

Smart Heart Rate, Oxygen Level and Temperature values Monitoring with Things peak

Inampudi Lipi

Velagapudi Ramakrishna Siddhartha Engineering College, lipi.edu01@gmail.com

Dr. S. Ramesh

*Velagapudi Ramakrishna Siddhartha Engineering College,
rameshsekarana@vrsiddhartha.ac.in*

Krishna PreethamBhavarisetty

Velagapudi Ramakrishna Siddhartha Engineering College, preethamk.967@gmail.com

Sharmila Golla

Velagapudi Ramakrishna Siddhartha Engineering College, sharmilagolla28@gmail.com

Abstract

The failure to recognize heart-related problems early enough is the primary cause of a large percentage of fatalities owing to cardiac damage. Early diagnosis and management of cardiac diseases are always aided by continuous monitoring and early prediction. Here, we intend to obtain a method for continuously monitoring and forecasting the subject's heart rate, oxygen level, and temperature values gathered from sensors, with their Internet-Of-Things capabilities via Thingspeak platform. The subject is equipped with the MAX30102, a commercial photometric biosensing module, and the LM25 temperature sensor which comprise the ability to gather heartbeat, spo2 and temperature values respectively. This project also makes use of incumbent components to analyze and convey the collected data to a cloud database. The acquired data is transferred to the Thingspeak cloud database where the values can be stored, monitored with access from anywhere, manipulated and inspected using MATLAB facilities. This work suggests using a Convolution Neural Network [CNN] based model for diagnosing atypical heart rate to predict illness risk using unstructured time-series data. By adding this smart system to the health service, we can provide better medical treatment, and lower diagnostic costs in healthcare.

Keywords: *Internet of Things, Convolutional neural network, Cardiac diseases, Deep Learning, Thingspeak, Cloud database.*

1 INTRODUCTION

In many countries, heart failure and cardiovascular disorders are among the leading causes of mortality, accounting for more than 15 million fatalities worldwide. In our day-to-day lifestyle, healthcare is fundamental. Various curing equipment including MRI, PET, CT, and others may quickly identify problems present within our

bodies or beneath the skin. Furthermore, many disorders such as heart attack and heat stroke can be readily avoided in their early stages. It is imperative to alleviate the strain on healthcare systems in order to maintain the quality of treatments offered at the highest possible level. The healthcare system is currently experiencing a cultural transformation from a conventional to a modernised approach.

Healthcare professionals play a vital role in the traditional approach. Patients must be examined for appropriate analysis and advice. This method has two major flaws. First and foremost, medical staff must always be present with the patient. Second, the patient is assumed to be in a hospital and is connected to medical equipment for an extended length of time. People should be able to access quality healthcare services at any time and from any location, and it should be cost-effective and user-friendly.

The “Internet of Things (IoT), cloud computing, and Artificial Intelligence (AI)” have all recently advanced, transforming the traditional healthcare system into smart healthcare. The widespread adoption and deployment of well-integrated hardware like contemporary medical sensors for specialised healthcare has resulted in the development of a new concept known as the “Internet of Medical Things (IOMT)”. It improves the healthcare facilities and the variety of IoT-enabled medical devices in order to maximize profits in the future. The research may follow a user's behaviour using data collected with the use of portable, ingestible, and included sensors, mobility patterns, and gadget usage patterns. Using state-of-the-art Machine Learning[ML] or Deep Learning[DL]-based approaches, it is feasible to expose their medical status with additional data collecting. However, if a person is in a critical condition with limited resources and requires a high level of efficiency and accessibility, a disconnection from the main network or a latency difference might have a significant negative impact and result in horrible repercussions in an emergency. As a result, by establishing scalable medical domain services, the above-mentioned methodologies could yield challenging consequences. Both diagnosis and ailment treatment are very robust when AI models, surgical gadgets, and mixed

reality apps are used. Furthermore, when compared to well-trained clinicians, such as pathologists and imaging experts, ML-based models are more accurate. The objective is to use AI and IoT converging approaches to create a disease diagnosis model for heart diseases.

Here, an IoT based health monitoring system is proposed and designed. The suggested IoT system delivers the s' heart rate values, oxygen levels, and temperature to a cloud service called IoT (Thingspeak). The sensors used are MAX30102 and LM35 temperature sensors. In MAX30102, pulse oximeters, which use photometric methods to determine saturation, are used to monitor SpO2 and HR in clinical settings. In this sense, the device's probe has two light-emitting diodes (LEDs) with wavelengths of 660 and 940 nm, as well as a photodiode. The user's finger acts as an interface between the LEDs and the photodiode, enabling the photodiode's light intensity to change in reaction to the quantity of oxygen in the blood and blood flow via the finger. The photoplethysmogram that results allows for both SpO2 and HR measurements. The temperature is monitored using an LM35 temperature sensor positioned on the breadboard. This sensor has higher memory, processing, and communication capabilities than conventional sensor nodes, which is a benefit. The values are transferred to a cloud database named Thingspeak. ThingSpeak is an open-source IoT platform that includes a central server that gathers, interprets, and analyses information, as well as libraries and APIs that allow IoT devices to communicate with one another. The “open-source central server” is available in both free and premium versions and may be hosted locally or in the cloud. ThingSpeak distinguishes out for its extremely user-friendly data handling and exhibition environment, thanks to Matlab's cloud deployment support,

which provides visual output and a variety of toolboxes. The platform supports a wide range of devices and all major IoT hardware platforms, by allowing web APIs that use both HTTP and MQTT communication protocols. The data retrieved in the database is employed to CNN [Convolution neural network] algorithm for disease diagnosis. The convolutional network, sometimes known as “CNN or ConvNet”, is a type of “deep neural network”. It's a “feed-forward Artificial neural network[ANN]” which is a DL system that can input and assign value (learnable weights and biases) to multiple input objects, as well as differentiate between them. The level of pre-processing demanded by a ConvNet is much less than that required by others. We verify the model upon data from real people. We propose employing a convolutional neural network approach to predict illness risk using unstructured patient data. The algorithm comprises mainly the convolution layer and pooling layer where the sensor data is convolved and pooled to obtain values that, when compared to normal human estimates can determine if the person has a normal heart rate or if he might be prone to any heart diseases. The live health data and output are viewed on a Liquid Diode Crystal[LCD] screen which can aid brisk resolution and rapid decision making.

This approach has the potential to be highly effective, supporting physicians in improving diagnostic procedures, lowering the occurrence of underexplored diagnoses and misdiagnoses, and allowing patients to get timely and appropriate medical care. Smart diagnosis can properly characterize a patient's health condition and illness in order to follow a tailored treatment plan. Our model design shows how integrating a smart diagnostic system into the healthcare system may lead to the development of better investigative tools, enhanced medical care, and decreased

diagnostic costs. Our architecture is simple in design, elegant in concept, sophisticated in training schedule, effective in outcome with far-reaching applicability in problems with unbalanced datasets and offers moderate resilience to data imbalance. Traditional cloud technology, which depends on the foundation for data storage and manipulation, is utilised to offer good performance, scalability, as well as in delay-based IoT domains.

2 Literature Study

Researchers have spent the last few years developing numerous models to diagnose a person's cardiac problems. If we take a broad view of the area, we may identify the issues that need to be addressed in the instance of heart disease. Many people offered their expertise and experimentation to help solve these difficulties. We've gone through some of the current options in this section.

Dr.A.A.Gurjar [2] suggested a framework in which the heart rate is monitored and the site of the heart attack is reported. The sensor is connected to a microcontroller, which allows it to read pulses and communicate them over the Internet. The user may control the heartbeat's fluctuation limitations. Later on, monitoring occurs to see whether the heartbeats are going too fast or too slow. The transmitting circuit is utilised with the patient, while the other circuit is used with authorised employees. The current pulse rate is determined by a heartbeat sensor and shown on the LCD panel. This proposed method can be utilised in any location with no restrictions. There is no requirement to use the gadget at home.

Poornima Singh [3] suggested a “neural network-based cardiac disease prediction system”. For prediction, the suggested technique took into account 15 characteristics. A multilayer perceptual neural network with

“backpropagation” was employed in the training model. The structured data was used as the dataset, and the model was able to achieve 100% accuracy.

Amin [7] presented a hybrid system based on a genetic algorithm and an “artificial neural network”. Based on the risk factor, this approach forecasts heart disease. They used backpropagation to train ANN in the same way they had previously trained it. They primarily emphasize the backpropagation algorithm's two fundamental drawbacks. The first is that determining the initial weights that are globally optimal is very difficult. Second, in terms of convergence, backpropagation is sluggish. They used a genetic approach to optimize the weights of ANN to handle these problems, and the results were better than basic ANN. On the training set, they were 96.2 percent accurate, and on the testing set, they were 89 percent accurate. The precision is perfect.

Mehmet Tastan [8] designed a mobile system that operates wirelessly to offer “patient monitoring” utilizing sensors to continuously measure the patient's state, which solved the real-time patient monitoring problem. They achieve this by taking measurements of “Heart Rate Variability”, and “Body Temperature”. The smartphone application notifies the patient and those nearby when the patient's vital data hits a predefined limit value. However, this technology can only detect the immediate hazard that the patient may experience, and it does not provide any indication of future threats.

Bashir [10] suggested a “Decision Tree, Support Vector Machine, and Naive Bayes hybrid machine learning model”. To arrive at the majority voting technique, they employed three distinct classifiers. This method operates in two stages. In the first stage, three classifiers

each make their own choice. These decisions are pooled in the second stage to create a new model based on the majority voting technique. This model's accuracy is higher than that of earlier models. The results show a sensitivity of 74%, an accuracy of 82%, and a specificity of 93% for heart disease prediction.

Gomathi [13] employed Naive Bayes and decision tree algorithms for forecasting different sorts of diseases. They primarily focused on heart disease, diabetes, and breast cancer prediction. The confusion measures were used to get the results.

In [15], the researchers created a low-cost patient monitoring system with the goal of diminishing health-related expenditures by lowering the emergency room and physician office visits and testing procedures. Many new “wireless transmission protocols and technologies” are easily adaptable to new uses. A “Max232, 555 timer, GSM module, health care sensors, and an AT89S52 microprocessor” were used in their system.

The researcher provided an assessment of IoT-based “Patient Health Monitoring Systems” in [16]. For health monitoring systems, this reference offers a variety of technologies and IoT applications. The technologies were explained and analysed, as well as applications, methodologies, and implementation for the health monitoring system procedure in the medical industry.

3 Materials and Methodology

3.1 Thingspeak: A IoT web Service

Thingspeak is a “web-based open API IoT source platform” that can gather sensor data from a wide range of “IoT devices” and present it in graphical format on the internet. Thingspeak communicates with the “host microcontroller” through an internet

connection that serves as a “datacarrier” between the associated “things” and the Thingspeak cloud, which obtains, stores, assesses, monitors, and interacts with the collected data from the connected sensors. One of the principal elements of the database used is ‘Channel’ which contains fields for the data, time, labels and status for variety of sensed information. The data may be analysed, processed and visualised using MATLAB, and it can be replied to with many forms of alerts after the channels have been built in ‘Thingspeak.’ The ‘Cloud’ employs a variety of operational processes, one being availability to users in the form of a virtual server, and communication between the objects and the cloud via conceivable internet connections accessible to the users, with the large percentage of objects employing sensors and actuators to provide us with health analogue data. The platform helps to link it all and enables us to communicate and view data with our own gadgets as well as engage with other ‘things’ with access.

3.2 ESP8266: Wi-Fi Module for IOT Service

The “ESP8266” furnishes an absolute and self-contained Wi-Fi networking solution, permitting it to either host or delegate all Wi-Fi networking functions to a separate application mainframe. Because the ESP8266 is the sole “application processor” in the device, it boots up right away from an external flash when it hosts the function. It has an integrated “cache” to improve the system's operation. Alternatively, wireless internet access may be added to any microcontroller platform design with ease-of-use relatively through the ‘U-A-R-T-interface’. The device's entire functionality is comprised of MAX30102's signal collection from the user's fingertips and a temperature sensor. The SPI protocol was then used to

transfer these signals. The ESP8266 is without a doubt the most well-known Wi-Fi module on the market. It allows customers to host the program or offload all tasks to another application processor, providing a comprehensive and self-contained Wi-Fi networking solution.

3.3 MAX30102 and LM35 sensors

The “MAX30102” is a biosensor module featuring a heart rate monitor and integrated pulse oximetry. The MAX30102 is a complete system solution that simplifies device design. In order to address emergency circumstances in healthcare, continuous monitoring is critical. As a result, we researched using MAX30102, a commercial photometric biosensing module, in conjunction with an ESP “system-on-a-chip” and its internet-of-things capabilities, to continually collect and analyze users' peripheral oxygen levels and heart rate. The “LM35” is an electrical measurement analog temperature sensor with the result in degrees Celsius. The LM35 sensor does not require any further calibration or trimming to reach standard accuracies. In comparison to other linear sensors which are calibrated at 0 Kelvin, the LM35 has the advantage of not requiring a considerable constant voltage to be removed from the output to enable realistic Centigrade scaling. The Wi-Fi module and breadboard are coupled to the sensors Max30102 and LM35 temperature.

3.4 Convolution Neural Networks

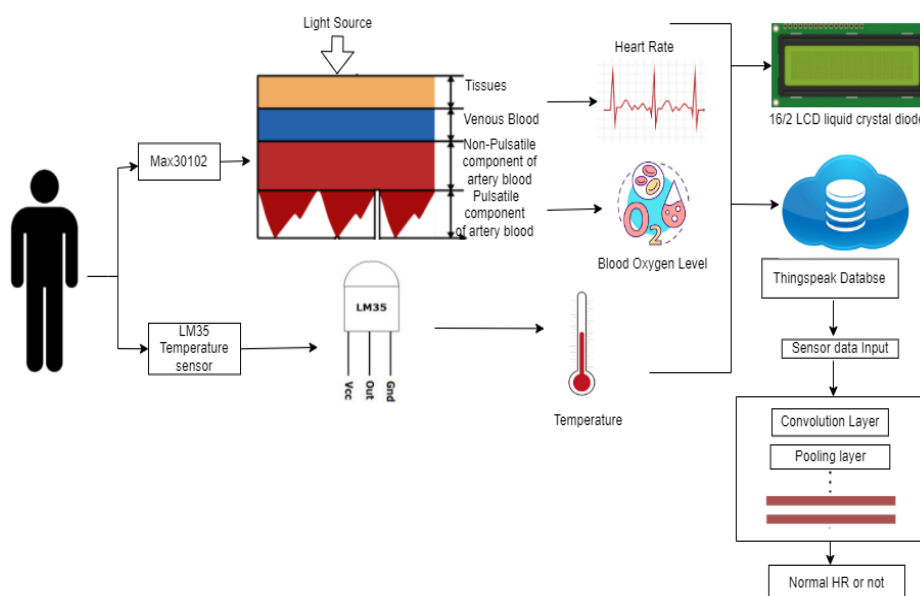
“Convolution neural networks” or CNN are a sort of deep neural network that has spectral layers for learning lower and higher-level information. Although CNN is well-known for image datasets, it may also be applied to time series data and may be more practical. We use real-world medical data to evaluate the prediction model. We propose utilizing this

approach to predict illness risk using temporal and perhaps unstructured subject data which is stored in the cloud database. Because processes are frequently quantified in terms of time, this form of data may be found in practically any activity. Stock prices, industrial operations, electronic medical, human impacts, sensor readings, and language are some examples. The convolutions for 1D data are also available, albeit they are relatively less well-known. As an outcome, CNN may now be used for a wider range of data sources, including textual documents and other time-series data. We utilize 1D convolutions to extract information along the temporal dimension instead of spatial information. Convolution and max-pooling layers compensate for the CNN. In a 1D CNN, the kernel only moves in a single direction. Time series forecasting has developed into a very active and recently growing area of study. In several application sectors, deep neural networks have shown to be effective and are attaining high accuracy[5]. We utilize 1D convolutions to extract information along the temporal dimension instead of spatial information. It is usually applied to Time-Series data which is obligatory in our project. The 1D convolutional layer generates a tensor of output by convolving a convolution kernel with the input layer across a single dimension. In some experiments, In order to enhance the functioning and to stabilise the deep neural network's learning process, batch normalisation was utilised to normalise the input after every convolutional layer and before the pooling layer. The convolutional layer is always succeeded by the pooling layer. For the problem of variability, pooling produces decent outcomes. The maximum filter activation from various points within a specific

window is collected by a max-pooling layer. Fully linked layers, on the other hand, aggregate inputs from all points into a 1-D feature vector.

3.5 Monitoring and Prediction

Live data is acquired using the mentioned sensors (which are linked to the subject's bodies) for monitoring various parameters and then provided as an input to the model in a hardware prototype. This prototype is used to capture human body values, with the MCU being powered through the laptop. The MAX30102 sensor should be put on the ring fingertip and the temperature sensor in the fist. Data logging is carried out. The Analog Channel is used by all of these sensors to deliver their data values. It is assigned to a Digital Value range on the Node MCU. The data is then sent to a processing device (laptop) via the Node MCU ESP8266. The data can be analysed and displayed using MATLAB or Google Collab, and can be replied to with tweets and other forms of alerts after the channels have been built. The data from the cloud server is monitored and if set in public, can be viewed by any personnel. This is beneficial for everyone, especially those who require continuous monitoring or live far away from healthcare facilities. With the availability of MATLAB facilities and the TensorFlow library, we implement Convolution neural networks algorithm for abnormal heart rate prediction. As a result, the person is classed as either having a risk of heart disease or a normal heart rate. The result can be viewed on the Liquid diode crystal screen within a few minutes, conserving time and complexity in providing necessary care.

Fig. 1. Architecture Diagram

The complete working procedure is depicted in Figure 1. The proposed solution is important in terms of communication and consumes less power while allowing users to move about freely. In addition, this strategy makes use of user-friendly IoT devices that are small and light. MAX30102, LM35 sensor, Liquid Crystal Diode [LCD], ESP8266 WiFi module, and other devices. The employed sensors are utilized to implement data accumulation in order to assess and discriminate between normal and abnormal heart rhythms. The subjects are equipped with the sensors which may be carried about also. The implanted MAX30102 and LM35 sensors are highly suggested for collecting data on the subject's cardiac characteristics. The functioning of their similar lifestyle may also be deduced from this data. These devices' functions include collecting signals, digitizing them, compressing them, and transmitting them over IoT. An ambulatory HR and oxygen level analysis using the gadget is faster and less expensive than existing technologies on the market, allowing the individual to be watched at all times. By using the ThingSpeak channel,

the person in charge of monitoring will be able to remotely see the heart rate and its variation over time. ThingSpeak receives data from the hardware devices in contact with the subject. Each channel has its own API key, which may be used in the programming section to access the live sensor data. Furthermore, each channel's data on ThingSpeak may be shared publicly or privately with certain individuals. The channel has been set to private for this system, and only the person in charge of monitoring the values or responsible individuals have access.

Developing a system that predicts cardiac sickness using a deep learning methodology should provide a more accurate diagnosis at a cheaper cost than earlier methods. This study proposes a CNN-based coronary disease forecast model for automated clinical analysis. We propose using CNN to predict illness risk from unstructured subject data. Using the subject's data residing in the cloud database, the technique is used to predict the risk of sickness. It is well known that the CNN algorithm outperforms previous approaches in classification and does not need feature

extraction. It can categorize the raw signals directly removing any human influence. Convolution and pooling layers play the main role in our system. The convolutional layer is always followed by the pooling layer. The pooling layer allows the architecture to tolerate tiny changes in the placements of the object's pieces, resulting in faster convergence. Fully linked layers, on the other hand, aggregate inputs from all points into a 1-D feature vector. Finally, the result regarding the person's heart rate is obtained. The person's live data output is intended to be displayed on a screen, in this instance a 16*2 LCD screen that may be used to see the output in the same way as a conventional screen. The live data collected for analysis can be viewed on the display to determine whether or not a person has a normal heart rate, temperature and oxygen levels at present. Our system is easy to access and affordable for even people living in remote areas without many utilities. Also, for the clinical data obtained, imbalance is an imminent challenge that exists due to the limited availability of data. Any modern clinical classification model suffers from the performance consequences of such data imbalance. Due to biological implausibility of replication of various qualities in the clinical data, one cannot effectively employ standard strategies, such as data augmentation strategy, to address the imbalance problem. By way of experimentation, we establish that CNN exhibits a considerable degree of resilience towards data imbalance, thereby producing accuracy superior to the existing machine learning models.

4 Results and Observations

The suggested IoT health monitoring system is composed of data acquisition, storage, implementation, monitoring, and prediction. The experiments were carried out on

the obtained real-time data. The prototyped system has the desired dimensions, allowing the ESP8266 and MAX30102 sensing modules to be correctly housed. In addition, pulse oximetry and heart rate measurements were taken and compared to a conventional pulse oximeter and heartbeat, which resulted in analogous values. Python modules and libraries like Scikit Learn, matplotlib, and TensorFlow were used in the software environment which is used for application and visualization purposes. The MAX30102 commercial photometric biosensing module and the LM35 temperature sensor, as well as their IoT capabilities, were used to continually acquire and process SpO2, heartrate, and temperature from users in this project.

Fig. 2. Live values view



Fig. 3. Live values view

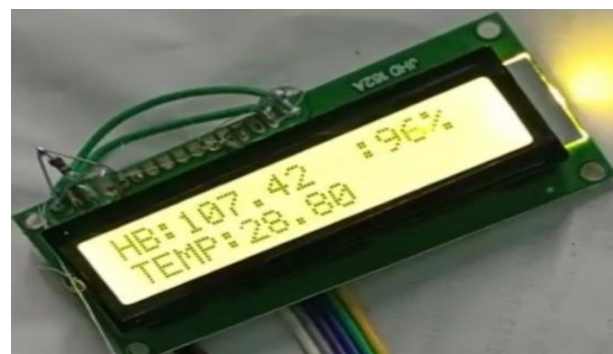
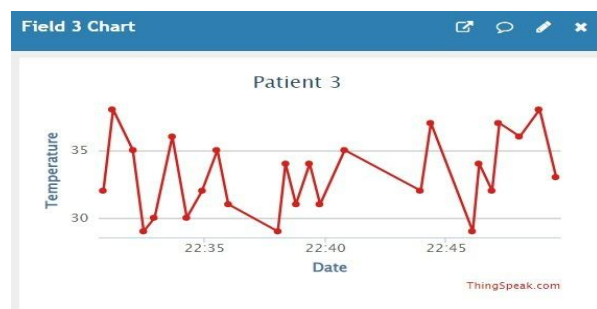
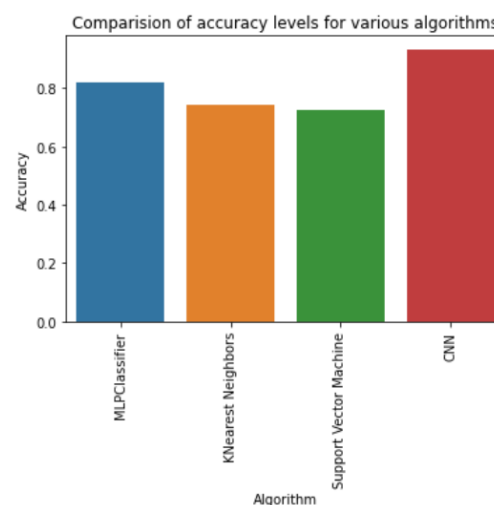


Fig. 4. Heart rate in BPM in database

The system was found to work consistently and in accordance with literature detailing photometric sensor operation, revealing light on the utilization of basic and inexpensive electronics in the development of biosensing medical devices. Due to the restricted availability of data, there is an impending dilemma of unbalanced clinical data. The Convolution neural networks technique compensates for this data imbalance, which has a negative impact on the performance of any state-of-the-art machine learning model.

Fig. 5. Oxygen levels in database**Fig. 6. Temperature in Celcius in database**

The 1D Convolution neural network we incorporated into the system, mainly utilised for time series data, like ours, yields an output to distinguish between the normal or abnormal heart rate. We emphasize a real-time medical comparison with the subject's pre-existing health state in this scenario. The balanced accuracy of our model (86.5%) is also better than individual accuracies of SVM, MLP and KNN. The CNN classifier results in high specificity and test accuracy along with high values of recall. The results were precise since the generated output determined the person's current state of heart health. This method helps in early disease prediction, time conservation, reducing hospital visits, and provides an edge financially also. Besides, continuous monitoring through any device of the concerned party can also help in keeping an eye on the health data from wherever and whenever personally and make quick relevant actions.

Fig. 7. Comparison of accuracies

5 Conclusion

If the early symptoms of irregular functioning of the heart are ignored, the patient may suffer severe consequences in little time limit. The number of people with cardiovascular breakdown has been steadily increasing. The

challenge of predicting the existence of any Coronary Heart Disease[CHD] in people refers to the task of visiting the healthcare provider, getting numerous tests, waiting for hours and wasting precious time and energy. To get out of this perilous condition and reduce the risk of heart failure, a system that can develop rules or categorize data using applicable live methodologies is required. The current research has established an expeditious, portable, and explicit Artificial Intelligence and IoT alignment technique that is expanding rapidly during the present day. Our system proposes a disease diagnostic model for smart healthcare systems for continuous proactive monitoring and also disease diagnosis with less time and effort. It is a sustainable healthcare monitoring system that allows subject's, helpers, and healthcare providers to remotely monitor their patients through the cloud with access. The system will be an effective solution for monitoring a patient's heart health, based on all of the experimental setup and observations. Our solution also focuses on offering a reliable cardiac disease prediction, which can function with live sensor data. As a result, the primary flaw in existing methods for delivering a real-time heart disease prediction system has been addressed. Our project showcases the procedure and implementation of the system which has not yet put to a greater use. The Internet of Things offers the society a variety of advantages, and through our project, we demonstrate the power of IoT by utilising the Thingspeak API and efficient sensors which can provide the services necessary to build a large number of IoT applications and assist in putting them into use on a public platform. The recommended hardware and software solution aids patients in early detection of cardiac disease. It will be beneficial for a mass screening method in communities without hospital facilities, i.e. rural regions. The

monitoring and prediction infrastructure can help save many lives by providing immediate action, especially when the patient is in a distant location with no or few medical services. The Internet of Things provides numerous benefits to humankind as well as the environment, and through our project, we can demonstrate the power of IoT by utilizing the Thingspeak API and machine learning algorithm, which is capable of contributing to the intention of building a large number of applications and assisting in their implementation in the future of the healthcare industry.

Fig. 8. Monitoring through mobile device with access



6 Future Scope

To obtain more efficient conclusions, the futurework will include gathering additional attributes of data by incorporating other sensors which are now unavailable. This technique can also be used to monitor and forecast other illnesses, such as diabetes. More Machine learning algorithms will be used and a wearable device that can function with a wide range of common ailments can be deployed. We plan to create a wireless IoT gadget that can

identify cardiac problems. It makes use of wireless components and a web-based surveillance system. The data will subsequently be collected and converted by a mobile device. In the event of an emergency, the current system frequently triggers a professional alert warning. A GPS tracker will send an alarm to the hospitals notifying them of the person in need of care immediately through the internet. Distance readings to satellites are followed by GPS. To discover the user's location, the system requires the usage of satellites, which determines the target location. The user's latitude and longitudinal placement will be tracked using GPS. This technique may be used to establish the patient's location as well as the addresses of neighbouring hospitals.

Reference

- A. Singh and R. Kumar, "Heart Disease Prediction Using Machine Learning Algorithms," 2020 International Conference on Electrical and Electronics Engineering (ICE3), 2020, pp. 452-457, doi: 10.1109/ICE348803.2020.9122958.
- Dr.A.A.Gurjar, Neha.A.Sarnaik, "Heart Attack Detection By Heartbeat Sensing using Internet of Things", 2018,IRJET,p-ISSN: 2395-0072
- Singh P, Singh S, Pandi-Jain GS. "Effective heart disease pre-diction system using data mining techniques." Int J Nanomed. 2018;13(T-NANO 2014 Abstracts):121–4.
- Jose F.Torres, Dalil Hadjout, Abderrazak Sebaa, Franciso Martinez-Alvarez, and Alicia Troncoso, "Deep learning for Time Series Forecasting: A survey", 5 Feb 2021, Big Data Vol 9 Issue 1, doi: https://doi.org/10.1089/big.2020.0159.
- R. K. Lenka, A. K. Rath, Z. Tan, S. Sharma, D. Puthal, N. Simha, M. Prasad, R. Raja, and S. S. Tripathi, "Building scalable cyber-physical social networking infrastructure using iot and low power sensors," IEEE Access, vol. 6, pp. 30 162–30 173, 2018.
- VirenViraj Shankar, Varun Kumar, Umesh Devagade, Vinay Karanth, , K. Rohitaksha, "Heart Disease Prediction Using CNN Algorithm", © Springer Nature Singapore Pte Ltd 2020, /doi.org/10.1007/s42979-020-0097-6
- S. U. Amin, K. Agarwal, and R. Beg, "Genetic neural network based data mining in prediction of heart disease using risk factors," in Information & Communication Technologies (ICT), 2013 IEEE Conference on, 2013, pp. 1227-1231
- M. Tastan, "Iot based wearable smart health monitoring system," Celal Bayar University Journal of Science, vol. 14, no. 3, pp. 343–350, 2018.
- A. Erdoğan and S. Güney, "Heart Disease Prediction by Using Machine Learning Algorithms," 2020 28th Signal Processing and Communications Applications Conference (SIU), 2020, pp. 1-4, doi: 10.1109/SIU49456.2020.9302468.
- Bashir, U. Qamar, and M. Y. Javed, "An ensemble based decision support framework for intelligent heart disease diagnosis," in Information Society (i-Society), 2014 International Conference on, 2014, pp. 259-264.
- M. S. Amin, Y. K. Chiam, K. D. Varathan, "Identification of significant features and data mining techniques in predicting heart disease," Telematics Inform., vol. 36, pp
- Aanshi Gupta, Shubham Yadav, Shaik Shahid,Venkanna U, "HeartCare: IoT based heart disease prediction system" SPM-IIIT Naya Raipur, India, 019 International Conference on Information Technology (ICIT).

- Gomathi K, ShanmugaPriyaa D. “Multi disease prediction using data mining techniques”, Int J Syst Softw Eng. 2016;4(2):12–4.
- Sangeeta, B.; Laxmi, S. A Real Time Analysis of PPG Signal for Measurement of SpO2 and Pulse Rate. Int. J. Comput. Appl. 2011, 36, 45–50.
- Purnima, Neetu Rout, Rahul Tiwary , and Renuka Bhandari, " ZIGBEE and GSM Based Patient Health Monitoring System ", International Journal of advanced Research in Electrical, Electronics and Instrumentation Engineering (ISSN (Online): 2278 – 8875), Vol. 3, Issue 1, 2014.
- Monika Gandhi, Shailendra Narayan Singh, "Predictions in heart disease using techniques of data mining", In 2015 International Conference on Futuristic Trends on Computational Analysis and Knowledge Management (ABLAZE), pp. 520- 525, IEEE 2015.