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Portable ECG Machine with Future Predictions

Eshan Joshi[1], Arundhati Nagdive[2], Aditi Galgalikar[3], Nitesh Chimurkar[4], Gaurav Vamsi Peri[5], Dr. Shubhangi Rathkanthiwar[6], Dr. Shreyash Dubewar[7]

[1,2,3,4,5] *Department of Electronics Engineering, YCCE ,Nagpur ,India*
[6]*Professor, Dept. of Electronics Engineering, YCCE college, Maharashtra, India*
[7] Post- Junior Clinical Fellow in Spinal injuries and Neuro Rehabilitation, Maharashtra

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Abstract - *Approximately thirty percent of people live in poverty in rural areas. The difficulty of limited access to nursing and diagnostic services stems from the outdated healthcare infrastructure. As a result, when heart failure strikes, people frequently neglect to get help and make use of the resources that are accessible. A study suggests a smart electrocardiogram (ECG) monitoring system for heart patients based on the Internet of Things to address these problems. The ECG sensing network (data gathering), IoT cloud (data transmission), result analysis (data prediction), and monetization are the various components that make up the system. The P, Q, R, S, and T ECG signal characteristics are gathered by the ECG sensor network. For the purpose of managing future health, these signals are then pre-processed, examined, and projected down to the age level. Hypertext Transfer Protocol (HTTP) servers and message queuing telemetry transport (MQTT) systems can both access the cloudstored data. To ascertain the influence of error rate and ECG signal properties, the study used the linear regression method. The prediction evaluates the PQRST regularity variation and its applicability to an ECG monitoring device. The suggested system seeks to attain acceptable results by identifying the quality parameter values, which would ultimately lower future medical expenses and challenges for heart patients.*

***Key Words*: Cardiovascular disease, Electrocardiogram monitoring system, Internet of things Linear regression , Message queuing telemetry , Transport server**

1. INTRODUCTION

The study, which recorded 854,253 deaths overall, found that heart disease was responsible for 21.1% of deaths, with heart attacks accounting for 180,408 of those deaths. According to the general pattern, people with cardiac illnesses usually wait until they feel ill before seeking medical assistance, frequently when the condition is severe and irreversible damage has already happened. There is a push for a paradigm change that would standardize passive healthcare in order to combat this. It is suggested that physicians keep a close eye on their patients' physical health in order to provide proactive treatment based on current conditions. Significant progress has been made in the field of medicine and healthcare systems in the last few years. Reduced cellular connectivity costs have made it easier to integrate health surveillance systems into commonplace devices like cellphones. The goal of this strategic integration is to solve problems like the lack of medical equipment and services. Particularly, there is potential for using Internet of Things (IoT) technology to monitor electrocardiograms (ECGs) and identify cardiac issues early. The use of IoT in ECG monitoring has been the subject of earlier study, which points to a promising future for technological integration in healthcare. The incorporation of machine learning algorithms into electrocardiogram (ECG) devices represents a noteworthy progression in healthcare technology, namely in terms of augmenting diagnostic skills and facilitating prospective forecasts. By adding these algorithms, conventional ECG machines are intended to become smart devices that may anticipate future problems in addition to identifying existing heart disorders. By examining patterns and trends in the gathered data, machine learning algorithms give ECG devices a predictive aspect. This takes a proactive approach to treating cardiovascular health, going above and beyond traditional diagnostic techniques. These algorithms use patient records, previous ECG data, and a wide range of pertinent characteristics to find minor patterns that may indicate impending cardiac events. The capacity to quickly identify abnormalities and departures from known patterns is a crucial component. Through the use of a variety of datasets, machine learning models can be taught to identify minute differences in ECG signals that could be early warning indications of heart problems. By taking proactive identification, serious health consequences may be avoided by enabling prompt intervention and preventive actions.

1.1 BLOCK DIAGRAM WITH DESCRIPTION :

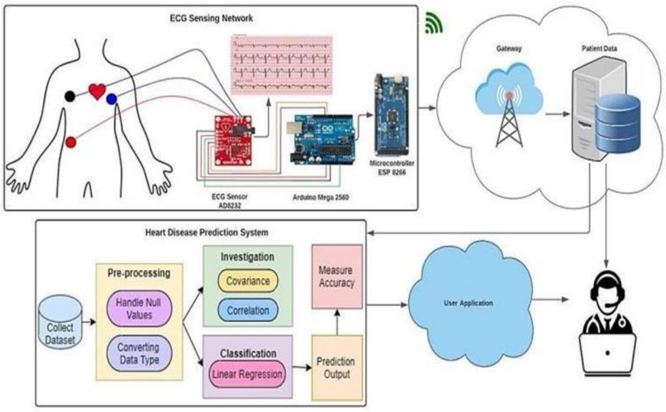
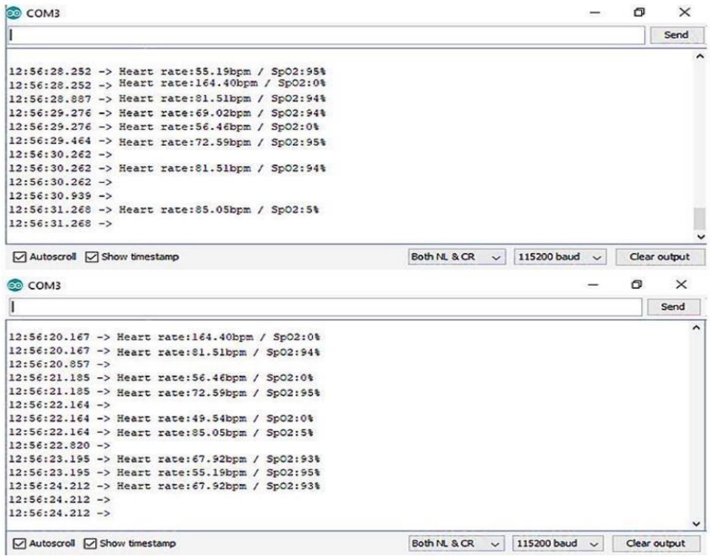


Figure 1. Proposed framework of smart IoT-based ECG monitoring system

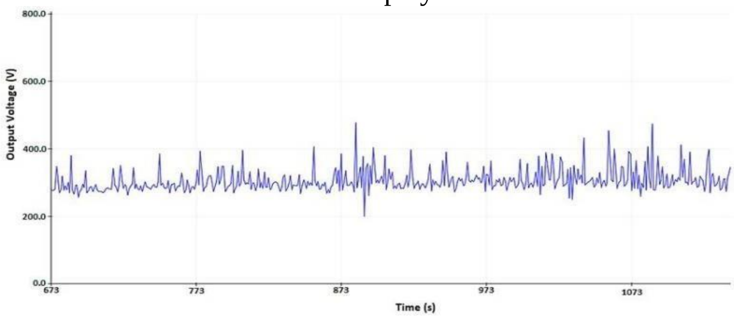
The convergence of wearable monitoring technology and the Internet of Things (IoT) is opening up revolutionary opportunities for a range of healthcare applications. Acknowledging the possibility of improving service consistency and dependability, the healthcare industry has quickly embraced IoT, especially when it comes to integrating its functionalities into medical devices. This adoption is especially helpful for people who need constant monitoring, are managing chronic illnesses, or are elderly. IoT devices generate a significant amount of health data because IoT-based healthcare systems are essential for gathering vital data, providing real-time adjustments in health parameters, and providing prompt notifications of the intensity of medical parameters. IoT is acknowledged by the healthcare sector as a critical technology with enormous promise. An inventive embedded Internet of Things (IoT) system for the management, observation, and forecasting of cardiac illness was suggested and created in this work. The patient had devices implanted in their chest that used Arduino Mega 2560 sensors to record a variety of ECG data. Through the use of an ESP8266 Wi-Fi module, this data was effortlessly transferred to a cloud server. Customers may quickly and easily retrieve ECG data because to the cloud environment's integration of message queuing telemetry transport (MQTT) and hypertext transfer protocol (HTTP) servers. A non-relational database was used to handle the gathered data, maximizing the variety and velocity of data storage. Using ECG data collected by sensors, a painstakingly crafted online application was developed to help medical professionals diagnose heart issues in patients. The suggested IoT-based cloud solutions guaranteed the efficiency, dependability, and precision of the data collected during the investigation. Figure shows the system in its entirety.

To find out if the pulse tracker is functioning, the heartbeat result is compared to the heartbeat output of an automated existing pressure measurement system. Data was collected from five different people with different ages.

This chart shows the data on a specific day and time.



By positioning the three electrodes on the patient's thorax, the ECG sensor is activated, producing the ECG readout. The ECG results are displayed below:



The following shows the Arduino com port result and the unique feature of the captured ECG data.

DATASET :

Table 2. Dataset parameters

Column	Null value presence	Data Type
Record No	No null	int64
Age	No null	int64
P	No null	float64
Q	No null	float64
R	No null	float64
S	No null	float64
T	No null	float64

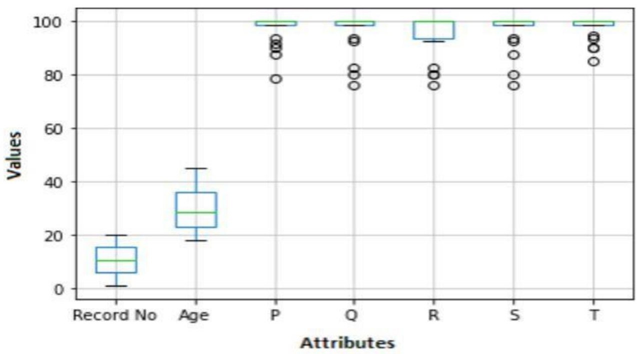


Figure 8. BOX plot of dataset

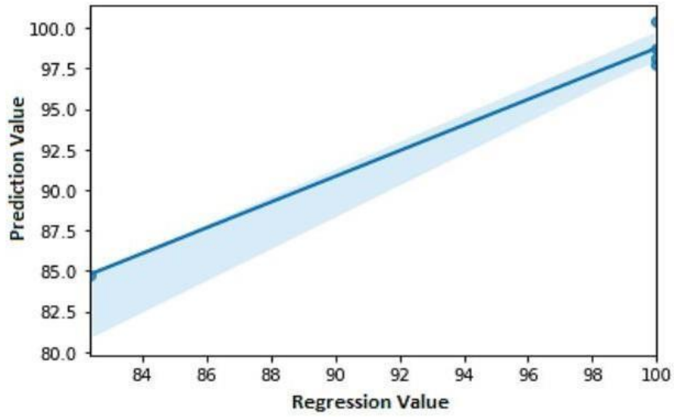
Table 3. Variable of covariance

	R. N	Age	P	Q	R	S	T
R. N.	34.9999	22.9527	5.9496	3.1419	9.3033	2.0927	6.9999
Age	2.8968	79.0154	23.0283	11.2086	20.9727	9.3649	3.8056
P	5.9157	23.1106	35.3116	-8.3645	9.9382	-9.0118	5.1673
Q	3.1160	11.2698	-8.2879	56.1017	52.8324	54.6937	14.8088
R	9.0139	20.9800	9.9900	52.8920	68.9900	50.2378	12.9169
S	2.4152	9.0671	-9.2035	54.0977	50.3761	50.9416	15.8902
T	6.8524	3.9089	5.4860	14.4958	12.8981	15.8530	19.7410

Table 4. Variables of correlation

	R. N	Age	P	Q	R	S	T
R. N.	1.0000	0.4431	0.1777	0.0657	0.1772	0.0408	0.2775
Age	0.4431	1.0000	0.4338	0.1623	0.2878	0.1383	0.1095
P	0.1777	0.4338	1.0000	-0.2135	0.2052	-0.2072	0.1713
Q	0.0657	0.1623	-0.2135	1.0000	0.8460	0.9893	0.4546
R	0.1772	0.2878	0.2052	0.8460	1.0000	0.8372	0.3474
S	0.0408	0.1383	-0.2072	0.9893	0.8372	1.0000	0.5011
T	0.2775	0.1095	0.1713	0.4546	0.3474	0.5011	1.0000

A linear regression model is utilized to ascertain the relationship between a predictor variable and the respondent in order to estimate unknown population characteristics: A pessimistic sign suggests that the response parameter will drop as the predictor variable grows, whereas an optimistic symbol suggests that the response parameter will likewise grow as the predictor variable increases. With only one variable, y, the research uses basic regression. The predictions form a straight line when Y is represented as a function of x.



The data are presented in the figure below, which shows that x and y have a positive relationship.

The predicted score on y for each potential value of x makes up the regression line.

This indicates that the prediction value of y will increase with increasing values of x.

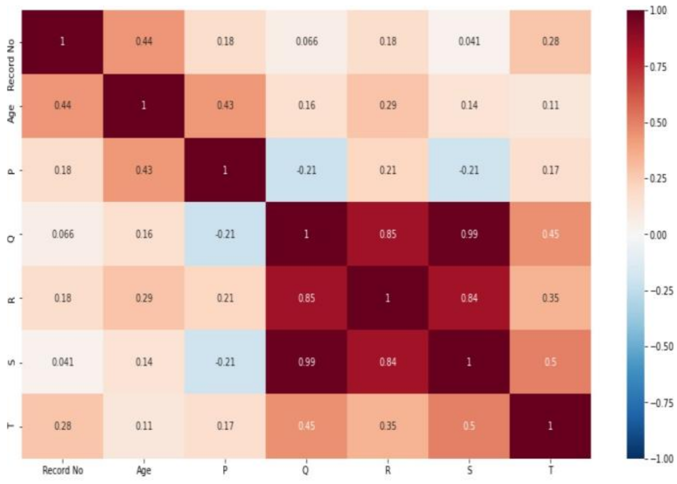


Figure 9. Heat map of correlation among variables

Equations and Mathematical Expressions

Examining the covariance and correlation. The degree to which the dataset's attributes coordinate with one another is determined by correlation. The metric used to ascertain the correlation between two random properties is covariance. Correlation and covariance are employed, respectively, to determine which attributes are responsible for cardiac conditions.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

$$cov_{x,y} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{N-1}$$

where N is the number of data in the dataset, r is the correlation coefficient, $covx,y$ is the covariance between x and y, xi is the value of the x variable from the dataset, yi is the value of the y variable from the dataset, $\bar{x}$is the mean of xi, and $\bar{x}$is the mean of xi.

2) The linear regression method is used to identify cardiac illness based on the ECG parameters P, Q, R, S, and T. The method lowers the variation between the current and end values by creating a solid path using the regression model. The y=mx+b type describes the optimal suit lines for the n points (S1, T1), (S2, T2),... (Sn, Tn). The slope and inception are determined by applying the (3) and (4), respectively.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

$$cov_{x,y} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{N-1}$$

One variable's expected score **is** based on the outcomes of another. The criteria parameter, sometimes known as y, is the variable that needs to be predicted. The variable that serves as the basis for the predictions is the predictor variable, or x.

3. CONCLUSIONS

In conclusion, this study demonstrates the possibility for comprehensive daily health monitoring through the use of an Internet of Things (IoT)-based healthcare network equipped with smart sensors. The emphasis has been on Internet of Things (IoT)based patient management systems, with an exploration of the advantages, difficulties, and future potential of the technologies used in smartphones and other devices. The technological contribution of this study resides in offering uninterrupted supervision using a web-based platform, a mobile application, live monitoring, and phone messaging services, emphasizing the critical necessity for continuous remote surveillance in medical patient monitoring. In the current period characterized by a demand for lower healthcare expenses, particularly in rural regions, this study serves as a transition from traditional medical procedures to innovative healthcare applications. Future research will likely include more parameters like RR, PR, QRScomplex, QRS-interval, QT, and QRST. The aim is to improve the system's ability to recognize heart illnesses with ease by analyzing these factors through the use of several machine learning techniques. The goal of this continuous improvement and growth is to help create healthcare solutions that are easier to access and more efficient, especially for underserved and distant areas.

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BIOGRAPHIES

Mr. Eshan joshi
College :- Yeshwantrao Chavan College of Engineering
Year :- 4th / Student

Ms. Arundhati Nagdive
College :- Yeshwantrao Chavan College of Engineering
Year :- 4th / Student

Ms. Aditi Galgalikar
College :- Yeshwantrao Chavan College of Engineering
Year :- 4th / Student

Mr. Nitesh R. Chimurkar
College:- Yeshwantrao Chavan college of Engineering
Year:- 4TH year / student

Gaurav Vamsi Peri
College :- Yeshwantrao Chavan College of Engineering
Year :- 4th / Student

Dr. Shreyash Dubewar
Junior Clinical Fellow in Spinal injuries and Neuro Rehabilitation Salisbury district hospital NHS Foundation Trust, Maharastra

Dr. Shubhangi Rathkanthiwar
Professor, Department of Electronics Engineering Dean , International Relations, Yeshwantrao Chavan College of Engineering