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Incorporating Machine Learning into an IoT-Based Healthcare System

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ABSTRACT

In recent years, there has been a surge of interest in studying the IoT among academics. In its most basic form, it is the linking of various electronic devices together through the internet. It is important to highlight some of the most effective uses of IoT technology in the domains of healthcare monitoring, in addition to its more general usage in relation to smart homes and autonomous vehicles. Providing excellent services for patients is the primary goal of our study work. The use of this tool can raise the bar for home health care, making it safer for patients and facilitating the delivery of essential nursing services. The right patient monitoring system is often lacking in rural areas of countries. Therefore, medical facilities in rural areas can greatly benefit from remote monitoring and prescribing through the secure exchange of patient records. Our suggested healthcare system employs supervise machine learning techniques to interpret ECG reports. An expert doctor can utilize the results of the analysis to formulate a prescription after storing them in the cloud. In order to assess performance, six supervised machine learning algorithms are applied to ECG data. One set of data is used for training the model, while the other set is used for testing. Cross validation, in conjunction with a random train-test split to weed out duplicates and anomalies, yielded the most accurate result.

Keywords: Machine Learning, IoT, Healthcare System.

INTRODUCTION

Recent developments in healthcare IT have centered on DL approaches, including convolutional neural networks (CNNs) and long short-term memories (LSTMs), to enhance patient monitoring and diagnosis. The goal of this algorithmic collaboration is to make the most of both CNNs' spatial feature extraction and LSTMs' temporal dependence comprehension capabilities. Investigated methods of tracking and assessing health conditions using collaborative medical big data from the IoT using a DL algorithm in [1]. But new studies in this field have shown that the machine learning algorithms deployed by failing companies still need human involvement to identify features from IoT-based big medical data.

Ambulatory electrocardiography, a non-invasive method of recording the heart's electrical activity over 24 hours, was used in [2]. Potential risk factors for cardiovascular disease can be identified by this test. By continuously monitoring a patient's heart rate, an intelligent model can estimate the patient's survival rate after a cardiac arrest. This model is built on a deep cardiac learning algorithm. Because of the greater focus on prevention and early intervention, the prognosis for patients with heart disease has improved with this strategy. An Internet of Things (IoT) solution for early COVID-19 detection using ensemble deep transfer learning was detailed in [3]. By using this method, we can detect and respond to potentially dangerous COVID-19 situations in real time. The suggested IoT architecture makes extensive use of DL models. According to the results, radiologists were able to more accurately and quickly identify COVID-19 patients using this technique. Additionally, a functional ID that is compatible with the IoT and complies with COVID-19 criteria is utilized.

Data transported from devices to the cloud is encrypted using PDH-AES in the method described in [4].

The DLMNN classifier divides decrypted data into two groups: normal and pathological. With this categorization, physicians can see the big picture of their patients' heart health and get notifications when problems are detected.

Results show that DLMNN is more accurate than other methods in detecting cardiac problems, according to the study. PDH-AES has a success rate of 95.67% while encrypting and decrypting data, and it is faster than AES overall. It also ensures optimum security throughout data transport.

In [5], the RTFMHS, which stands for "real-time face mask with health screening," was proposed as a potential pandemic prevention strategy. An Internet of Things (IoT) node can do intelligent face mask detection in real-time thanks to the system's multi-level high-speed augmented CNN. In addition, it connects to a fog cloud, where vital signs, such as non-contact thermometers and blood oxygen saturation readings, can be seen and adjusted. An MLHS-CNN-based method ensures correct mask use, while a fog server's real-time RNN tracks the health of each user and the disease's propagation. When it comes to cloud-hosted IoT fog, data analysis and diagnosis are made possible by deep learning technologies. In comparison to the state-of-the-art, it fared better on tests measuring accuracy, precision, memory efficiency, and computational complexity.

Attempts to foretell the onset of paralysis, numbness, blindness, mental confusion, and speech and motor impairments as well as the risk of abrupt death were made in [6]. Although mobile health research has the potential to save lives in emergency situations, it has not yet reached an advanced enough level to utilize distant intelligence for stroke detection. Another suggestion made in this article to improve stroke detection and prediction is to include a Hybrid Intelligent remote diagnostic tool in health applications for smartphones. When training neural networks, hybrid methods use a mix of deep learning approaches, such as Sparse Auto-Encoders and the Group Method of Data Handling (GMDH).

LITERATURE REVIEW

Machine Learning Applications

To begin developing a machine learning solution, one must first identify an appropriate challenge to address using ML. The healthcare industry has a treasure trove of information.

It is not enough for a model to just generate understanding; it must also be able to influence patient treatment in some way. Listed below are a few examples of applications that make use of the productive model in this section.

Medical Imaging

Medical imaging—the practice of creating pictures of human anatomy for the goals of diagnosis and treatment—is one area where machine learning finds use. Two examples of imaging techniques utilized currently are magnetic resonance imaging (MRI) and X-ray radiology.

The standard procedure now involves collecting these pictures and then having a medical expert manually review them for anomalies. Not only is it tedious, but it also has a high error rate. Consequently, disease prediction, detection, and diagnosis are made more accurate and faster with the use of machine learning algorithms [7]. Medical imaging can benefit from machine learning methods, such as artificial neural networks (ANN), according to researchers. ANNs can help with disease prediction, diagnosis, and detection through the use of computers. Medical imaging relies heavily on image and video processing, a field that has benefited greatly from the advent of deep learning techniques, particularly convolutional neural networks (CNNs) [8]. The majority of medical imaging applications rely on images as its input data [9]. This includes X-rays and CT scans. Commonplace in healthcare facilities, X-ray and CT scanners are instances of IoT devices used in machine learning configurations [10]. The supervised learning approach is typically employed in the field of medical imaging and machine learning.

Diagnosis of Disease

The diagnosis of a disease is an essential part of providing care since it dictates the course of action to take. Because it allows for the analysis of physiological and environmental aspects, machine learning is useful for disease diagnosis. Models connecting variables to an illness can be created using this method. To put it plainly, machine learning can help doctors find symptoms and risk factors faster and more accurately, which could lead to better diagnoses. Machine learning has greatly improved the accuracy of diagnosing glaucoma, age-related macular degeneration, and other eye illnesses [11]. Support vector machines, backpropagation networks, convolutional neural networks, and deep learning systems are some of the ML methods deployed in illness diagnosis [12].

A variety of input data types are necessary for various diseases. Use of image data is common in most machine learning initiatives pertaining to imaging diagnostics. Additionally, time series data is utilized in the diagnosis of chronic diseases. This data comprises patient monitoring, demographics, gene expression, symptoms, and similar information. [13]. Medical diagnostic machine learning (ML) can find patterns in patient data using supervised or unsupervised learning approaches. Which Internet of Things (IoT) gadgets and sensors are employed is dependent on the required input data. Scanning devices are the main IoT devices used for imaging-based diagnosis. Vital indicators, such as weight, heart rate, and blood pressure, can also be collected by Internet of Things (IoT) sensors to aid in the diagnosis of illness.

Behavioural Modification or Treatment

Helping a patient alter negative habits is what behavioural modification is all about. Treatments for patients whose behaviors are causing or exacerbating their health problems generally include behavioral modification. Due to the Internet of Things (IoT), which collects massive amounts of data on people, machine learning can be applied to influence their behavior. Consequently, people's conduct can be analyzed and appropriate modifications suggested by machine learning algorithms. Aside from notifying and alerting individuals to change, machine learning algorithms may teach people about themselves and suggest tools to help them alter their behavior. Finding the best effective behavioral change therapy for a specific patient is one of many uses for machine learning [14]. Implementing machine learning techniques, such as support vector machines (SVMs), decision trees, and Bayes networks, leads to enhanced behavior.

These methods take feature extraction tabular data as input. There is a great need for Internet of Things (IoT) devices that record voice, video, and still images with the purpose of characterizing human behavior.

Clinical Trial Research

Research evaluating the efficacy and safety of potential medicinal, surgical, or behavioral therapies is known as a clinical trial. Clinical trials, which are the last stage of research, sometimes involve human people and must be conducted with the highest level of care to guarantee their safety. By analyzing health record data, publicly available biological and clinical statistics, and empirical evidence from sensors, clinical trials can be run more efficiently with the use of machine learning [15].

Medical practitioners can now use machine learning algorithms to sift through mountains of data in search of answers about an intervention's efficacy and safety. One area where ML has the potential to make a difference is in clinical trials aimed at developing COVID-19 medicines. When doing research using ML learning algorithms for clinical trials, feature extraction from datasets is the first step. Images and tables pertaining to the clinical trial are thus included in the input data. It is imperative that the used Internet of Things devices can gather data pertaining to the clinical experiment's components. Weight, heart rate, blood sugar, and blood pressure are examples of typical vital signs data gathered by sensors.

Smart Electronic Health Records

Electronic health records have made it possible for medical professionals to gain immediate access to patient records, enhancing the quality of care that patients receive.

Machine learning provides a means of incorporating intelligence into EHRs. Put another way, EHRs can do more than just store patient information; machine learning can give them smart features. For instance, intelligent EHRs can evaluate patient information, suggest the best course of therapy, and facilitate clinical decision-making. Actually, ophthalmology has been proven to benefit from integrating machine learning with electronic health records [16]. Smart computerized records can also sift through mountains of data to find out how safe and high-quality a facility's care is and where it falls short. Many different types of machine learning models can be integrated into EHRs. These include SVMs, ANNs, logistic and linear regression, and many more. You can enter everything from text to images to tables to time series. Predicting postpartum depression using patient medical record information is one use of time series data [17]. Recurrent deep learning architectures show accurate disease prediction when coupled with electronic records. These machine learning models use data from a variety of sources, including sensors connected to the internet of things (IoT). These sensors are able to assess vital signs like as temperature, blood glucose, heart rate, blood pressure, and weight. Incorporating sensor data that represents symptoms of the ailment or disease under consideration is the basic principle.

Epidemic Outbreak Prediction

Emerging illnesses, especially those that spread quickly, pose a significant threat to communities and are notoriously difficult to contain. As a result, many involved in healthcare recognize the significance of creating plans and tools to foresee and mitigate the effects of epidemics. With the availability of big data, healthcare workers, administrators, and regulators can employ machine learning algorithms to predict the spread of epidemics. Disease prediction makes use of machine learning technologies like LSTM and deep neural networks (DNN) [18]. Text, numbers, time series, and category information are just some of the many data types that machine learning algorithms can be fed. Future disease trends can be predicted using time series data in machine learning. Machine learning algorithms take into account a variety of variables for making illness predictions, including vaccination rates, clinical case classifications, hotspots, population density, and geographic mapping. Hence, Internet of Things devices like drones and satellites could be used to measure population density and other geographical factors. The possibility of epidemics can be predicted by gathering data on weather patterns and other environmental variables. Also helpful are clinical data collected at the patient level, such as vital signs, blood pressure, and glucose levels. In order to prevent epidemics and ensure that stakeholders are prepared for them, disease surveillance is obviously very important.

Heart Disease Prediction

Cardiovascular disease is one of the leading causes of death in many parts of the world. Changes in lifestyle are one of several risk factors contributing to the global increase in the incidence of cardiovascular disease. The global death toll from cardiovascular diseases reached 17.6 million in 2016, marking a 14.5% rise from 2006 levels [58]. Being able to anticipate the onset of heart disease and then implement preventative and therapeutic measures is a crucial component of heart disease management. Machine learning has allowed medical professionals to analyze patient records and predict the onset of cardiac disease [19]. Interventions can be suggested to patients who are determined to have a high risk of cardiovascular disease in order to reduce that risk. Images, time series, text, and tabular data are just some of the formats that machine learning algorithms for cardiac disease prediction can accept. The occurrence of cardiac disease can be predicted using tabular data and methods such as Naive Bayes, K-NN, SVM, decision trees, and decision tables [20]. The data that should be input into the system from the Internet of Things sensors should concentrate on the risk factors for heart disease. Consequently, trackers for vitals like weight, HR, BP, and activity levels are a must-have.

RESEARCH METHODOLOGY

The World Health Organization reports that among adults, 2.6 million died from obesity-related causes, 4.9 million from lung cancer, 4.4 million from high cholesterol, and 7.1 million from hypertension. For individuals whose health concerns require regular doctor's visits, an Internet of Things (IoT) patient monitoring system can be convenient. The fundamental idea behind the Internet of Things (IoT) is the integration of technological devices that communicate with medical professionals or those responsible for health monitoring. The proposed setup comprised a nodeMCU, an electrocardiogram (ECG) simulator, and a Raspberry Pi. Furthermore, with the help of a Raspberry-pi and a WiFi access point, the acquired data or parameters are displayed on the cloud, allowing experts or doctors to access them instantly. Beginning with the first electrodes, the controller gets the QRS parameters. Specifically, an ECG signal is processed and sent to ThingSpeak by means of a Raspberry-pi, which acts as the controller in this case. Wireless data transmission from Raspberry-pi devices is received by the ThingSpeak cloud, an open IoT platform.

MATLAB analytics help doctors and professionals see the data, and then they make a choice based on it. The nurse or family member can also use the LIVE monitoring feature to assess the patient's vitals in an emergency, and various machine learning algorithms can tell the difference between a normal and abnormal electrocardiogram. Following that, we investigated the feasibility of illness prediction using data that was already available for a subset of disorders. Even for disorders we didn't work on, the model we developed to distinguish between normal and abnormal ECGs and forecast their outcomes can be applied. On top of that, we wanted to determine which algorithm is most effective in disease prediction. We determined the accuracy level of several algorithms and examined the outcomes that our model predicted. Half to three quarters of all electrocardiograms (ECGs) show the traditional cardiac cycle components: the P wave, QRS complex, T wave, and U wave. Following the T wave (or, in certain instances, the U wave) and before the subsequent P wave is the baseline, which is indicated by the flat portions of the electrocardiogram trace.

The baseline is nearly equal to the isoelectric in a healthy, normal heart. Three main pieces of embedded electronics make up the system: the NodeMCU, the AD8232 ECG Sensor Module, and the Raspberry Pi 4 Model B. Adaptable and user-friendly hardware and software form the basis of NodeMCU, an open-source electronics prototyping platform (Figure 1). You may find open source prototype board designs for the NodeMCU firmware on the internet.

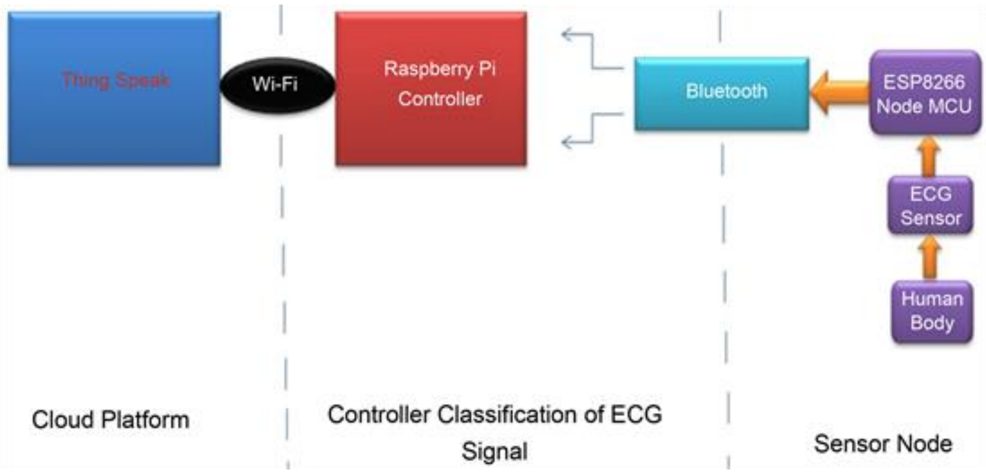

Figure 1: Block hardware implementation.

The ESP-12E module, featured on the development board, is equipped with an ESP8266 chip. This device contains a 32-bit LX106 RISC microprocessor from Tensilica Xtensa®. It supports real-time operating systems and works at a clock frequency configurable between 80 and 160 MHz. A 9-volt battery is utilized in this setup. The ECG sensor and the ESP8266 NodeMCU are powered by 3.3 volts. A voltage of 5 volts powers the Bluetooth module. Since Raspberry Pi is the central control unit, connecting it to the power source is the first step in getting the system up and running. The ECG sensor and a few manual buttons make up the input side of this device. However, both the ThingSpeak online platform and the serial plotter in the Arduino IDE display the output. When used with a

Raspberry Pi and WiFi, the NodeMCU and Bluetooth Module allow for data transmission. After the Raspberry Pi uploads the ECG analogue data to the cloud, we may access it from any computer or laptop by logging into the server. After the patient has inserted the three ECG pads into their body, the data is communicated over the WiFi capabilities of the Raspberry Pi, the NodeMCU, and the Bluetooth Module. After that, the ThingSpeak cloud platform and the serial plotter in the Arduino IDE show the ECG curve. The block diagram in Figure 2 shows the hardware method.

Proposed Security Model and Framework

In order to examine ECG data, we have independently used four algorithms: Decision Tree, Nearest Neighbor, Naive Bayes, and Support Vector Machine (SVM).

Decision Tree

It is a supervised learning method that is commonly used to solve problems with classification. It is applicable to both continuous and categorical input and output variables. The model derives its fundamental decision rules from the characteristics of its data before predicting the value of a target variable.

To rephrase, the method involves selecting the most important input variable differentiator and then using that information to split the sample or population into two or more similar groups.

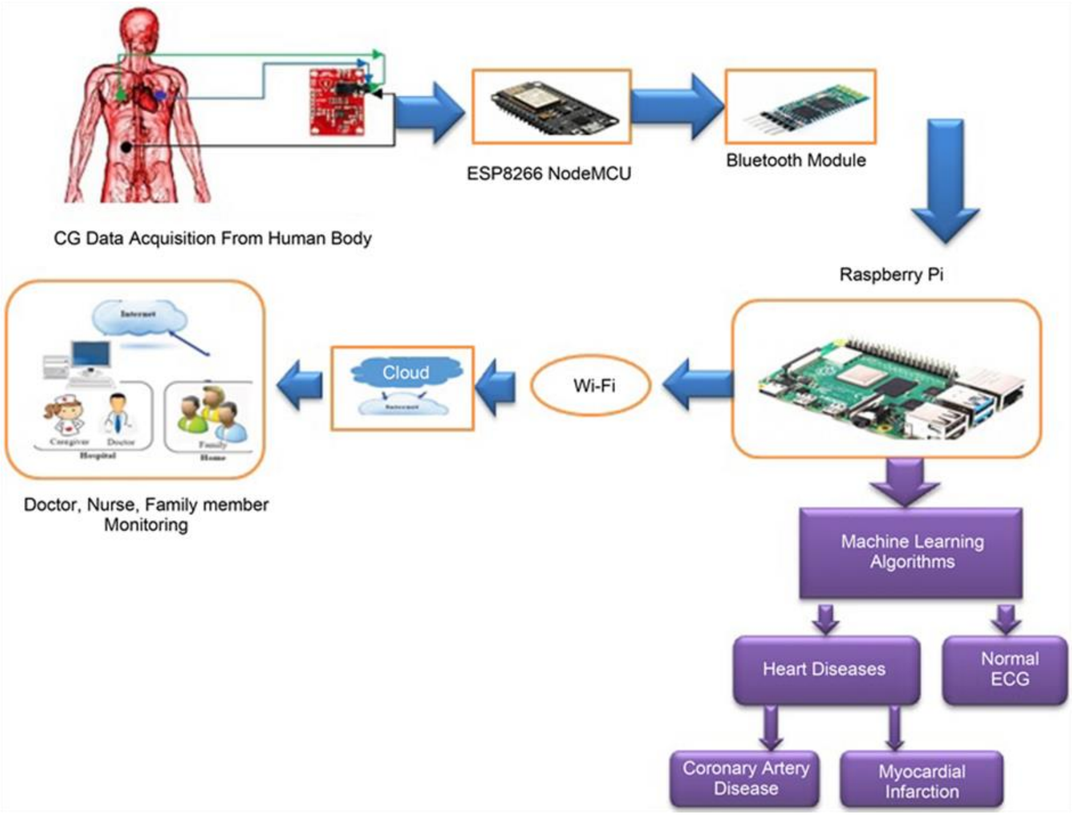

Figure 2: Proposed system model.

Nearest Neighbor

The method relies on storing instances of the training data, similar to instance-based learning. Put simply, it uses a collection of training examples to determine how far away the new point is from the preset number of training samples, and then uses that information to forecast the label.

Naive Bayes

It is a method for training and classifying data with multivariate Bernoulli distributions. For linear classification, it works well. Even though there might be more than one characteristic, we'll treat them all as if they were binary variables. Consequently, the algorithm's decision rule relies on, and samples in this class must be represented as feature vectors with binary values.

Support Vector Machine (SVM)

Classification, regression, and outlier identification are all part of this supervised learning set. In order to classify new samples using labelled training data, the system produces an ideal hyper plane. To accomplish classification tasks, it builds hyper planes in a three-dimensional space to divide instances with various labels into their respective classes. Within the usual range of 60 to 100 beats per minute (particularly 82 bpm), the heart beats in a regular sinus rhythm. Alterations to the PQRST section can cause various forms of cardiac illness.

RESULTS AND DISCUSSION

The execution of the test bed is illustrated in Figure 3. Additionally, we have verified that the different machine learning techniques work by comparing their results to the dataset stored in the UC Irvine Machine Learning Repository. The results of various machine learning systems' forecasts are shown in Figure 4.

Since Naive Bayes Classifier achieved the best overall score of 94% for CAD prediction, it is clear from looking at Table 1 that it is the ideal method to utilize. Decision Tree Classifier was the most effective in predicting myocardial infarction. We got a 96%. The method achieves a 95% success rate for Sinus Tachycardia, with the exception of Nearest Neighbor. A 95% success rate was likewise achieved by the Decision Tree Classifier when it came to Sinus Bradycardia. Finally, with a score of 96%, Support Vector Machine (SVM) came out on top.

Figure 3: Test-bed scenario.

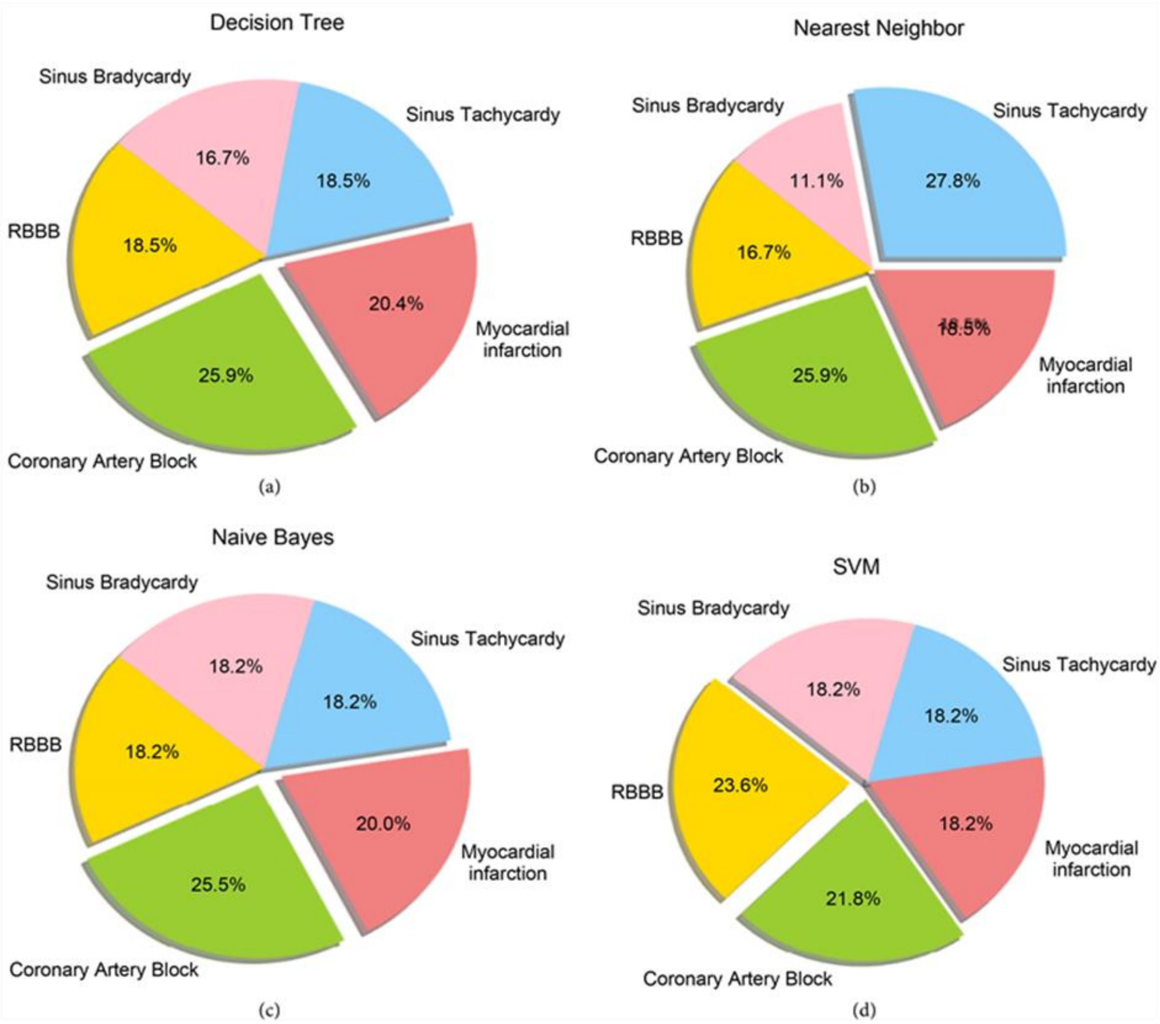

Figure 4: Prediction rate for different Machine learning method.

Table 1: Result analysis.

Disease Name	Algorithm	Accuracy
Right Bundle Branch Block	Support Vector Machine (SVM)	96%
Myocardial Infarction	Decision Tree	96%
Sinus Tachycardia	Nearest Neighbour	95%
Sinus Bradycardia	Decision Tree	95%
CAD	Naive Bayes	94%

CONCLUSION

This research presents an Internet of Things (IoT)-based healthcare platform that may be used for everyday checkups by connecting to smart sensors worn by individuals. This study paves the way for real-time patient monitoring through the use of the open-source ThingSpeak cloud platform, which can detect normal and irregular heartbeats using machine learning. The platform also includes a remote monitor and a mobile SMS service. The optimal algorithm for disease prediction was also identified. Results demonstrate that SVM and Decision Tree perform better than other methods, even though machine learning methods are helpful in detecting heart illness.

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