R2	Row 2
3	R3	Row 3
4	R4	Row 4
5	C1	Column 1
6	C2	Column 2
7	C3	Column 3

5.4.2 4x3 Keypad Specification

Operating Voltage : 12 V DC

Operating Current : 0.1 A

Contact Resistance : 500 Ω

Insulation Resistance : 100 MΩ

Dielectric Strength : 250 V_{RMS}

5.5 DS18B20 Temperature Sensor

Fig 5.7 DS18B20 Temperature Sensor

The DS18B20 digital thermometer provides 9-bit to 12-bit Celsius temperature measurements and has an alarm function with nonvolatile user-programmable upper and lower trigger points. The DS18B20 communicates over a 1-Wire bus that by definition requires only one data line (and ground) for communication with a central microprocessor. In addition, the DS18B20 can derive power directly from the data line ("parasite power"), eliminating the need for an external power supply. Each DS18B20 has a unique 64-bit serial code, which allows multiple DS18B20s to function on the same 1-Wire bus. Thus, it is simple to use one microprocessor to control many DS18B20s distributed over a large area. Applications that can benefit from this feature include HVAC environmental controls, temperature monitoring systems inside buildings, equipment, or machinery, and process monitoring and control systems.

5.5.1 DS18B20 Temperature Sensor Pin Detail

Table 5.3 DS18B20 Temperature Sensor Pin Detail

Wire Colour	Pin Detail	Description
Red	V_{CC}	Power Supply of 5 V DC
Yellow	Data	Serial Data Communication
Black	Ground	Ground connection

5.5.2 DS18B20 Temperature Sensor Specification:

Operating Voltage : 3.5 V to 5.5 V

Output : Serial Data

Temperature Range : -55°C to +125°C (-67°F to +257°F)

Resolution : Programmable Resolution from 9 Bits to 12 Bits

Accuracy : ±0.5°C Accuracy from -10°C to +85°C

5.6 Button Switch

Fig. 5.8 Button Switch

A push button switch is a mechanical device used to control an electrical circuit in which the operator manually presses a button to actuate an internal switching mechanism.

5.7 Resistor

Fig 5.9 Resistor

A resistor is a passive two-terminal electrical component that implements electrical resistance as a circuit element. In electronic circuits, resistors are used to reduce current flow, adjust signal levels, to divide voltages, bias active elements, and terminate transmission lines, among other uses.

5.8 MAX30100 Pulse Oximeter Sensor

Fig 5.10 MAX30100 Pulse Oximeter Sensor

MAX30100 sensor is a device that is used to monitor the heart rate and it is also used as a pulse oximeter. The Pulse oximeter consists of Light-emitting diodes and IR sensor and signal processing unit to improve the quality of the output signal.

5.8.1 MAX30100 Pulse Oximeter Sensor Pin Detail

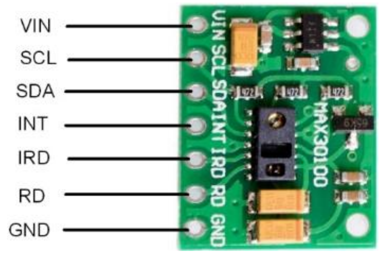


Fig 5.11 MAX30100 Pulse Oximeter Sensor Pin Detail

Table 5.4 MAX30100 Pulse Oximeter Sensor Pin Detail

Pin Number	**Pin Detail**	**Description**
1	VIN	Voltage Input
2	SCL	I2C Serial Clock
3	SDA	I2C Serial Data
4	INT	Active Low Interrupt
5	IRD	IR LED Cathode and LED Driver Connection Point (Leave floating in the circuit)
6	RD	Red LED Cathode and LED Driver Connection Point (Leave floating in the circuit)
7	GND	Ground Pin

5.8.2 MAX30100 Pulse Oximeter Sensor Specification

Operating Voltage	:	1.8 V to 3.3 V
Operating Current	:	20 mA
Input Power	:	1.7 V to 2 V
Temperature Range	:	-40 °C to +85 °C
LED Current	:	0 mA to 50 mA

LED Pulse Width : 200 µs to 1.6 ms

Supply Current in Shutdown : 0.7 µA to 10 µA

5.9 16x2 Liquid Crystal Display (LCD)

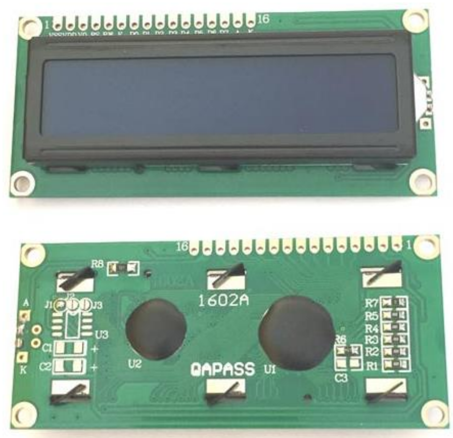


Fig. 5.12 16x2 Liquid Crystal Display (LCD)

JHD 162A 16 x 2 LCD is an industry standard Liquid Crystal Display (LCD) device designed for interfacing with embedded system. LCD understands ASCII values/codes. It has its own activation code. LCD screens come in common configurations of 8x1 characters, 16x2 characters and 20x4 characters. The largest such configuration is 40x4 characters, but these are rare and are actually two separate 20x4 screens seamlessly joined together.

5.9.1 16x2 LCD Pin Detail

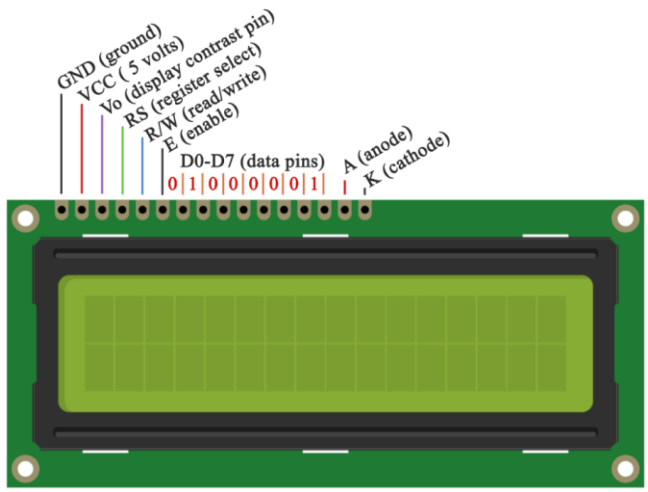


Fig. 5.13 Pin Detail of 16x2 LCD

Table 5.5 Pin Detail of 16x2 LCD

Pin Number	Pin Detail	Description
1	GND	Ground
2	V_{CC}	Power Supply of 5 V DC
3	VO	Contrast Control Pin
4	RS	Register Selector Pin
5	RW	Read/Write
6	EN	Enable
7	D0	Data Pin 0
8	D1	Data Pin 1
9	D2	Data Pin 2
10	D3	Data Pin 3
11	D4	Data Pin 4
12	D5	Data Pin 5
13	D6	Data Pin 6
14	D7	Data Pins 7
15	BLA	Backlight LED (+ve Terminal)
16	BLK	Backlight LED (-ve Terminal)

5.9.2 16x2 LCD Specification

Operating Voltage	:	5 V
Operating Current	:	1 mA (Without Backlight)
Rows	:	2
Column	:	16
Number of Characters Display	:	16 Characters per row
Pixel Matrix	:	5x7 for Single Character
Mode of Operation	:	8 Bit Mode and 4-Bit Mode

5.10 DS1307 RTC Module

The DS1307 is a popular real-time clock (RTC) integrated circuit (IC). It is widely used in electronic projects and devices that require accurate timekeeping. The DS1307 has a built-in provision for a small coin cell battery. This allows it to keep track of time even when the main power source is disconnected.

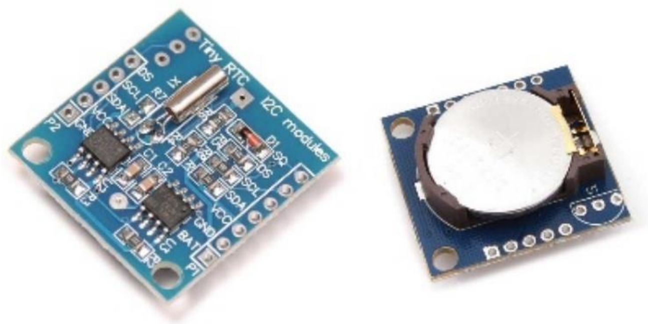


Fig 5.14 DS1307 RTC Module

5.10.1 Pin Configuration of DS1307 RTC Module

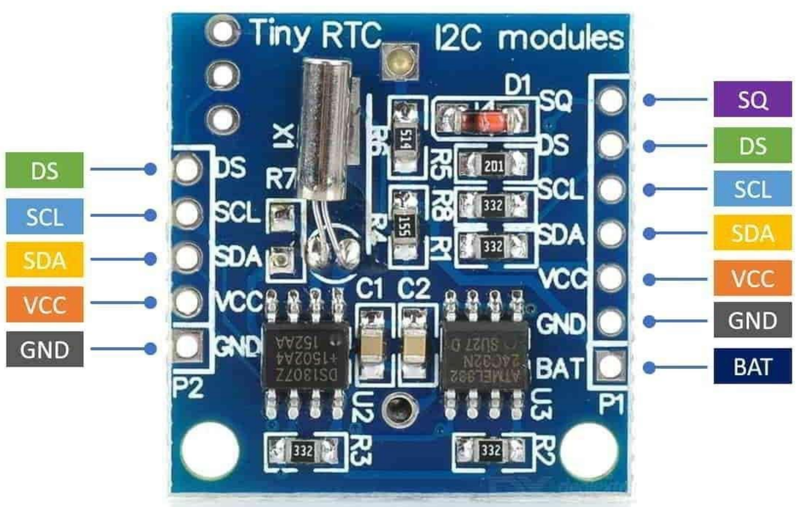


Fig 5.15 Pin Diagram of DS1307 RTC Module

Table 5.6 DS1307 RTC Module Pin Detail

Port 1 (P1)		
Pin Number	**Pin Detail**	**Description**
1	SQ	The pin may be programmed to emit one of four square-wave frequencies: 1Hz, 4kHz, 8kHz, or 32kHz.
2	DS	If the module has a DS18B20 temperature sensor fitted immediately next to the battery holder, the pin is designed to output temperature information (labeled as U1).

3	SCL	I2C interface's clo000ck input, which is used to synchronize data transfer across the serial interface.
4	SDA	I2C serial interface's data input/output.
5	VCC	This pin powers the module. It can range from 3.3 to 5.5 volts.
6	GND	This is a ground pin.
7	BAT	This is a backup supply input for any standard 3V lithium battery or another energy source that allows the gadget to keep a precise time when the primary power is lost.
Port 2 (P2)		
Pin Number	**Pin Detail**	**Description**
1	DS	If the module has a DS18B20 temperature sensor fitted immediately next to the battery holder, the pin is designed to output temperature information (labeled as U1).
2	SCL	I2C interface's clock input, which is used to synchronize data transfer across the serial interface.
3	SDA	I2C serial interface's data input/output.
4	VCC	This pin powers the module. It can range from 3.3 to 5.5 volts.
5	GND	This is a ground pin.

5.10.2 DS1307 RTC Module Specification:

Operating Voltage	:	5V DC
Operating Temperature	:	-55 °C to +125 °C
Clock Operating Frequency	:	32.768 KHz
I2C Interface	:	Standard I2C interface, with 7-bit addressing
SRAM Memory	:	56 bytes of battery-backed SRAM
Battery Backup	:	3V Lithium Coin Cell or equivalent
Operating Current	:	55µA (at 3V battery)
RTC Operating Current	:	Max. 200µA
I2C Communication Speed	:	100KHz and 400KHz
Real-Time Clock Counter	:	Hours, Minutes, Seconds, Day, Date, Month and Year

CHAPTER 6
SOFTWARE REQUIREMENT

6.1 Arduino CC IDE

The Arduino CC Integrated Development Environment - or Arduino Software (IDE) - contains a text editor for writing code, a message area, a text console, a toolbar with buttons for common functions and a series of menus. It connects to the Arduino hardware to upload programs and communicate with them.

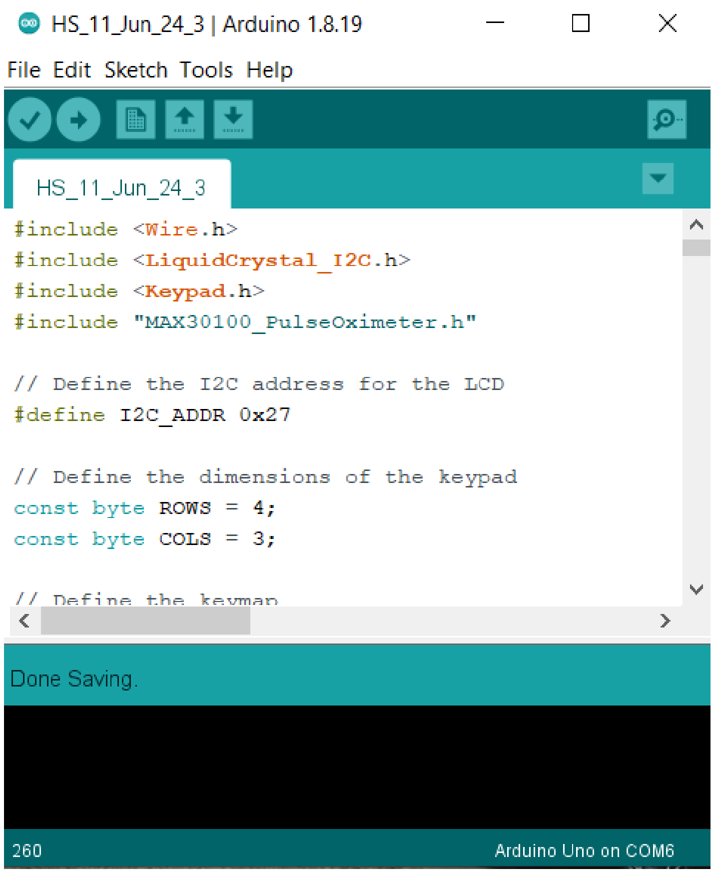


Fig 6.1 Arduino CC IDE

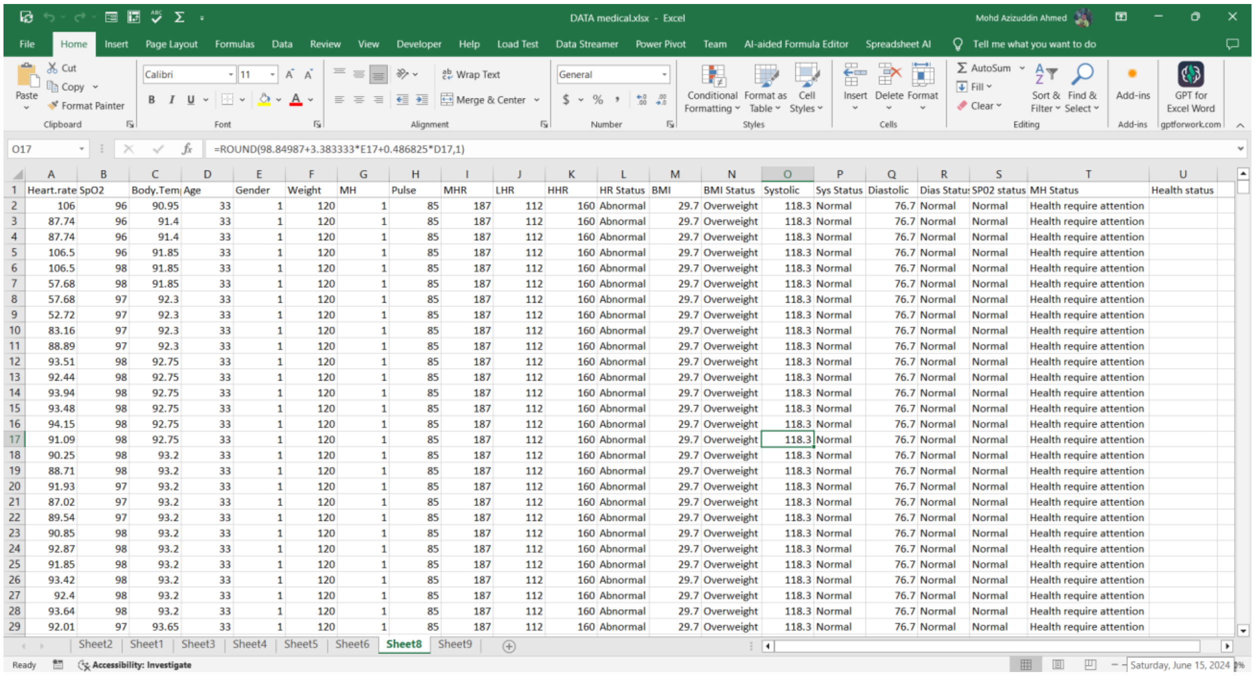
6.2 R-Studio

RStudio IDE (or RStudio) is an integrated development environment for R, a programming language for statistical computing and graphics. It's used in data analysis to import, access, transform, explore, plot, and model data, and for machine learning to make predictions on data.

6.3 MS Excel

Microsoft Excel is a spreadsheet program created by Microsoft that uses tables to record and analyze numerical and statistical data with formulas and functions.

In simple words, MS Excel is a powerful spreadsheet program included with Microsoft Office and is mainly used to record data in tables.



	Heart.rate	SpO2	Body.Tem	Age	Gender	Weight	MH	Pulse	MHR	LHR	HHR	HR Status	BMI	BMI Status	Systolic	Sys Status	Diastolic	Dias Statu	SP02 status	MH Status	Health status
2	106	96	90.95	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
3	87.74	96	91.4	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
4	87.74	96	91.4	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
5	106.5	96	91.85	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
6	106.5	98	91.85	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
7	57.68	98	91.85	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
8	57.68	97	92.3	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
9	52.72	97	92.3	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
10	83.16	97	92.3	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
11	88.89	97	92.3	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
12	93.51	98	92.75	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
13	92.44	98	92.75	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
14	93.94	98	92.75	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
15	93.48	98	92.75	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
16	94.15	98	92.75	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
17	91.09	98	92.75	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
18	90.25	98	93.2	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
19	88.71	98	93.2	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
20	91.93	97	93.2	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
21	87.02	97	93.2	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
22	89.54	97	93.2	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
23	90.85	98	93.2	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
24	92.87	98	93.2	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
25	91.85	98	93.2	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
26	93.42	98	93.2	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
27	92.4	98	93.2	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
28	93.64	98	93.2	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	
29	92.01	97	93.65	33	1	120	1	85	187	112	160	Abnormal	29.7	Overweight	118.3	Normal	76.7	Normal	Normal	Health require attention	

Fig 6.2 MS Excel

CHAPTER 7

RESULT AND DISCUSSION

7.1 Phase 1

7.1.1 Multiple Regression Equation for Patient's Data

The data of the subject's obtained from hospital were analysed using Multiple Linear Regression and Analysis of variance. Four parameters were taken into consideration for the analysis. These are- Age, Body temperature, Pulse pressure (calculated from Systolic pressure and Diastolic Pressure), and percentage oxygen (SpO_2). The health status of Subjects were categorised into three level- 1 (Fit), 2 (Suffering from diseases or under medication) and 3 (Undergoing hospitalization). 320 numbers of patient data were analysed using multiple linear regression and the mathematical relationship of the coefficients were obtained as follows:

Health Status = 0.008512 x Age + 0.043032 x Temperature + 0.003686 x PPR - 0.034284 x SpO2 + 0.795464

where Temperature is in °F, PPR is the Pulse pressure in Pa, SpO_2 is the oxygen level in percenta ge.

The Multiple regression also showed the correlation of the individual parameters with the health status of the subjects. From the analysis, it was found that Age is highly correlated with health status as it has got the P-value < 0.02. The next correlation comes to be moderate between Health status and Pulse pressure ≈ 0.01. However, the correlation of the health status with Temperature and SpO2 was found to be low, with the correlation index close to 0.5.

The correlation is shown using the bubble graph:

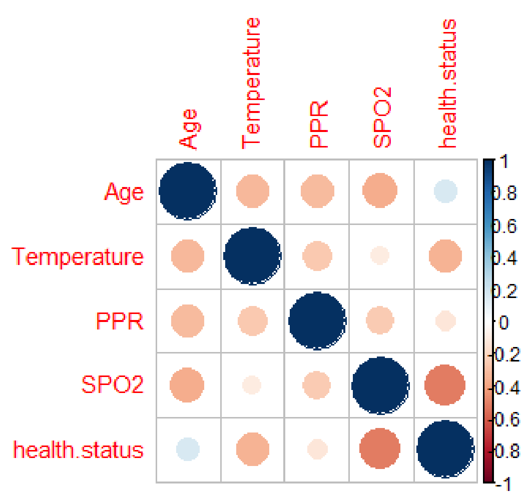


Fig. 7.1 Correlation of different parameters in Multiple regression with the health status of the subjects

To test the effect of the individual parameters with the health status, the Analysis of Variance (ANOVA) test was employed. Since there are four parameters, the one, two, three and four -way ANOVA test with interaction were used for the analysis. In ANOVA test with interaction, two or more parameters are correlated with the output (or the variable to be predicted).

7.1.1.1 One-way ANOVA Test Observations

Initially, the one-way ANOVA was performed between the health status and Age. The P-value is less than 0.02, which means that these two parameters are highly corelated. This can also be visualized using the Q-Q plot (Plot of the Residuals).

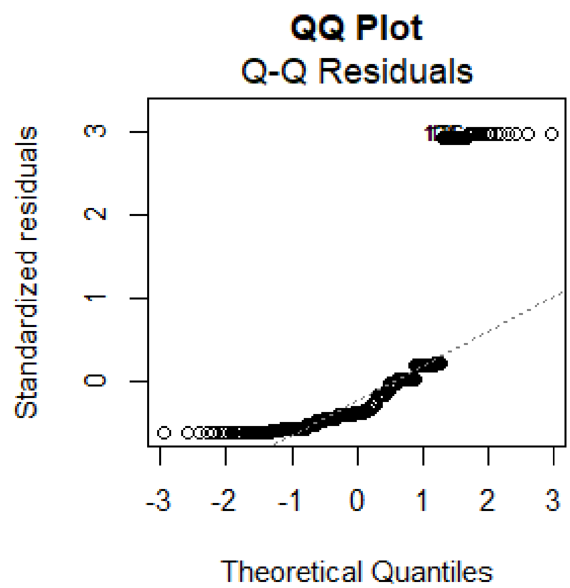


Fig. 7.2 Plot of the Residuals in one-way ANOVA between the health status and Age

7.1.1.2 Two-way ANOVA Test Observations

After performing the two-way ANOVA test, the results show the following observations. In the case of the ‘Age’ factor, it is seen that the P-value is highly significant, suggesting that there is a significant difference in means between at least two age groups. In the case of ‘PPR’ factor, the P-value is significant at the 0.05 level, indicating a significant difference in means between at least two PPR groups. When we look at the ‘Age-PPR Interaction’, the P-value is not significant, suggesting that the interaction effect between Age and PPR is not statistically significant. In summary, though the interaction between ‘Age’ and ‘PPR’ is not significant, the results suggest that both the ‘Age’ and ‘PPR’ factors have a significant effect on the dependent variable.

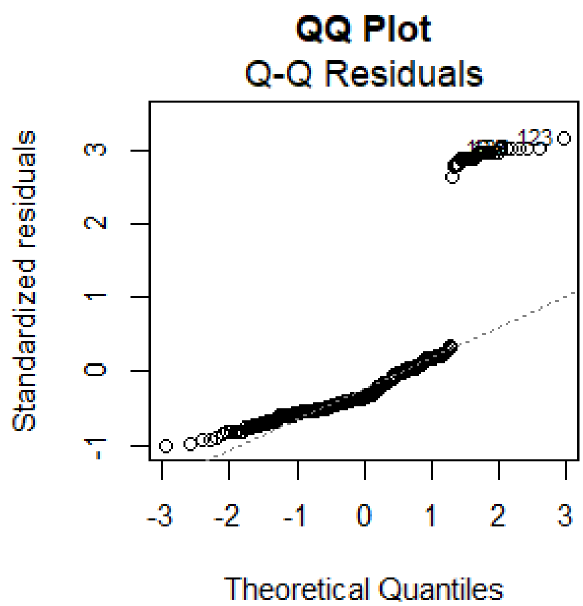


Fig. 7.3 Plot of the Residuals in two-way ANOVA between the health status and Age-PPR interaction

7.1.1.3 Three-way ANOVA Test Observations

From the three-way ANOVA test, the factors are 'Age', 'Temperature', 'PPR', and 'SpO_2', and the following observations were acquired. In the case of the 'Age' factor, the P-value is highly significant, suggesting that there is a significant difference in means between at least two age groups. Similarly, for the 'PPR' factor, the P-value is significant at the 0.05 level, indicating a significant difference in means between at least two PPR groups. However, in the case of the 'SpO_2' factor, the P-value is not significant, suggesting that there is no significant difference in means between at least two SpO_2 groups. When we look at the 'Age-PPR Interaction', the P-value is not significant, suggesting that the interaction effect between Age and PPR is not statistically significant. Similarly, for the 'Age-SpO_2 Interaction' and 'PPR-SpO_2 Interaction' the P-value is not significant, suggesting that the interaction effect between Age and SpO_2 and the interaction effect between PPR and SpO_2 is not statistically significant. The results suggest that 'Age' and 'PPR' have significant main effects, while 'SpO_2' and the interactions involving 'SpO_2' are not significant.

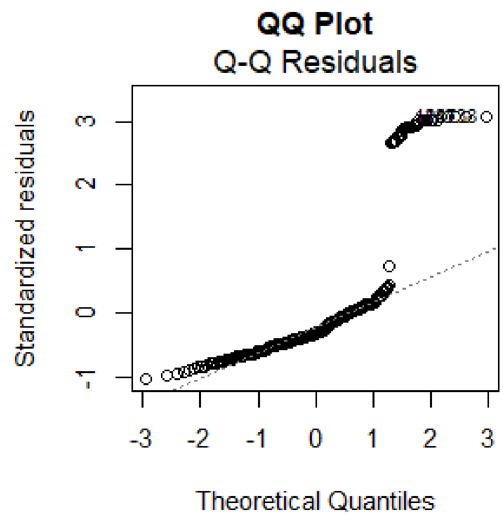


Fig. 7.4 Plot of the Residuals in three-way ANOVA between the health status and Age-PPR-SpO_2 interaction

7.1.1.4 Four-way ANOVA Test Observations

The four-way ANOVA test has the four factors ‘Age’, ‘Temperature’, ‘PPR’, and ‘SpO_2’. We acquired the following observations. In the case of the ‘Age’ factor, the P-value is highly significant, suggesting that there is a significant difference in means between at least two age groups. Similarly, for the ‘PPR’ factor, the P-value is significant at the 0.05 level, indicating a significant difference in means between at least two PPR groups. In the case of the ‘Temperature’ factor, the P-value is not significant, suggesting that there is no significant difference in means between at least two temperature groups. Similarly, for the ‘SpO_2’ factor, the P-value is not significant, suggesting that there is no significant difference in means between at least two SpO_2 groups. Multiple interactions between factors such as ‘Age-Temperature’, ‘Age-PPR’, ‘Temperature-PPR’, etc., are tested, and the P-values for most interactions are not significant, suggesting that these interactions are not statistically significant. Thus, the results from the four-way ANOVA test suggest that ‘Age’ and ‘PPR’ have significant main effects, while ‘Temperature’ and ‘SpO_2’ do not.

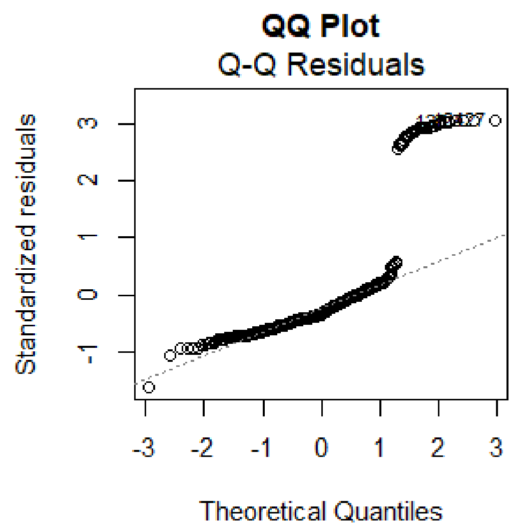


Fig. 7.5 Plot of the Residuals in four-way ANOVA between the health status and Age-PPR-SpO_2-Temperature interaction

From the analysis, it was found that only the Age and Pulse pressure has significance in predicting the health status of a subject. To create the hardware model, different sensors like the pulse oximeter, temperature sensor, heart sensor are used. In addition, the age and weight of a person are used as input. These data after feeding into the system are obtained, are sent to a computer and stored in a .csv file. These are then used for multiple regression and ANOVA.

7.2 Phase 2

7.2.1 Multiple Regression Equation for Normal Health Condition Subjects

A small hardware was made with different sensors like the MAX30100 sensor (pulse oximeter and heart sensor), and DS18B20 (temperature sensor). In this phase, the readings of normal human beings are taken, where the subjects are of the category 1 (Fit) and 2 (Suffering from disease or under medication). From this dataset, it has been found, by using the one, two, three and four -way ANOVA test, there is significant interaction among the parameters- Age, Weight, SpO_2 and Heart rate. The P-value < 0.02 in the interaction among the four parameters. This can be validated by the Residual plot as shown below:

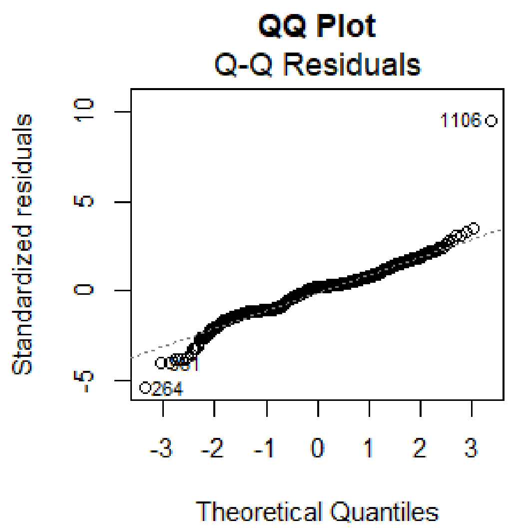


Fig. 7.6 Plot of the Residuals in ANOVA for the parameters- Age, Weight, SpO_2 and Heart rate

The dataset is further used in multiple linear regression model, where the data are split into training and testing set in the ratio of 70% and 30%. From the testing data, the accuracy of the prediction model was tested using the Root Mean Square Error (RMSE), that was found to be 0.0063. the lower the value of RMSE, the better is the model.

From the analysis of the second dataset, it is found that the four parameters Age, Weight, SpO_2 and Heart rate are significant indicators of health status of a subject.

The corelation plot of the four parameters with the health status is shown below:

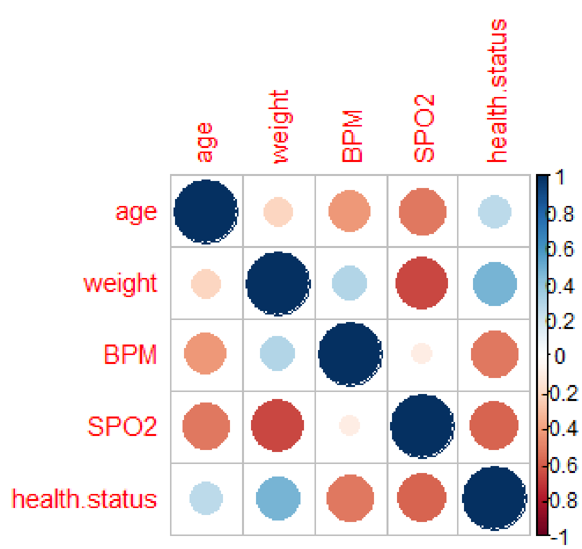


Fig. 7.7 Correlation of different parameters in Multiple regression with the health status of the subjects

7.3 Phase 3

7.3.1 Multiple Regression Equation

The data of the subject's obtained were analysed using Multiple Linear Regression and Analysis of variance. The parameters were taken into consideration for the analysis are - Age, Body Weight, Gender, Room Temperature and Humidity, Body Temperature, Blood Pressure (Systolic and Diastolic), Pulse pressure (calculated from Systolic pressure and Diastolic Pressure), Heart Rate and Percentage Oxygen (SpO_2). The health status of Subjects was categorised into two level- 0 (No Medical History) and 1 (Suffering from diseases or under medication). 3426 numbers of subject sample data were analysed using multiple linear regression. For the analysis of the outcome after using regression the health status of a person is taken into consideration. The health status of a subject is categorised as follows:

Category 1: *Subject with No Medical History and Normal Body Parameter.*
Category 2: *Subject with Medical History and Normal Body Parameter.*
Category 3: *Subject with Medical History and Abnormal Body Parameter.*

The multiple regression algorithm was used with the Age, Heart Rate, SpO_2 Level, Body Temperature, Weight, Medical History, Systolic, Diastolic and Heart Beat as input and health status as output. The regression model gives the following output as follows:

Health Status = -0.3437839 - 0.0042512 x Age - 0.0002326 x Heart rate + 0.0152411 x SpO2.Le vel + 0.0361975 x Body Temperature - 0.0061736 x Weight + 1.3325061 x MH - 0.0122023 x Sy stolic - 0.0125121 x Diastolic - 0.0037094 x heart beat

The regression model also gives an estimate of the relation of health status with the individual parameters. The relations are as follows:

Table 7.1 Coefficient Detail

Coefficients	Estimated P Value	Significant Codes
(Intercept)	-0.8681417 0.5890837 -1.474 0.14068	
Age	-0.0039628 0.0009647 -4.108 4.12e-05	***
Heart.rate	-0.0003728 0.0004385 -0.850 0.39532	
SpO2.Level	0.0200113 0.0054565 3.667 0.00025	***
Body.Temperature	0.0365028 0.0040001 9.125 < 2e-16	***
Weight	-0.0064010 0.0004782 -13.386 < 2e-16	***
MH	1.3363770 0.0290278 46.038 < 2e-16	***
Systolic	-0.0118405 0.0005289 -22.388 < 2e-16	***
Diastolic	-0.0128640 0.0007036 -18.283 < 2e-16	***
Beat	-0.0032128 0.0005768 -5.570 2.80e-08	***

Significant Codes: 0 '***', 0.001 '**, 0.01 '*', 0.05 '.' , 0.1 ' ', 1

7.3.2 Correlation

It has been found from the regression model that the P-value is less than 2.2e-16 which suggest that there is a good correlation among the given variables and the output variable, health status. Further studied this correlation, the Pearson and Spearman model are used and the following results are obtained.

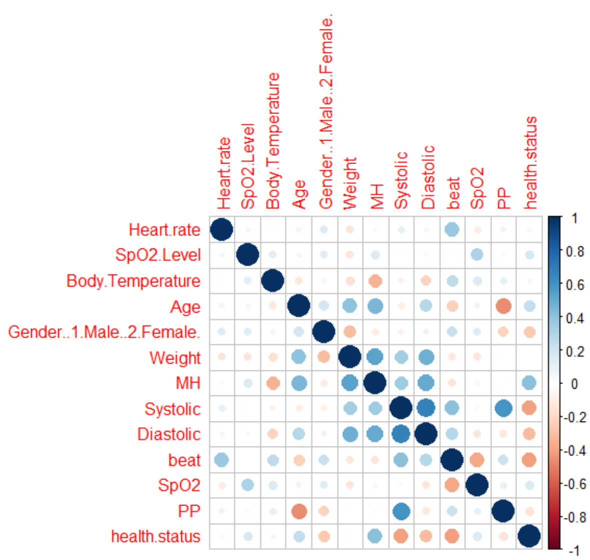


Fig. 7.8 Pearson Model

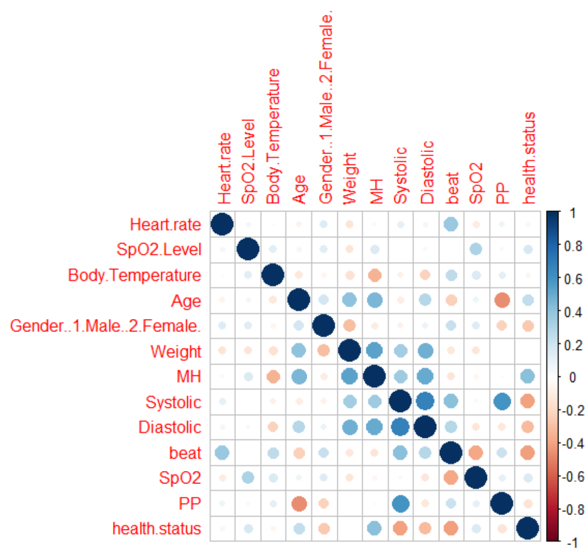


Fig. 7.9 Spearman Model

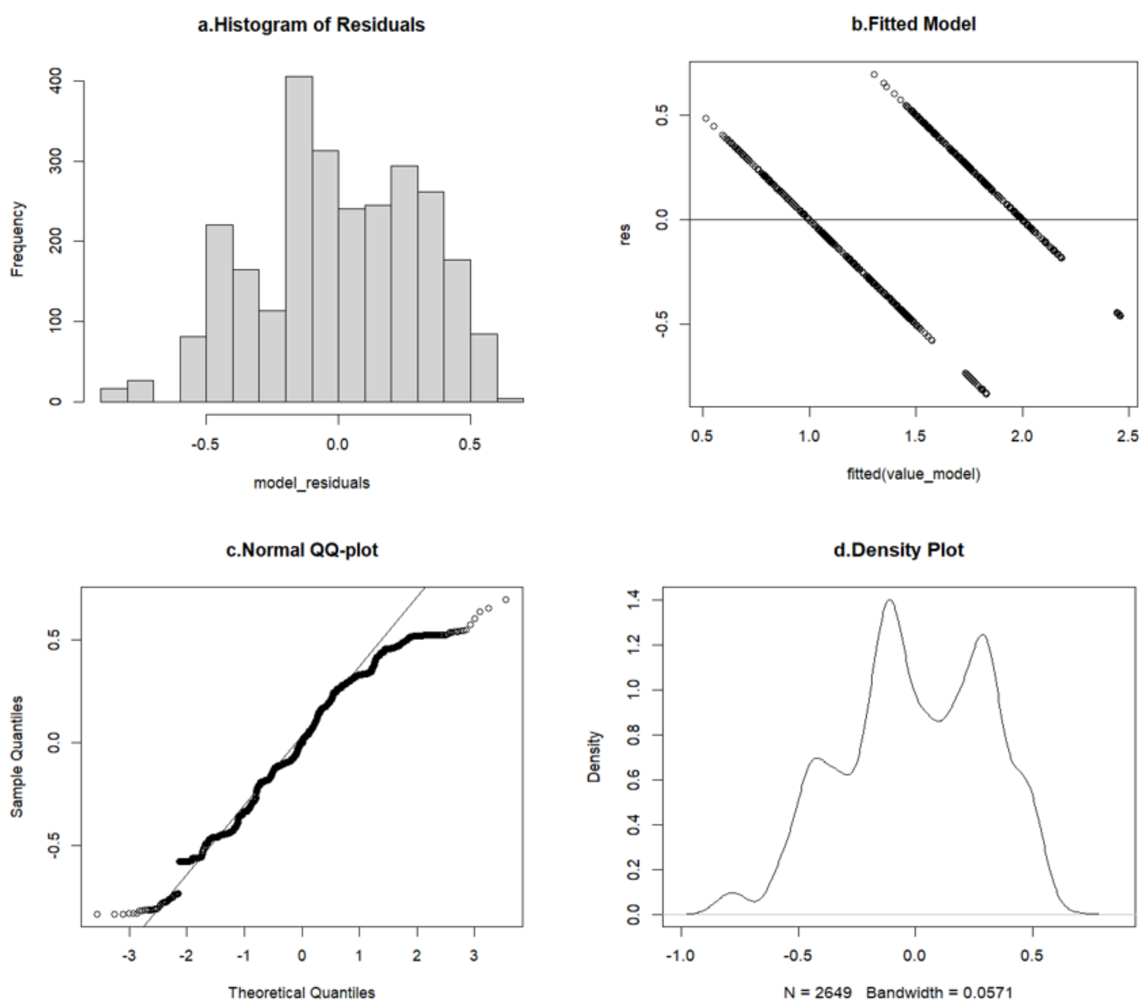


Fig. 7.10 Plot of Residuals

In Fig. 7.10 (a) the plot of residuals is shown in the form of histogram. In Fig. 7.10 (b) the plot of residuals is shown in the form of Fitted Model. In Fig. 7.10 (c) the plot of residuals is shown in Q plot and in Fig. 7.10 (d) the plot of residual is shown in the form of Density Plot.
From the testing data, the accuracy of the prediction model was tested using the Root Mean Square Error (RMSE), that was found to be 0.0017. the lower the value of RMSE, the better is the model. The R-Square (R2) is found to be 0.43 for the same. R2 tells you about correlation between two datasets, RMSE tells you about the difference between them.

7.4 Phase 4

7.4.1 Part 1

Using the collected data, machine learning has been done. The regression model gives the following output as follows:

Diastolic = Age x 0.39866 + Heartrate x 0.09574 + SpO2x 0.11672+ Weight x 0.28688 + 18.82214

Systolic = Age x -0.1903 + Heartrate x 0.1256 + SpO2x 0.7959 + Weight x 0.351 + 14.3735

Health Status = heart rate x 0.008054 + SpO2 x 0.074822 + Age x 0.003745+ Gender x 1.411719 + Weight x 0.014761 + MH x 0.989165 - 0.001256 x systolic - diastolic x 0.022645 - 4.342315

7.4.2 Part 2

From the literature review, the height-weight relationship is taken and BMI is obtained. Using the multiple regression, further relations of BMI with weight and gender are found. Additionally, the multiple regression is done for finding equations for diastolic and systolic blood pressure. The regression model gives the following output as follows:

BMI = 12.69048 + Gender x 0.978835 + Weight x 0.133264

Diastolic = 69.44148+ Gender x 3.33333 + Age x 0.120224

Systolic = 98.84987+ Gender x 3.383333 + Age x 0.486825

Health Status = Heart Rate x 1.182 + SpO2 x 18.232 + BMI x 2.830 + Medical History x 5.034 – Systolic x 2.340 - Diastolic x 3.592 - 20.267

7.5 Conclusion

In this project, a system is developed to monitor health status using machine learning algorithm (multiple linear regression, logistic regression, ANOVA and decision tree algorithm). Phase 1 identified age and pulse pressure as significant predictors for patients. Phase 2 incorporated sensors, yielding an accurate prediction model with an RMSE of 0.0063. In the result, it is found that for the patient prediction error rate is 1.6 and for tested data prediction error rate is 0.6 which defines the deviation of the health status of a patient to health status of a normal human being. Phase 3 enhanced the parameters which include age, weight, gender, medical history, SpO2, heart rate, pulse rate, blood pressure, room Temperature and humidity, using decision trees for health categorisation. Phase 4 further enhance the system which is significant to set standards. The results highlight the feasibility of this hardware-based approach for health status prediction, demonstrating reliable performance across diverse subjects.

7.6 Future Scope

The system can be integrated with IoT system to store and analyse the data in cloud. Utilize cloud computing for data storage, processing, and scalability, allowing the system to handle large volumes of health data from multiple users. The system can be integrate with more medical device and further prediction using machine learning can be perform.

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