SEMARAK ILMU PUBLISHING
202103268166(003316878-P)

Journal of Advanced Research in Applied Mechanics

Journal homepage:
https://semarakilmu.com.my/journals/index.php/appl_mech/index
ISSN: 2289-7895

Real Time Patient Vital Monitoring and Alarm System with Prediction of Anomalies and Future Clinical Episodes using Machine Learning Models

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ARTICLE INFO

Article history:
Received 25 May 2023
Received in revised form 29 July 2023
Accepted 9 August 2023
Available online 18 August 2023

Keywords:
Real time vital monitoring; wearable devices; Machine Learning; disease prediction

ABSTRACT

Heart disease is a leading cause of death in India. Many times, heart diseases do not show symptoms until they become a matter of concern. This silent nature calls for real time monitoring of vitals. In this paper, we propose a healthcare monitoring system which makes use of existing wearable devices to measure vitals of the user's body. The data gathered is used to perform real time analysis to detect any irregularities and simultaneously to predict if there are any underlying problems that might be of future concern.

1. Introduction

Heart attack is one of the prime causes of death world- wide and a global health problem. Every year approximately 17.9 million people die of a heart attack. According to the WHO, about 23 million people may suffer from heart attacks until 2030. To reduce a person's risk to heart attacks, we need to be able to detect their susceptibility to it. The growing unhealthy and irregular lifestyle and food habits of people have significantly increased the chances of suffering from a heart disease, thereby putting one's life in danger.

Even though heart attacks are life threatening, it may have early symptoms. Early detection and reporting in a timely manner to the health care facilities about these symptoms could greatly help in saving many lives and avoiding consequences.

Global cardiovascular disease risk assessment estimates the 10 year risk, but it does not capture the dynamic changes in personalised risk that closely follow lifestyle habits. Moreover, the cost associated with it is quite high which proposes the need for a low cost solution.

The coronavirus disease pandemic (2019) saw a significant increase in the need for remote and decentralised patient care. There was an immediate surge in the need to balance medical

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https://doi.org/10.37934/aram.109.1.7383

emergencies with infectious risk. The alarming rate of increasing cross infections that occurred while travelling to and attending community clinics demanded for a remote real-time monitoring tool. There is evidence to suggest that during pandemic patients with acute cardiovascular diseases did not receive appropriate treatment due to fear of reporting to a hospital and delay in setting up an overwhelmed hospital setup at home.

One of the most fatal types of cardiac disease is myocardial infarction (MI), also known as a heart attack. One of the coronary arteries that supplies the heart muscle with oxygen-rich blood becomes blocked as a result.

According to Fox *et al.,* [7] It affects 805,000 persons in the USA each year. Among them, 200,000 people have repeated heart attacks and 605,000 people have their first heart attack. Recurrent heart attacks have a six-fold greater mortality rate than do initial attacks. Additionally, 20% of heart attacks are silent, which means that the victims are not aware of the harm being done. Additionally, if the sufferers receive therapy within 90 minutes of the MI starting, they have a better probability of surviving.

The requirement for real-time monitoring and MI identification is underscored by the quiet nature of MI, greater risk of recurrent MI, and prompt need for MI treatment. Patients with MI are currently observed and managed in a clinical setting using sophisticated medical technology. Due to the devices' portability issues and high battery consumption, a solution like this is not practical for daily and real-time MI monitoring.

Since they do not have these constraints and the constant advancement of technology and software, wearables can be used for remote and real-time monitoring Garc´ıa Magarin˜o *et al.,* [8]. Utilizing modern technologies enables you to implement cutting-edge healthcare systems. These wearables have numerous sensors and considerable computational power, facilitating for the monitoring and use of health insights. Wearables haven't yet been used well for remote healthcare, though.

i. Hardware which involves detection using sensors and noise removal from the received signals and communicates it to the decision making system
ii. Software device which makes decision from the signal This corresponds to the Machine Learning component which involves preprocessing, feature selection, training the models, prediction, and measuring the accuracy of prediction by the models.

Machine learning classification algorithms for heart attack detection requires several steps as shown:

i. Preprocessing- A crucial phase in the design and creation of a reliable real-time patient vital monitoring and prediction system is the preprocessing of data.
ii. Feature selection- The process of feature selection involves choosing attributes for the master feature vector that will be used to train the ML classifier. Additionally, feature selection techniques are frequently used to optimise the features extracted and are most pertinent for a real-time patient vital monitoring system. Efficiency is increased, and classification errors are decreased.
iii. Classifiers- In the last phase, a machine learning (ML) classifier is trained using the master feature vector to make predictions and determine whether the patient is likely to develop a heart condition, enabling early detection and preventative measures.

In the proposed system we present health monitoring system that makes use of the data generated by the wearable devices. Relevant machine learning techniques are applied on the gathered data to perform real time analysis through big data techniques to detect any irregularities and simultaneously to predict if there are any underlying problems that might be of future concern. When the values generated cross a certain threshold value an alert is sent to the medical authority along with the patient's remote family thereby safeguarding patient health.

2. Literature Review

Healthcare is a critical field that has a need for immense accuracy and quick development. With the recent technological advancement there has been a massive growth in the wearable device domain due to higher availability of IOT enabling components, as well as breakthroughs in wireless communication technology. Recent surveys and studies show the growing popularity of wearable devices all around the world, this makes wearable devices more feasible for real time monitoring of patient vitals.

With the current outbreak of Covid-19 there is a growing need for advancements in remote healthcare and research by Channa *et al.,* [4] shows the capability of wearable devices and that the severity of the pandemic would have likely been significantly less severe if health services had adopted available technology more quickly over the previous few years. Another study by Ming *et al.,* [14] shows how wearable devices can be used in real time analysis and monitoring of patients in various settings like a hospital to provide early warning in case of a clinical deterioration or in patient management at home for geriatric patients. In addition, Lu *et al.,* [12] classifies wearable devices based on their application areas, namely: health & safety monitoring, chronic disease management, disease diagnosis and treatment, and rehabilitation. They emphasize that wearable medical devices will become more prevalent as technology advances and customized health concepts become more widely known and accepted. and better incorporated into people's day-to-day lives.

The following studies show the implementation of such systems where wearable technology can be used in the field of healthcare. A study by Mizuno *et al.,* [15] points out the various factors that affect a person's cardio vascular health. They show how wearable devices can be used to record them and also provide a risk reduction strategy in order to aid in the well-being of the patients.

As Dias and Cunha [5] explain in the schematic overview of data mining process, wearable devices can be divided into 2 main areas namely: The activity area and the medical area. Since the wearable devices nowadays can function in both areas, they can aid in all the stages that fall within the scope of Home/Remote and when the patient is not critical. In addition, they also mention the valuable vital signs that can be captured with the help of the wearable devices such as SpO2 levels, Respiratory Rate, Heart Rate, etc. They propose an extensive wearable health devices system that makes use of the various products available in the market.

Research done by Pantelopoulos and Bourbakis [16] highlights the various Biosensors available on the market and the Biosignals captured by them. They also highlight the various technologies available for the development of a Wearable health Monitoring System (WHMS) and propose a few prototypes such as Systems-Based on a Microcontroller Board or on Custom Designed Platform, a system based on based on commercial Bluetooth sensors and cell phones and a few others.

Yeri and Shubhangi [19] conducted a study where they build a IoT based system for real time health monitoring. They propose a system where they use basic vital sensors such as pulse sensor, temperature sensor and a few other sensors in order to measure the vital values and if these readings go over a certain threshold, an alert is sent to the doctor via a mobile application.

Research conducted by [10] proposes an IoT based system to monitor heart diseases where they define a step by step approach of using IoT sensors to gather data and also two sub-processes of data transmission. They suggest 4 operation modes of the monitoring system based on the risk level of the patient and the amount of data transmitted by the devices.

According to M Abd El-Aziz *et al.,* [13], Data Science Technique is used for data collection and processing so that this data can visualised in real time. They also mention an Improved Pigeon Optimisation Algorithm for data col- lection, compilation, and storage for enhancing the speed of forecasting. In addition to that they use a BS-DNN to monitor the health of the patient wearing the IoT device. The advantages of real-time perspective are that it offers information on time subject to the present user condition at present. However, the paper does not predict susceptibility to underlying diseases and potential risks. This study lacked the implementation of a system that utilises the data collected over a long term for prediction of potential risks.

A thorough study by Ranganathan *et al.,* [17] performs the data analysis and visualization of data in order to see how each of the features correlate to the likelihood of the person to have a heart attach and proposes K-Means Clustering algorithm to predict if a person is susceptible to the same.

Research by Aldahiri *et al.,* [1], March 2021 focus on using the IoT sensors and Machine Learning Algorithms and analyses machine learning algorithms for prediction and classification of data collected from wearable devices. The authors compile all the results of the various Machine Learning models used and list their positives and negatives. It is concluded that KNN is the most accurate classification algorithm but may take longer to work in real time applications. So, it states that a collection of LSTM and RNN models may improve the performance in real time.

Another research Sharma *et al.,* [18] defines a model for remote monitoring and alarm system using IOT wearable device. It collects biomedical data such as pulse, ECG, PPG, temperature and accelerometer data. The term IoMT has been used which stands for Internet of Medical Things which has huge potential in the healthcare industry. It integrates IoMT in a cloud environment along with a Kernel Multiview Canonical Correlation Analysis (KMCCA) using SVM and KNN to perform multi vital correlation and pre- diction. Intelligent apps can be used to connect users to doctors when either of them are in remote locations.

However a few concerns regarding the security aspect of wearables and patient health data are a big concern as pointed out by Chacko and Hayajneh [3], Koren and Prasad [9]. They have highlighted the various threats to patient data considering their extremely sensitive nature such Medjacking where the data is tempered by a hacker. They have also highlighted the importance of regulations such as HIPAA in order to protect patient data.

Based on the pros and cons and proposed, we use Preprocessing to reduce size of multivariate data Aldahiri *et al.,* [1]. Alert system to notify about anomalies in vitals. Machine Learning models to predict and classify if the user is susceptible to any underlying condition that may be of future concern Aldahiri *et al.,* [1]. Cloud storage to make data available at any time M Abd El-Aziz *et al.,* [13]. The prediction model for efficient forecasting. Real time monitoring to know the user's condition at the present time Forkan and Khalil [6].

3. Proposed Methodology

This section describes in detail the methodology used for Real time patient Vital monitoring System. The architecture of the proposed system where the interaction of the users and the system along with its components are shown in the Figure 1.

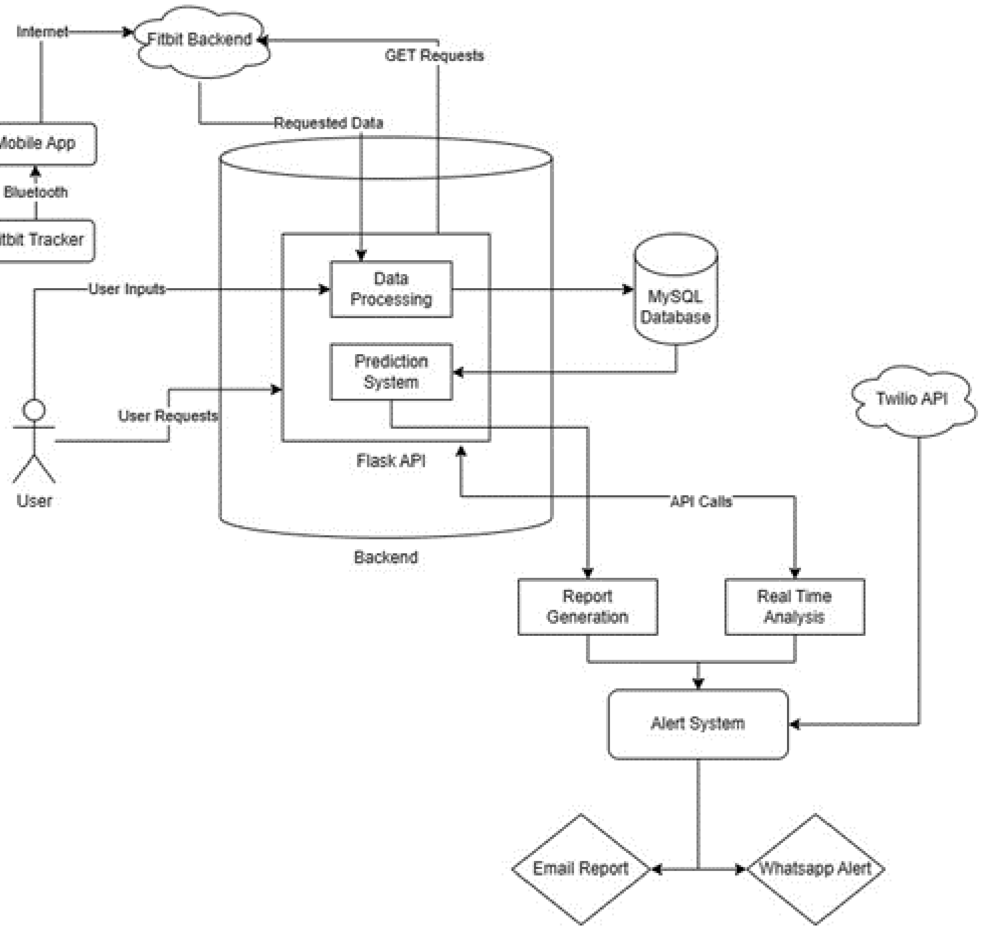


Fig. 1. System Architecture

In our application, we have 2 data producers, the User and the Wearable device. The user interacts with the frontend, and all the operations on the frontend are done by the backend. The backend houses an API that responds to all the requests sent by the user. The user enters data such as chest pain, etc from the UI and the remaining data is fetched from the Fitbit API. The user entered data is relevant for 5-6 months since the blood profiling doesn't need to be done that often and hence only needs to be entered 1-2 times a year. The remaining heart data is automatically captured by the wearable and doesn't need any user intervention. Once the data is received, we process the data and store it in the database in a form that is required by our model to predict the output. This data is then used by the prediction system using a Sequential Neural Network to predict if the user is susceptible to a heart disease or not. Once predicted, a report is generated. An external real time analysis system keeps fetching data from the API and based on certain thresholds produces an alert. Both the report and the alert are sent to the user by an alert system built with the help of Twilio API.

The steps involved for Real time patient Vital monitoring System are:

- Model generation using data corpus for training.
- Using the model on the data generated from the Fitbit API and the user entered data.
- Alert system to notify about anomalies in vitals.

The High level design is given in Figure 2 and further explanation of the steps is given in detail in the subsequent sections.

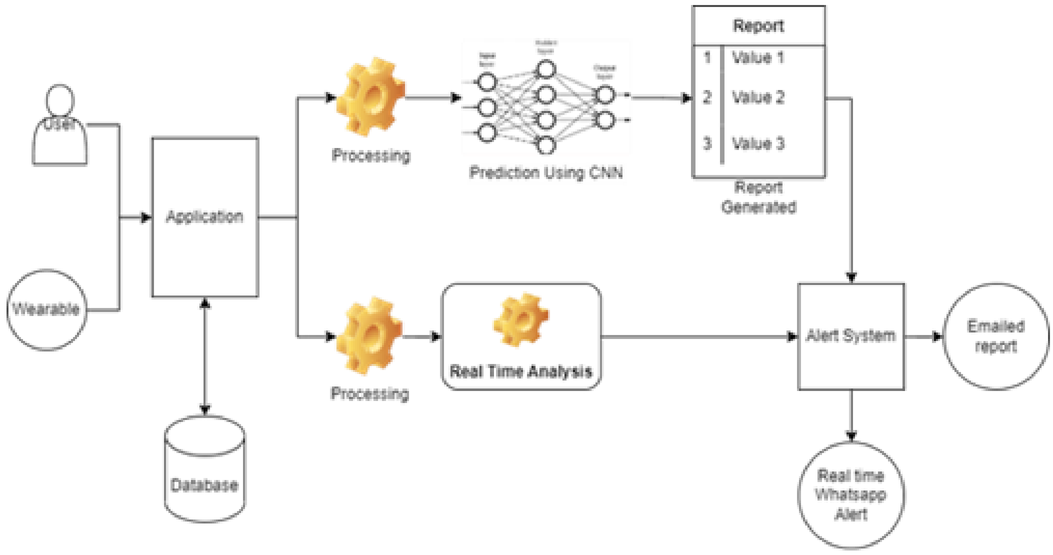


Fig. 2. High Level Design of the system

3.1 Model Generation using Data Corpus for Training
3.1.1 Data set

The Heart Attack Analysis & Prediction Data set corpus was used for training our model. The corpus comprises of more than 1200 rows, 14 features. Table 1 shows the features found in the corpus and which would be used in to perform prediction of a heart attack.

Table 1
Features used and their description

Feature Name	Description
age	Age
sex	Gender
cp	Chest Pain
trtbps	Resting Blood Pressure
chol	Cholesterol in mm Hg
fbs	Fasting Blood Sugar greater than 120 mg/dl
restecg	Resting ECG
thalachh	Maximum Heart Rate Recorded
exng	Exercise Induced Angina
oldpeak	Previous peak value
slp	Slope
caa	Number of Major Vessels
thall	Thalium Stress Test Level

From the following correlation heatmap in Figure 3, we can see those attributes like exng, oldpeak, caa and thall have very low correlation and barely affect the output. As a result, they have been dropped.

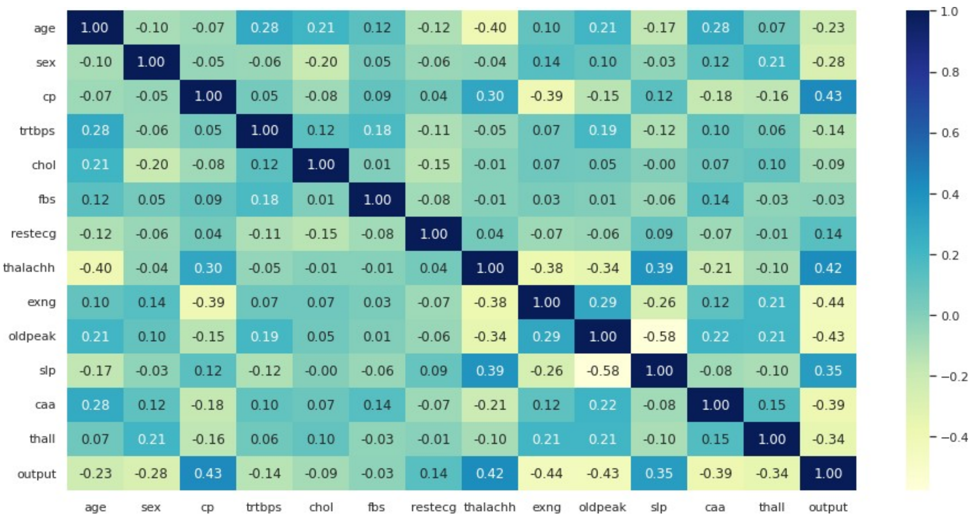


Fig. 3. Correlation Heatmap

3.1.2 Data collection and preprocessing

The data collected is a combination of user inputs and the data collected from the Fitbit API. Once the device is registered to an account in the application, user data and vitals are collected and stored in the database.

Before storing in the database, the data is converted to binary or numerical form required to perform the prediction using a sequential Neural Network. A few insights of the dataset are as follows:

i. There are no NaN values in the data.
ii. There are certain outliers in all the continuous features.
iii. There are more than 2 times the number of males than females.
iv. Figure 3 suggests that there is some correlation in output and cp, and thalachh and slp.
v. Although it makes sense that older persons might have a larger risk of heart attack, Figure 4 shows that this isn't the case.
vi. According to Figure 4, higher maximum heart rate may indicate increased susceptibility to heart at- tacks.
vii. Bivariate analysis tells about the following:

- Non-Anginal chest pain leads to more odds of having a heart attack.
- Males have higher chance of heart attack.
- Thall greater than 1 suggests higher chance of heart attack.
- People without exercise induced angina, can also be at a risk of having a heart attack.

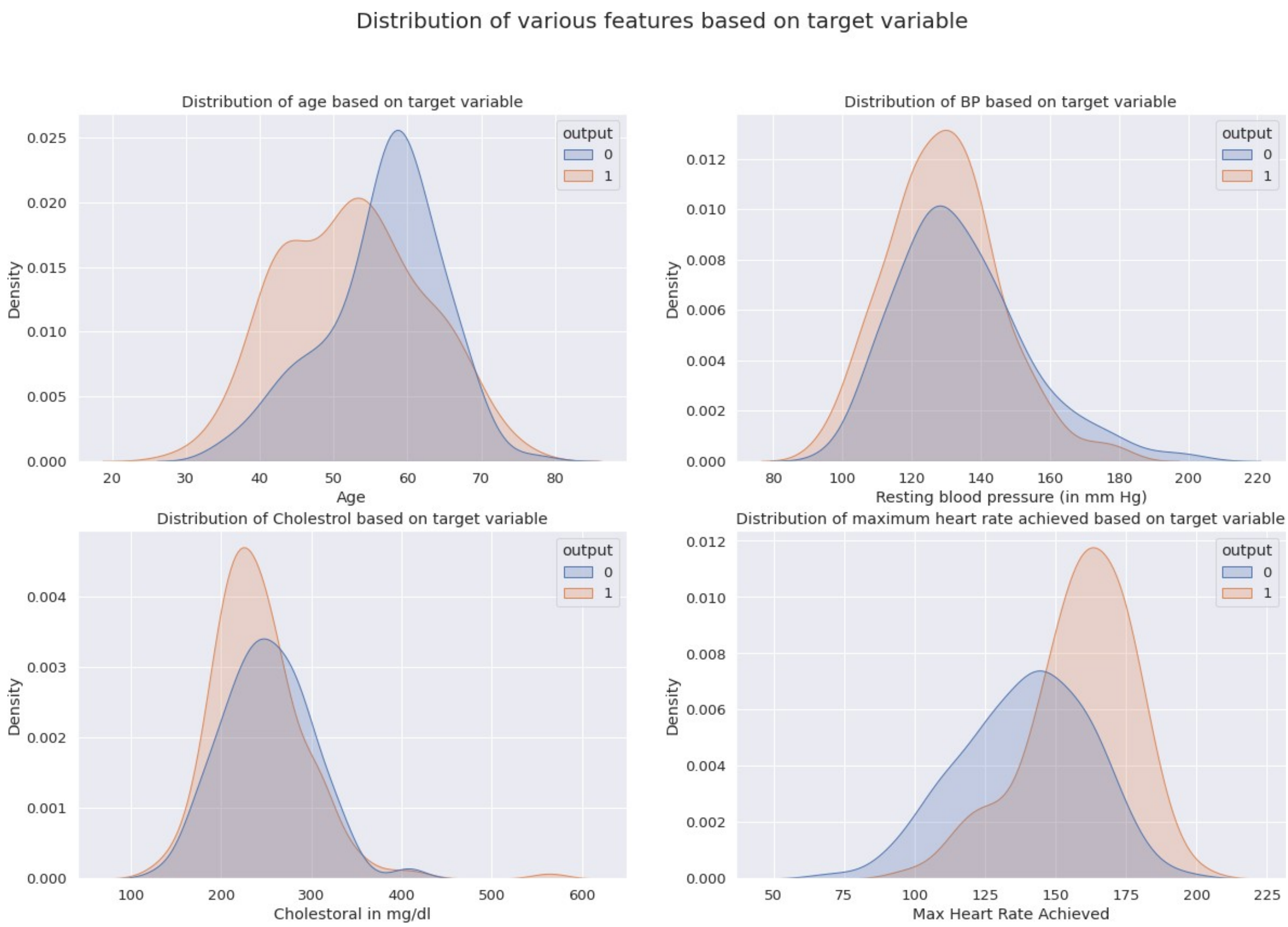


Fig. 4. Distribution of various features based on target variable

3.1.3 Proposed model

The dataset was split into train and test set using Stratified Shuffle Split. Several models were generated on the preprocessed dataset. The result obtained is shown in Figure 5

	Model	best_score	best_params	type
4	KNN	0.808197	{'algorithm': 'auto', 'n_neighbors': 28, 'p': ...	oneHotEncoder
0	LogisticRegression	0.788525	{'C': 0.1, 'penalty': 'l2'}	oneHotEncoder
1	SVC	0.786885	{}	oneHotEncoder
9	KNN	0.784426	{'algorithm': 'auto', 'n_neighbors': 29, 'p': ...	labelEncoder
6	SVC	0.782787	{}	labelEncoder
3	GradientBoostingClassifier	0.782787	{}	oneHotEncoder
5	LogisticRegression	0.782787	{'C': 0.1, 'penalty': 'l2'}	labelEncoder
2	RandomForestClassifier	0.780328	{}	oneHotEncoder
8	GradientBoostingClassifier	0.763934	{}	labelEncoder
7	RandomForestClassifier	0.741803	{}	labelEncoder

Fig. 5. Results

Highest accuracy was obtained from KNN model, along with this we also implemented a Sequential Model in Convolutional Neural Network (CNN) and predicted the output using the same data and got an accuracy of ~83%. As a result, we chose the chose the following algorithm in our prediction system.

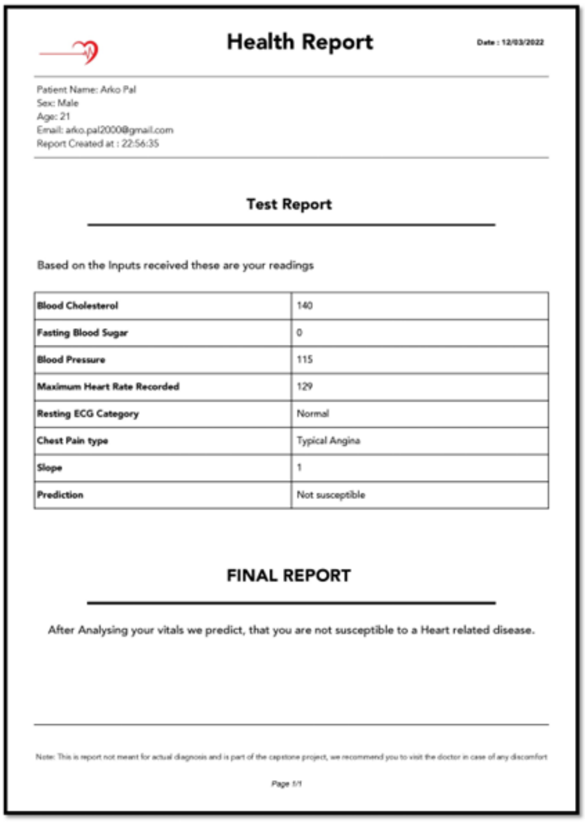
```
estimators = []
estimators.append(('standardize', StandardScaler()))
estimators.append(('mlp', KerasClassifier(model=create_model, epochs=100, batch_size=5, verbose=0)))
pipeline = Pipeline(estimators)
kfold = StratifiedKFold(n_splits=10, shuffle=True)
results = cross_val_score(pipeline, X, Y, cv=kfold)
print("model scores: %.2f%% (%.2f%%)" % ((results.mean()*100), (results.std()*100)))

model scores: 82.84% (3.02%)
```

Fig. 6. CNN accuracy result

3.2 Using the Model on the Data Generated from the Fitbit API and the User Entered Data

The models are populated from the data obtained from the Fitbit API and the data entered by the user. The user is supposed to register himself and manually enter the values of certain parameters - such as chol, fbs, restecg, thalachh, which remains constant for a long period of time. The remaining parameters which keep changing are obtained every minute from the Fitbit API. The email id of the user is the primary key and has to be unique. Once the output is predicted, a PDF report is created given in Figure 7 is sent to the user.



Health Report

Date : 12/03/2022

Patient Name: Arko Pal
Sex: Male
Age: 21
Email: arko.pal2000@gmail.com
Report Created at : 22:56:35

Test Report

Based on the Inputs received these are your readings

Blood Cholesterol	140
Fasting Blood Sugar	0
Blood Pressure	115
Maximum Heart Rate Recorded	129
Resting ECG Category	Normal
Chest Pain type	Typical Angina
Slope	1
Prediction	Not susceptible

FINAL REPORT

After Analysing your vitals we predict, that you are not susceptible to a Heart related disease.

Note: This is report not meant for actual diagnosis and is part of the capstone project, we recommend you to visit the doctor in case of any discomfort

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Fig. 7. Generated PDF report

3.3 Alert System to Notify about Anomalies in Vitals

The data collected from Fitbit isn’t real time therefore a forecasting algorithm had to be used in order to predict the heart rate based on the given trends and hence try to achieve almost real time data to perform analysis. For this we use the forecasting model prophet.

Once the data is collected and based on various studies like Arnold *et al.,* [2], Fox *et al.,* [7], Zhang *et al.,* [20] thresholds are set and the data is checked if it is in the normal range. Else a whatsapp alert is created and sent to the phone number of the user/emergency contact.

For testing purposes, Twilio API's whatsapp sandbox feature was used to send the alert to a preset number. For production purposes this alert would be sent to the user's provided number.

4. Conclusion and Future Work

Currently, our system was implemented in a local environment. However, in the future we plan to deploy this system on a cloud platform to make it scalable, and to improve availability, and to make it capable of being used at a national or global scale.

Our model for Real Time monitoring will be of remarkable use in case of any unforeseen pandemic like the Covid 19, in the future. Especially with a country with a population as large as India where the doctor to patient ratio is extremely less. This system will enable doctors to monitor at least 40-50 patients at a time remotely, which is critical to ensure doctor and patient safety.

There is significant scope for improvement in the implementation of our product which could not be implemented due to various resource constraints but with dedicated time and effort this can be a scaled to improve doctor-patient safety and build a system like Lin *et al.,* [11] proposed with all the necessary data protection and security features as suggested by Chacko and Hayajneh [3] and others can be implemented in order to make this a feasible and practical product for the masses.

Acknowledgement
This research was not funded by any grant.

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