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Portable ECG Machine with Future Prediction

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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 The difficulty of limited access to nursing and diagnostic services stems from the outdated healthcare infrastructure.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.

Keywords: Cardiovascular disease, Electrocardiogram monitoring system, Internet of things Linear regression , Message queuing telemetry , Transport server.

I. 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.

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A. Block Diagram With Description

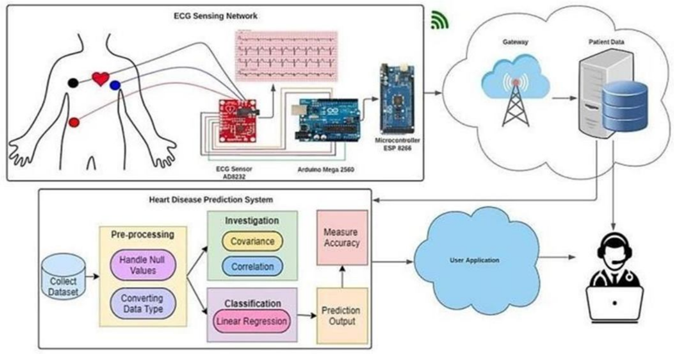
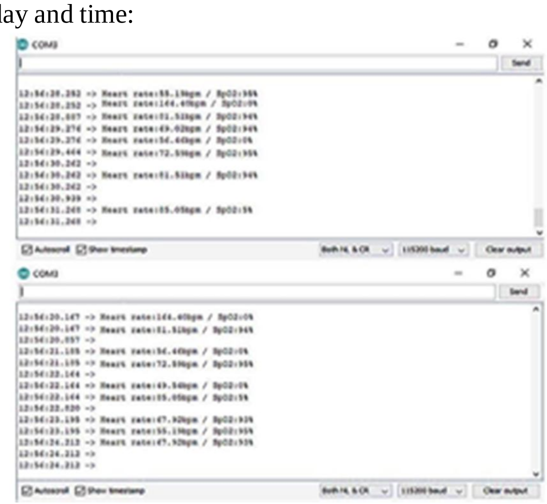


Figure 1. Proposed framework of smart IoT-based ECG monitoring system

Healthcare has undergone a transformation thanks to the convergence of wearable monitoring technologies and the Internet of Things (IoT), which has made real-time monitoring and management solutions possible. When it comes to medical devices in particular, this integration provides reliable and consistent services that help those who need care for the elderly, manage chronic illnesses, or require constant monitoring. Wide-ranging health data generated by IoT devices is essential for in-the-moment modifications and timely alerts. This work presents a novel Internet of Things (IoT) solution for the management of cardiac sickness that uses Arduino Mega 2560 sensors that are inserted into the patient's chest to record ECG data. Through the use of an ESP8266 Wi-Fi module, the data is smoothly transported to a cloud server, making it simple for medical experts to access via MQTT and HTTP servers. The data is handled well by a non-relational database, enabling the creation of an online application for the diagnosis of cardiac problems. The For improved patient care, IoT-based cloud solutions guarantee accurate, dependable ,and efficient data collecting and processing.
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:

B. Future Prediction Analogies

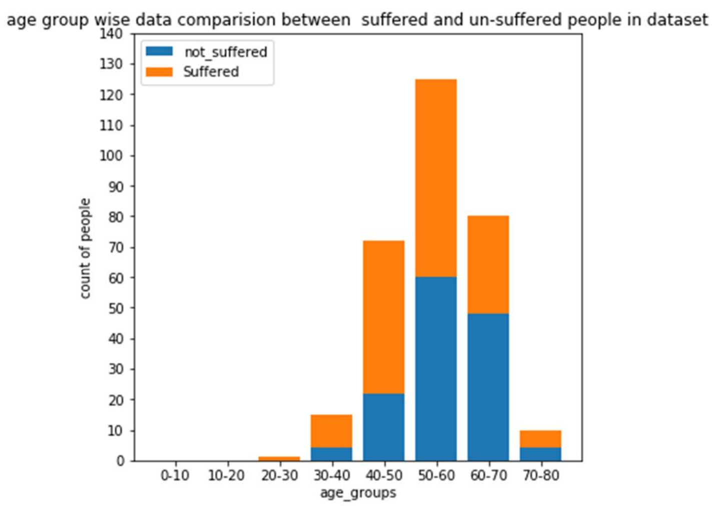
To predict angiographic disease state, we are using the Heart Disease UCI dataset, a subset of the Cleveland database that has 14 variables. Patients are classified using the goal variable as follows: 0 represent less than 50% diameter narrowing in major vessels, and 1 represent higher than 50% diameter narrowing in major arteries. We start by loading the dataset and importing the required libraries.

Then, we investigate the relationship between the target variable and important variables such as age, sex, cholesterol, and exercise-induced angina. This visualisation aids in our improved understanding of the facts. Afterwards we utilise diverse categorization techniques in order to construct prediction models. Our goal is to accurately forecast the status of angiographic diseases by training these models on the properties of the dataset. The purpose of this research is to enhance early diagnosis of coronary artery disease and provide insights into cardiovascular health.

[2]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

The Heart Disease UCI dataset is filtered by the code segments according to the target variable. The subset 'data_with_disease' comprises instances where the target is 1 (indicating > 50% diameter narrowing), and the subset 'data_without_disease' contains instances where the target is 0 (indicating < 50% diameter narrowing).
relation between age and target variable:-



The code segments count the incidence of heart disease within each age group and classify the individuals into those groups. A bar chart is then used to visualise the distribution. Age groups are represented on the x-axis, while the number of persons is displayed on the y-axis. Bars are stacked to show the percentage of each age group that had heart disease (orange) compared to those that did not (blue). The graph provides information on the prevalence of heart disease in the dataset for various age groups.
The distribution of people with angiographic disease in various age groups is depicted in the pie chart. Notably, the chart shows that the age range of 50–60 represents the biggest number of patients with angiographic illness status (1). Furthermore, a notable segment of impacted individuals is noted to be between the ages of 40 and 70. Targeted healthcare interventions and preventative efforts are made easier with the help of this visual representation, which offers a clear knowledge of the age demographics most prone to angiographic disease.

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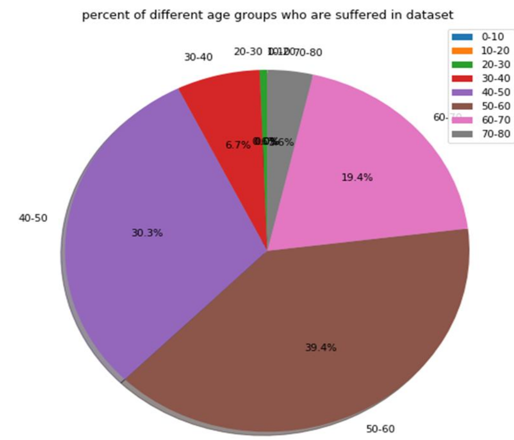
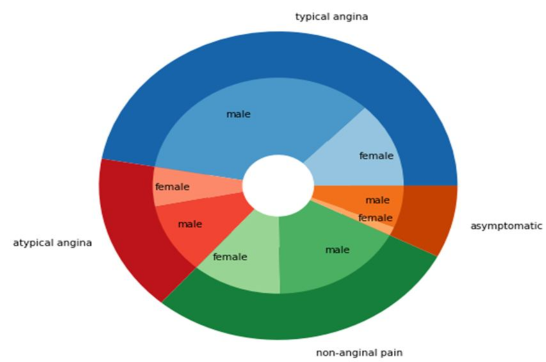
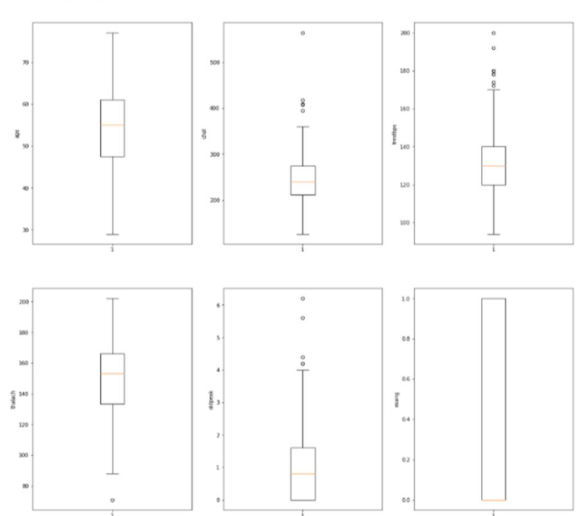


Taking into account both gender and disease state, the algorithm creates two visualisations that show the distribution of different types of chest discomfort among individuals. In the first visualisation, a double-ring pie chart is displayed, with the inner ring identifying male and female people and the outer ring representing the overall distribution of chest pain kinds. The second visualisation consists of two bar charts that show the percentages of those with heart disease (left) and those without (right) who experienced various forms of chest pain.



The Heart Disease UCI dataset's distributions of important attributes are displayed in a grid of six boxplots created by the code. These characteristics include age, maximal heart rate attained (thalach), resting blood pressure (trestbps), cholesterol levels (chol), exercise-induced angina (exang), and ST depression generated by exercise relative to rest (oldpeak). For each property, a boxplot shows information about the presence, spread, and central tendency.



Model selection:- Comparing the classification prediction algorithms on the dataset.

The Heart Disease UCI dataset was used to train and assess the logistic regression model. Confusion matrix analysis demonstrated how well the model performed in correctly identifying occurrences. To evaluate its generalizability, ten-fold cross-validation was also carried out. The model's overall performance was measured by the mean accuracy attained across folds, and its stability was assessed by the standard deviation. Furthermore, a thorough assessment of the model's prediction performance was given by the F1 score, which is a harmonic mean of precision and recall and is especially useful in binary classification tasks.

```
[[18  5]
 [ 5 17]]

accuracy
0.8356125356125356

standard deviation
0.06805377032101455

Out[14]:
0.7727272727272727
```

With a standard deviation of 0.068 and an accuracy of 83.56%, the logistic regression model showed sustained performance. The approximate F1 score is 0.773.

C. K-Nearest Neighbour

With six neighbours, the Euclidean distance metric, and p=2, the K-Nearest Neighbours (KNN) classifier produced a confusion matrix with 22 accurate predictions of the existence of heart disease and 10 accurate predictions of its absence. A standard deviation of 0.07 and an average accuracy of around 0.79 were obtained using ten-fold cross-validation. The precision and recall-based F1 score came out to be roughly 0.73.

```
[[22  1]
 [ 7 15]]

accuracy
0.8157663817663818

standard deviation
0.057449604082861365

Out[15]:
0.7894736842105263
```

With one false positive and seven false negatives, the confusion matrix shows that there were 22 accurate predictions of heart disease presence and 15 accurate predictions of absence. The model had a 0.057 standard deviation and an accuracy of roughly 81.58%. The model's precision and recall are indicated by the F1 score, which is roughly 0.789.

D. Decision Tree

A confusion matrix showing 21 accurate predictions of heart disease presence and 15 accurate predictions of its absence was produced by the Decision Tree classifier using the entropy criteria. The results of ten-fold cross-validation showed an accuracy average of roughly 0.73 and a standard deviation of 0.09. The precision and recall harmonic mean, or F1 score, was almost 0.71.

```
[[18  5]
 [ 5 17]]

accuracy
0.7575897435897436

standard deviation
0.05663732852323211

Out[19]:
0.7727272727272727
```

Decision Tree classifier attained an accuracy of 75.76% with a standard deviation of 0.057. The F1 score is approximately 0.773, indicating good overall performance.

II. CONCLUSIONS

Finally, a potential direction for preventive cardiovascular healthcare is the application of machine learning algorithms to improve electrocardiogram (ECG) equipment with future prediction capabilities. Significant progress has been made in reliably forecasting the status of angiographic diseases by the examination of several machine learning techniques, including as logistic regression, K-Nearest Neighbours, and Decision Trees. High accuracy and an F1 score were displayed by the logistic regression model, demonstrating dependable predictive performance. To assure clinical efficacy, additional optimisation and validation are necessary. In cardiovascular care, the effective use of ML-driven ECG devices holds great promise for early identification, individualised treatment plans, and better patient outcomes.

To fully utilise ML algorithms in transforming cardiac care and lowering the prevalence of cardiovascular illness, more research and development in this area are required.

III.ACKNOWLEDGMENT

Finally, a potential direction for preventive cardiovascular healthcare is the application of machine learning algorithms to improve electrocardiogram (ECG) equipment with future prediction capabilities. Significant progress has been made in reliably forecasting the status of angiographic diseases by the examination of several machine learning techniques, including as logistic regression, K-Nearest Neighbours, and Decision Trees. High accuracy and an F1 score were displayed by the logistic regression model, demonstrating dependable predictive performance. To assure clinical efficacy, additional optimisation and validation are necessary. In cardiovascular care, the effective use of ML-driven ECG devices holds great promise for early identification, individualised treatment plans, and better patient outcomes.

To fully utilise ML algorithms in transforming cardiac care and lowering the prevalence of cardiovascular illness, more research and development in this area are required.

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