Remote Patient Monitoring System with Conv1D Classification

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***Abstract*—IoT has been a vital topic that is almost present in all the major sectors and has many varied applications in the healthcare sector. Remote patient monitoring (RPM) is an essential application of IoT in the medical industry that focuses on developing patient-centric health systems. RPM constitutes evaluating the patient's health parameters using sensors, and make it remotely available to the doctor by storing it on the cloud. This paper focuses on remote ECG monitoring of the patient and proposes a remote ECG monitoring system with predictive capability. In the proposed system, ECG data is collected using a micro-controller and sensor and transmitted to the cloud over the MQTT protocol. MQTT is a lightweight and secure data transfer protocol that sends the data from sensors to the cloud using the publisher-subscriber model. Storing the data over the cloud makes patient records' available at the doctor's fingertips. The hardware module can accommodate GPS and GSM modules to make it easier to contact or locate the patient's during emergencies. Here the emergencies can be notified to the doctor by sending an alert message to the cellphone. These alerts are generated using a Conv1D ECG classification model. The model is trained on pre-processed MIT-BIH Arrhythmia Dataset and achieves and achieves an accuracy of 95.21 percent. The model can classify a heartbeat into either of the five categories defined in the pre-processed dataset and can be used to classify the ECG readings incoming to the cloud. These predictions made by the model on real-time data can help in the early diagnosis of heart disease and can be advantageous for cardiac patients. The proposed model can also be extended by incorporating additional sensors to evaluate the patient's pressure, oxygen, temperature, and glucose or other e-health parameters, making it a versatile and secure ECG measuring device.**

***Index Terms*—MQTT Protocol, RPG, ECG, Holter Meter, Conv1D, Data Analytics**

I. Introduction

The Internet of Things (IoT) refers to connecting various devices using the Internet to complete specific tasks and using the Internet to enable communication between the two connecting devices. According to the formal definition, the Internet of Things basically refers to the interconnection between computers, machines, etc., using the Internet for exchanging the data using sensors for real-time monitoring, tracking and managing the data [8]. The Internet of Things is involved with all the sectors, be it environment, health and safety, education, smart appliances, automation, etc. Also, during this pandemic situation, it is required to use e-health and increase the usage of IoT in the health sector. Governments are leveraging more and more funds for research and innovation in the medical in many countries, such that there are lower chances of loopholes while treating people's health. As there are a lot of people and a lower number of medical staff, also medical hospitals these days have become so much costly for even a small routine checkup. There has been a steep increase in the number of regular checkups for older people. This case would not work in case of situations like global pandemics such as COVID-19. Thus, there is an urgent need to enhance Remote Patient Monitoring (RPM), where doctors can evaluate the patient's condition from a remote location. This would also make it easier to get opinions from an expert sitting in some other country. RPG has really been easy to implement by involving IoT in medicine these days. A lot of research and innovations have been going on across the world to make it easier for people to get operated from a distant location. This is highly useful for the elderly population all over the world, as they do not have to visit hospitals every now and then. This helps them to stay away from the virus infection during the circumstances like COVID-19 as well as their reports get evaluated for the best opinion from the best physician. RPM mainly refers to evaluating the patient's health parameters online. This is possible by using various health-related sensors such as blood pressure sensors, oxygen sensors, heart rate sensors, etc. This enables continuous evaluation of the parameters from the patient's body until and unless the patient gets rid of the measuring device. This data collected from the sensors are stored in the cloud, where the doctors can successfully view all the related e-health parameters. The doctors can also suggest changes regarding the medicines if there are any fluctuations in e-health parameter readings. An alert message can be sent to the physicians in case of any emergency situation. Another significant advantage is the data can be successfully stored for doctors to view past reports and evaluations. Especially, for cardiac patients, RPM is beneficial as they need to keep track of their heart condition. Electrocardiography (ECG) is one of the most powerful tools for health monitoring methods and provides useful diagnosis data about the cardiovascular system [6]. It is used as a powerful indicator to determine heart condition. It has been stated that cardiovascular diseases are the main reasons for deaths all over the globe [9]. Thus, we need to take care of personal health, especially monitor the heart condition after a certain age. In addition to that, the older heart patients need continuous monitoring of the ECG, as they are more prone to such diseases. In the circumstances of a global pandemic like COVID-19, when elderly patients cannot go for regular checkups due to the high-risk factors, continuous ECG monitoring devices prove to be useful. In addition to that, sending the collected heart data to the physicians for evaluations can help crowds all over the globe. Holter monitor is the device that collects the patient's electrocardiography (ECG) data for 24 hours [13]. This device can be used to detect any abnormalities going on in the heart rhythm. This is a portable device that is useful for storing the data continuously over a long time. This data can be analyzed and then sent to the doctors for evaluation and checkups. This device has benefits over the large machines in hospitals, as Holter monitors can evaluate the information for a more significant period. Any defects over time can be easily analyzed and corrected by the doctors as soon as possible. However, there is a critical cost issue when it comes to buying a Holter monitor. The device is itself intact with all the necessary parts; there is no scope of extending the tool by adding more sensors and evaluating more e-health parameters. Thus, in the research paper, we present a low-cost Holtmeter monitor called ECG based RPM (ERPM) that can be made using simple IoT devices such as Arduino Uno, WiFi Module and ECG AD8232. We are also using two IoT platforms, such as Ubidots and ThinkSpeak, for data visualization and storage, and a trained ECG classification for detecting the abnormalities in ECG signals. There is an additional scope where different e-health parameters sensors such as blood pressure sensors, oxygen sensors, temperature sensors, etc. can be combined in the proposed model. So, it is a versatile model and can incorporate several other sensors with little model changes. Additionally, the data transfer in the model would happen using Message Queuing Telemetry Transport (MQTT) protocol such that the data packets can be securely transferred from publisher to subscriber. The Global System for Mobile Communication (GSM) and Global Positioning System (GPS) modules enable accessible communication and locate the patients in case of emergencies. This proposed model has been designed by keeping in mind the cardiac health patient's condition and doctor's reviews on their health condition based on e-health parameter readings. The following section would provide a brief idea about the motivation Behind choosing the topic, after that, Contribution Clarity and Novelty behind the selected topic is described. The following section offers a view about the Literature Review. After which the in-depth Methodology is described. Section nine and ten provides Discussions and evaluations and Challenges faced while implementing the Proposed System is mentioned. After this, the Results, Analysis and Conclusion are described for the related Proposed System.

II. Motivation

The main reason for choosing this topic was the deadly pandemic strike during the Coronavirus breakout when human contact became a dangerous myth. So, IoT is a blessing during this time. For instance, patients in China were operated by an e-hospital. Where robots were implanted as nurses, thus, this is the era of the Internet of Things. Remote Patient Monitoring has been an important concept nowadays. And many countries are adopting such remote health care facilities. They are trying to imbibe more and more IoT facilities in the healthcare sector. One such prototype of the Patient Healthcare Monitoring System has been proposed in this Project, where people (patients and physicians) can virtually monitor their Heartbeats at any time and any place. This does not require a patient to visit a healthcare institute to have their ECG cardiogram. There is an additional provision where patients can send their report to the doctors or their associated healthcare person online. A history is maintained of the records, and doctors can timely monitor their stories. This reduces time, cost and effort for patients as well as doctors.

III. Contribution Clarity and Novelty

According to the existing research, there are numerous ECG measuring models such as Holter monitor that are majorly focused on data collection and storage. Various researchers try to combine a variety of hardware components to efficiently and accurately collect ECG reading from a remote patient. However, no analysis is performed on the medical data that is collected using such devices. With the development in the field of machine learning and deep learning, numerous independent prediction models are built to perform prediction and classification on ECG based data. But there are hardly any researches on prediction models combined with the hardware. Thus, to fill this gap between RPM and Data analytics, we propose a remote ECG monitoring system comprising deep learning classification ability. The proposed system has an added advantage of data collection using IoT based ECG measuring instrument and data classification using a trained Conv1D deep learning model.

we present a low-cost Holtmeter that can be made using We are also using two IoT platforms, such as Ubidots and ThinkSpeak, for data visualization and storage, and a trained ECG classification for detecting the abnormalities in ECG signals.

IV. Literature Review

In the paper [4] by Mohammad Salah Uddin; Jannat Binta Alam and Suraiya Banu clearly state how vast the Internet of Things is can be. They successfully proposed a patient monitoring system in an ICU system. They combined all the health-related sensors such as Temperate and humidity sensors, heart rate sensors, ECG sensors, Movement Sensors, Blood Pressure Sensors, etc. in one model to keep a check on patient's overall condition. These sensors data can be visualized in a mobile application for doctors and nurses. This is a good concept where the health care associate can check on multiple patients at a time. Concerning the proposed ERPM model, which is designed for patients to check on their health parameters in their own house or any other place. This proposed model's central concept is to integrate all the sensors for the remote patient monitoring system. The data can be visualized into different formats timely, to alert the physicians in case of urgent situations. This model is imbibed with the GPS and GSM units to locate the person in a matter of urgency. The model uses the MQTT protocol for secure communication and collects real-time data for better communication. ERPM is a portable device that can remotely monitor patients at any place.

The paper [3] proposed by Rani G. Utekar, and Jayant S. Umale, focuses on two crucial concepts, firstly, ”Remote Patient Monitoring for the heart-related data” and ”prediction of the possible diseases based on the heart dataset.” For data analysis, the Cleveland UCI hearth dataset is considered, upon which several classification algorithms such as C4.5 Algorithm, J-48, Naïve Bayes, Random Forest, and KNN is implemented. It has been successfully concluded that the decision tree with the provided data set works well. For RPM, the heart rate and body temperature values are taken into considerations. The doctors and nurses are alerted using e-mail notifications. The ERPM proposed model mainly focuses on the hardware part, where ECG is the focus and a complete RPM along with GPS and GSM module. The notification methodology is in a better way, i.e. in the form of a message or a call/buzzer. Additionally, developing an AI/ML model to make predictions on the collected health data can add decision making power to the proposed system. However, the MQTT protocol makes an added advantage to the ERPM system for secure data transmission.

Hoe Tung Yew and et. al. proposes a paper [2] where an excellent RPG model has been showcased for the Heartbeat monitoring system. The main focus of the article is on packets delivery and secure communication by using checksum and MQTT protocol. The server has been created and implemented from scratch while in the ERPM model, the system uses an online IoT platform like Ubidots and Thinkspeak. The proposed ERPM has an added advantage of the GPS and GSM module, along with the versatility of the model, which can be extended to other e-health sensors such as pressure, glucose, and oxygen sensors.

In the paper [1] proposed by Nitin P. Jain ; Preeti N. Jain ; Trupti P. Agarkar mainly focuses on the remote patient monitoring system for ICU patients and also regulate their medicine dosage. It is integrated with the GSM module for secure communication in case of any urgency. Various health parameters such as body temperature, blood pressure and heart rate of patients are monitored. The collected data is stored for future reference. The uniqueness in the proposed system is doctors can take the preliminary actions from a remote location as the feedback system is also provided. The feedback is given using the GSM and feedback motor, unlike the proposed ERPM system, where data can be collected from any patients from a remote location. Data analytics is performed using a trained model on the data collected using the ECG monitor, and an alert message is sent to the nearest doctor. There is no feedback mechanism provided. However, the doctor can locate the patient using GPS in the device, and the patient can communicate with the doctor using GSM modules.

Jiaming Chen ; Ali Valehi ; and Abolfazl Razi proposed a paper [23], where article majorly focuses on the predictive analysis of the ECG Signals. The early detection feature is proposed to solve the issues of inter-patient variability. The process is divided into two-classification stages. The primary step comprises a global classifier trained by processing large datasets containing the annotated ECG signals. This is done to detect the abnormalities in the messages. Secondly, there is a personalized classifier, where the ranges of defects are identified and developed based on the fluctuations in the regular beats. As compared with this proposed system, ERPM comprises hardware and classification of ECG signals.

Haydar Ozkan et.al in their research paper [7] proposed a monitoring system mainly consisting a stretchable singlet designed with a couple of TE’s (Silver Ag/AgCl -Textile electrodes), snap fasteners, Velcro, sponges, external circuits and an additional BLE (Bluetooth Low Energy). The intention of this constructive project is to monitor health rate (HR) of a person wearing underwear/singlet remotely via a webpage on a smart device. Apart from the TE being dry-cleaned for long term use, the system possess a holter-based ECG feature which is designed to evaluate the TE-based ECG system. The BLE is responsible for transmitting the filtered digital signal with a high signal-to-noise ratio of 45.62 dB to the smartphone for the medical practitioners at the other end to monitor the HR. For emergency purposes, there is a ‘HELP’ button on the user’s singlet, which can be activated in case of high rise of HR and demand immediate physician attention [1]. The battery in the holter-based ECG lasts for 14 days and can be replaced if needed. The tele-monitoring system captive of this core idea comprises of four components such as initial underwear setup with TE’s, followed by data flow from BLE to the IoT server and the later phases consists of IoT server storing the ECG data and forwarding it to the physicians smartphone for mitigation access. Describing the ECG front-end circuit design in this novel architecture, the ECG device mapped to the singlet consists of a CR2450 coin battery for measurement and ECG signal transmission. From the signal computations, the smallest MAE and MAPE are obtained as 1.1 percent and 1.83 percent respectively between the TE based system and the pulse oximeter. The implemented application can be utilized to reduce the congestion of hospitals and inexpensive medical examination as the patients can be monitored remotely for health/heart related diagnosis.

Lamia Nabil Mahdy et.al in their research [5] on smart ECG holter monitoring system mentioned the idea of preventing cardiovascular disease using a cost effective method which requires an application installed on a smartphone for monitoring the ECG variations. The paper presented a small ECG holter device developed to detect arrhythmias in real-time data based android mobile application. The ECG signals are obtained directly from the three-electrode sensor and then forwarded to the smartphone’s application via a Bluetooth module [HC-06]. The dataset consisting of training and testing partitions worth 20 attributes each is acquired from the El-Monofia

University hospitals. A total of 303 cases were studied for constructing the dataset out of which 162 are normal cases and the rest include patients suffering from coronary artery disease, myocardial infractions and sinus tachycardia. The system methodology begins with connecting the ECG sensors to the patient's chest and acquire the purified signals through the EKG/EMG shield, which is in turn connected to the Bluetooth based Arduino external circuit [2]. For the feature extraction from dataset, the QR detection algorithm (ECG pre-processing) algorithm was implemented on the Arduino side and heart rate (HR) was measured. The KNN algorithm was used to classify the input signal when the algorithm detects abnormalities in the signal and warns the patient through an alarm. The accuracies obtained with KNN classifier when the training-testing size is 70-30 for 303 cases ranges from 62 – 78 percent for different categories of diseases bifurcated in the dataset. Its detection accuracy has been achieved around 78 percentage for normal ECG signal, 62 percentage for Coronary Artery, 70 percentage for Old Anterior Myocardial Infarction, and 76 percentage for Sinus tachycardia. The primary objective of the system is to classify the ECG signal dataset into two classes such as normal and abnormal for each category of signal and display the visualizations to the experts for heart rate analysis.

Mohammad Kachuee et.al in their research paper [10] proposed a method based on deep convolutional neural networks for heartbeat classification further leading to classify five different types of arrhythmias in correspondence with AAMI EC57 standard. Furthermore, the myocardial infarction (MI) classification task was followed with the same knowledge. The experimentation with deep CNN on datasets mentioned above output a classification accuracy ranging from 93.4 percentage to 95.9 percentage on arrhythmia and MI classification respectively [3]. The novel framework proposed in the paper for ECG analysis is able to represent the signal in a way to differentiate tasks. In this paper, the authors have used PhysioNet MIT-BIH Arrhythmia and PTB Diagnostic ECG Databases as data source for labeled ECG records. The MIT-BIH dataset consists of ECG recordings from 47 different subjects recorded at 360 Hz frequency. The data pre-processing operations consisted of breaking down the signal and extracting beats out of it. Normalization, finding the min-max occurrences and selecting the R-peak candidates in R-R interval made the latter steps of signal data pre-processing. From the findings of comparative study of classifiers on the same data, the proposed approach with Deep CNN guarantees an accuracy of 93.4 percentage for heartbeat classification and 95.9 percentage accuracy for MI classification. To cover up the accuracy trails, the precision and recall for MI classification ranges in between 95 to 95.2 percentage respectively. Concluding the experimentation results and analysis on the mentioned data, the visualization of the learned representations were drawn out using t-SNE techniques.

Jiuqiang Xu and Jinpeng Zhang in their research [11] proposed a novel ensemble learning model for detecting abnormal beats from the holter ECG using feature extractors such as LSTM and 1-D convolutional neural network (CNN) [4]. After calculation of interval features of the methods, the classification can be fused together by using back-propagation method. Considering the ECG records from MIT-BIG arrhythmia as test data, the research experiences the conclusion that the accuracy percentage of the fusion of two classifiers is greater than two individual classifiers. For starters, the data pre-processing of ECG records comprise of Denosing, waveform detection, heartbeat segmentation followed by feature extraction. The output of data pre-processing is forwarded to 1-D CNN, LSTM and interval ¬features to make a concrete input or fusion of classifiers for the BP neural network. Nevertheless, the integrated BP neural network classifier will be used for beat classification as normal and abnormal beats. After the computations, the experimental results achieved the accuracies from all single and fused classifiers and the results with CNN model delivered a 95.96 percentage accuracy on the complete ECG dataset whereas, the accuracy obtained with LSTM model is 96.40 percentage. The accuracy, sensitivity, and specificity acquired from the fused DNN model (proposed ensemble learning model) are 99.84 percentage, 100 percentage and 99.71 percentage respectively. The primary reason of improved accuracy by DNN model is because of added RR interval feature. On comparing the proposed model with others, the classifiers which achieved the closest accuracy on the complete dataset are Bagging, MLP and AdaBoostM1 with 99.23 percentage, 99.26 percentage and 98.63 percentage accuracy.

G. Rajender Naik and K. Ashoka Reddy in their research paper [12] proposed a new algorithm for ECG basic classification as normal and abnormal from the complete dataset. The primary objective of this research is to compare two selected methods – Neuro-fuzzy algorithm (existing method) and the other proposed method i.e. multimodal decision learning algorithm. The parameters considered by the researchers would be true positive, true negative, false positive, false negative, false rejection ratio (FRR), false acceptance ratio (FAR), global acceptance ratio (GAR), confusion matrix (GM), and Kappa coefficient (KC) [5]. The filtered signals from the MIT-BIH ECG dataset selected for this research is considered for pre-processing and the further filtered signals are used for feature extraction followed by the best feature selection. Talking about distance coefficients, the comparative study gives out the best results of 93.33 for the proposed multimodal decision learning model and 89.65 for the neuro-fuzzy algorithms. The classification accuracy obtained is 87.50 percentage with the proposed model and 81.25 percentage with the neuro-fuzzy model. The authors stated that their proposed research could be improved by implementing multimodal learning SVM's and ANN'S.

V. METHODOLOGY

The complete architecture of the proposed ECG monitoring system is shown in the Fig. 1 below.

The system consists of 5 essential components:

- Micro-controller Arduino

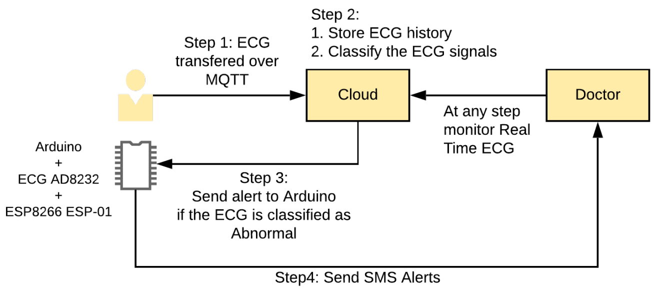

Fig. 1. Propose Architecture Model.

- ECG sensor AD8232
- WiFi chip ESP8266 ESP-01
- Cloud-based IoT platform
- Trained ECG classification model.

While working on the prototype, we experimented with ThingSpeak and Ubidots IoT platform. We also build a Conv1D, using the pre-processed MIT-BIH Arrhythmia Dataset produced by [10], which can be used in the future to classify the real-time ECG signal collected by the Arduino. The entire process flow of the proposed system is divided into many phases each of which is covered in detailed in below sections.

VI. Data acquisition

In the proposed ECG monitoring system, we have used the Arduino UNO R3 platform fitted with ATMega328 micro-controller as our main micro-controller from the wide variety of available Arduino boards. Arduino is preferred over low-power MSP430F5529 MCU of Texas Instrument because it is readily available and easily programmable using Arduino IDE [16]. It also has the added advantage of a broader community base. The ECG AD8232 sensor is used to measure the ECG activity, and the data is transferred to the Arduino Uno. ECG AD8232 is a cost-effective single lead analog board that measures and amplifies the heart's electrical activity. The single-lead ECG sensor is connected to a three-conductor sensor cable with electrode pad leads, which are directly attached to the human body. The ECG sensor is suitable for portable applications as it consumes only 170 microamperes [13]. The connection of ECG AD8232 with Arduino UNO is shown in the Table 1 below.

TABLE I
ECG AD8232 to Arduino Connection

Arduino	AD8232
3.3V	3.3V
Pin 10	LO+
Pin 11	LO-
Analog 0 (A0)	Output
GND	GND

In the first phase of prototype development, a simple program was uploaded to the Arduino using Arduino IDE. The program transfers the ECG readings from the Arduino to a computer using the serial library.

Analysis of the generated ECG waveform can help in understating the condition of the heart. Various factors such as distortion in the QRS segment or ST-segment or abnormal distance between two R peak (R-R interval) can represent an arrhythmic heart [24].

In the second and third phase of the prototype, these readings are then sent to the WiFi module ESP8266 serially. The data is then transmitted on the internet over HTTP protocol and MQTT protocol in the second and third phase of the prototype.

VII. Data Transfer

ECG readings collected using the AD8232 sensor are transferred from the Arduino Uno board to the ESP8266 WiFi module using Rx and Tx pins on the Arduino. The ESP8266 chip is then used as an IEEE 802.11 network adaptor to transfer the ECG data from the remote location to the cloud [8]. The connection of ESP8266 with Arduino UNO is shown in the Table 2 below.

TABLE II
ESP8266 to Arduino Connection

Arduino	ESP8266
3.3V	VCC
3.3v	CHPD
Pin 2	TX
Pin 3	RX
GND	GND

In the second phase of prototype development, with the aim of uploading our ECG reading to the cloud, we uploaded a script to Arduino to send data to the ThinkSpeak IoT platform. The program allows the Arduino to communicate with the ESP8266 module using the AT commands. The AT commands are used to control the ESP8266 Modules. When the program first starts executing, it sends AT commands shown in Table 3 to setup ESP8266.

TABLE III
Setup Commands

Command	Action
AT	To check if the ESP-01 is running
AT+CWMOD	To program the ESP-01 into a Station
AT+CWJAP	To connect the ESP-01 to WiFi

Once the setup is done for every ECG reading the program executes the AT commands shown in Table 4 to send the data.

The Fig. 2 below shows the data ECG data received at the ThingSpeak platform.

Considering we are using a free trial ThingSpeak account, the data transfer occurs at the rate of 1 sample per 15 seconds due to which the graph does not represent an ECG graph. Additionally, visualization functionality is limited for a free ThingSpeak account.

TABLE IV
DATA SENDING COMMANDS

Command	Action
AT+CIPMUX	To allow the ESP-01 to have multiple TCP connections
AT+CIPSTART	To start a TCP connection with ThingSpeak on a particular port
AT+CIPSEND	To Send the data over the TCP /UDP

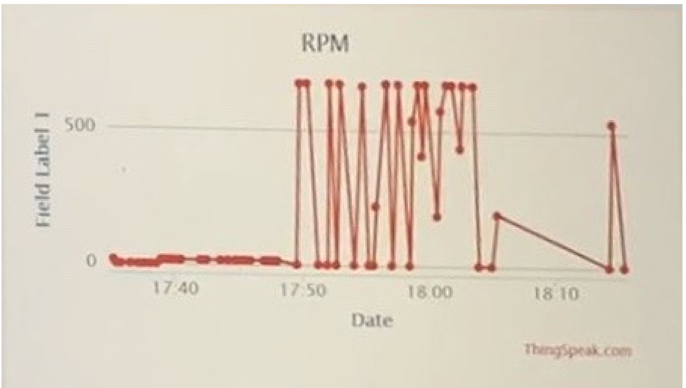

Fig. 2. ECG monitoring Output from ThingSpeak

To overcome the above challenge faced with the ThingSpeak platform and to ensure an efficient transfer of data over the WiFi, in the third phase of the prototype, we focused on sending data over the MQTT protocol to another IoT platform called UbiBots. We chose Ubidots because it has a library, UbidotsESPMQTT, to support ESP-01 communication over MQTT. In an IoT based system, MQTT protocol is considered more fitting than HTTP for the transfer of data [2]. In this phase of prototype, we developed two different scripts one for the Arduino to send data to the ESP-01 using a serial connection and second script for ESP-01 to transfer the received data to Ubidots over MQTT. The second script was generated using Ubidots documentation and articles. However on the execution of the module, the data obtained is not aligned with the expected output. On researching it, we concluded that we were facing some connection issues. As the scripts are running fine when executed independently, data is not transmitted from Arduino to ESP-01 when implemented as a whole system. Section 3 describes in details the potential issues and possible solutions to the this problem. At present the data is not getting transmitted over MQTT.

VIII. DATA CLASSIFICATION

A significant drawback of the existing remote ECG monitoring system is the lack of intelligence to analyze and predict health issues form the collected ECG data. Such prediction can help in early diagnosis of heart diseases and generate alerts [15]. In this paper for the proposed ECG monitoring system, a CONV1D model trained on processed MIT-BIH Arrhythmia Dataset is recommended.

A. Dataset

The MIT-BIH Arrhythmia Dataset is considered a golden standard for building and evaluating the ECG classifiers. [29].In consists of 48 half-hour excerpts of two-channel ambulatory ECG recordings obtained from 47 subjects [30][31]. Working on the original version of the MIT-BIH dataset requires extensive research in the field of signal processing. Therefore in this study, a pre-processed version of the MIT-BIH dataset published by the authors of paper [10] on kaggle [19], is used for ECG classification. The dataset consists of the train and test data in a separate file. The dimension of the train and test dataset is 87554×188 and 21892×188. Pandas library is utilized for reading the dataset. Table 5 below, shows the head of the dataset.

TABLE V
DATASET HEAD

0	1	2	...	187
0.959677	0.887097	0.419355	...	0
1.000000	0.850877	0.166667	...	1
0.381418	0.361858	0.215159	...	2
1.000000	0.867305	0.615595	...	3
0.794020	0.498339	0.518272	...	4

Each entry in the dataset represent samples of a single heartbeat. All the samples in the dataset are cropped, downsampled and padded with zeroes if necessary to the fixed dimension of 188 [29]. Each sample in the dataset is associated with a label between 0 and 4. Table 6 below represents the link between the label and the associated category.

TABLE VI
TARGET LABEL

Label	Category
0	N
1	S
2	V
3	F
4	Q

Each category above is assigned a set of annotations. Detail explanation of the each category and the associated annotations can be found in the paper [10].

B. Data Preprocessing

For the study kaggle notebooks were used as references to have a better understanding of the already pre-processed dataset and pre-processing steps that can be performed. The dataset suffers from class imbalance, as indicated by the Fig. 3 below. Thus to balance the data, oversampling is performed on the train data only, using the resample functionality from the Sklearn library. Once resampled, the data is reshuffled to help the model to learn better.

C. Proposed Model

The paper proposes a CNN model to perform ECG classification. Fig. 4 below shows the complete architecture of the

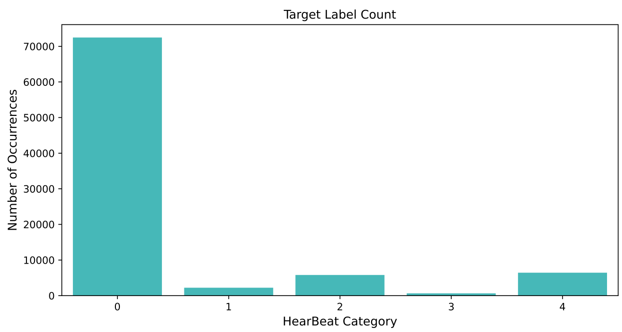

Fig. 3. Target Label Count.

CNN model built using Keras library. The proposed model is evaluated using, accuracy, precision, recall, F1 score, and confusion matrix. Furthermore, the training and validation loss over the epochs were plotted to get the optimal count of epochs before the model starts to overfit additionally; a dropout layer is used in the model to avoid overfitting.

D. Model Evaluation

During the research, different permutations and combination of the hyper parameters, model parameters, and model layers were tried and tested. The proposed model performs the best with the configurations shown in Table 7 below.

TABLE VII
PROPOSED MODEL PARAMETERS CONFIGURATIONS

Parameter	Configurations
Kernel	2
Batch size	32
Epoch	100
Optimizer	Adam
Activation function	ReLU and softmax

Table 8 below shows the model performance metrics achieved while testing the model using the above mentioned parameters.

TABLE VIII
PROPOSED MODEL PERFORMANCE METRICS

Metric	Value
Accuracy	0.95
F1 Score	0.95
Precision	0.96

The model achieves a training and validation accuracy of approximately 98 percent and training and validation loss around 0.04. For hyper parameters optimization and validation of the model GridSearchCV and Cross Validation can be used. Both the modules are implemented in script, however they were not executed due to the higher execution time and the connection loss issue with Google Colab on running a script over a longer period.

E. Model Overfitting

Fig. 5 and Fig. 6 shows the accuracy and loss of the training data and validation data over hundred epochs. It can be clearly seen in figures that the validation data loss is steadily decreasing with training loss, and the accuracy of both data is steadily increasing. Since their is now inconsistency between training and validation results the model is not overfitting.

F. Result Analysis

As mentioned before, the proposed Conv1D model is trained on the dataset preprocessed in the paper [10]. In paper [10] the authors implemented a deep Conv1D network consisting of 13 weighted layers and achieved an average accuracy of 93.4 percent, which is 2 percent lower than the model proposed in this paper. Also, it is essential to note that the authors have evaluated their model only on 4079 samples of the dataset, whereas in our study, we evaluated the model on 21892 samples. A completely different approach to the original dataset is followed by Tae Jun et al. in their paper [32]. The authors have converted every ECG beat into a 2D grayscale image and passed as input to a Conv2D model. With batch normalization and data augmentation, the author achieved 99.05 percent accuracy indicating the effectiveness of using ECG readings as images to detect arrhythmia. The advantage of a heterogeneous model is built using LSTM, and CNN is also highlighted in paper [11]. In the paper, the LSTM and Conv1D model independently provide an accuracy of 92.59 percent and 91.70 percent, respectively. However, when both the models are used in conjunction with a BP neural network, the accuracy jumps to 98.08 percent.

IX. DISCUSSIONS AND EVALUATIONS

In the proposed ECG monitoring system, there two major modules. One is the Hardware part that constitutes the part of data collection and transfers the health data to the cloud. The model is versatile enough to accommodate other sensors for measuring pressure, temperature, oxygen, glucose, etc. Data transmission is done using the MQTT protocol; thus, the publishers and subscribers get the correct data without any data transmission error, and it also makes the system more dependable than other methods based on HTTP. The data is stored on the cloud for storage and remote monitoring. The alert mechanism is a significant functionality of the proposed system used in conjunction with GPS and GSM modules. This makes the model more useful during emergencies by locating the patients efficiently and communicating with their acquaintances. The second module of the proposed system is the ECG Classification model that makes predictions on the collected health data and raises an alert. Further work needs to be done to improve the accuracy of the model as some existing models have 99 percent accuracy. Also, research is required to identify the preprocessing steps to perform on the Arduino reading before it can be passed as input to the trained model.

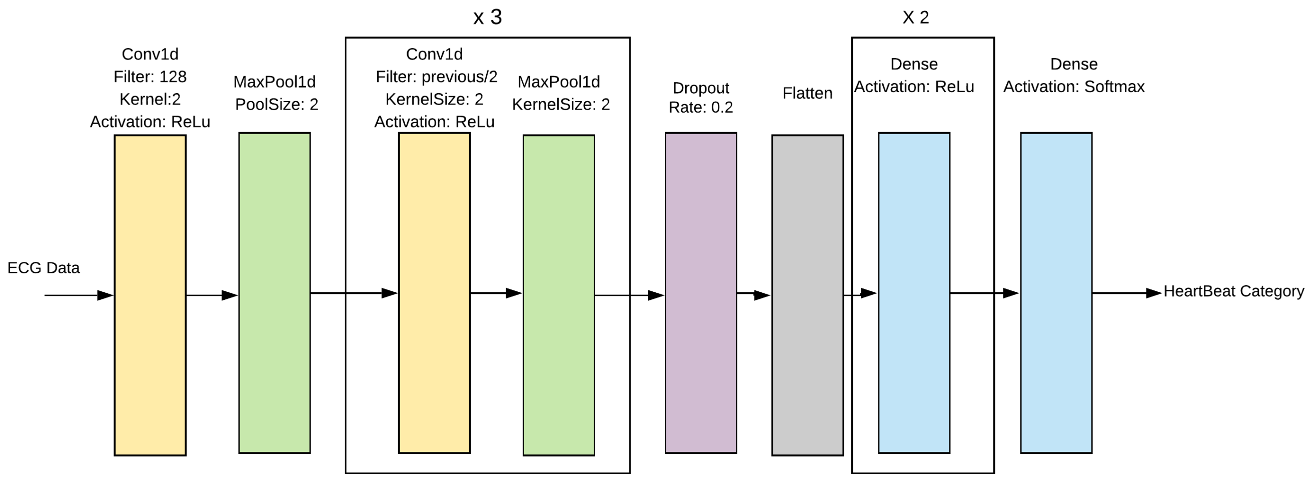

Fig. 4. Proposed CNN Architecture.

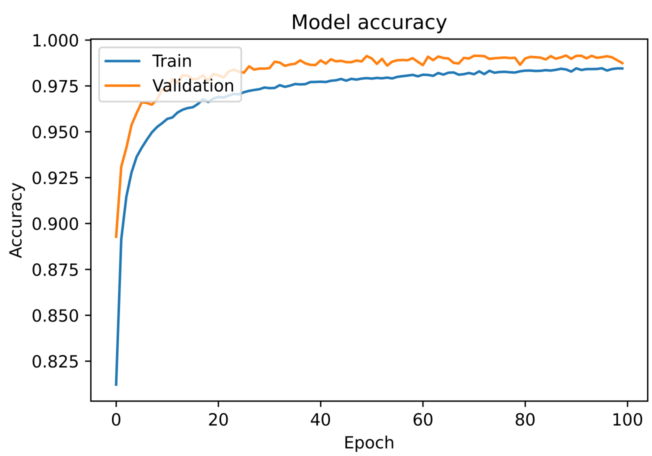

Fig. 5. Training and Validation Accuracy.

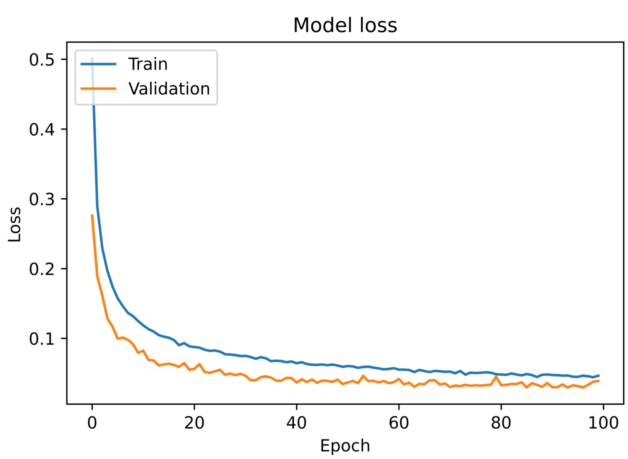

Fig. 6. Training and Validation Loss.

X. Challenges

This section briefly mentions the challenges faced while implementing the proposed system. As already mentioned, there are two significant modules in the Project, first is the hardware part, and the other constitutes the data classification portion. There were several significant challenges that we faced while building the proposed model. The problems that were encountered while assembling the hardware were: As we are implementing an IoT network, there are several issues faced related to communication over the Internet. It is challenging to handle the delay to fulfill the real-time requirements. Due to this, there is an irregular plot over the IoT platform, ThinkSpeak. This is due to the 15 seconds time delay in the proposed model. Constructing off the self ECG sensing device is again challenging as the ideal system needs real-time communication of sensors with the interface. Eventually, the sensitivity of the electrodes reduces. This needs to be replaced timely. There is a considerable effect of the placement of the electrodes for the measurement of ECG values. Locating the correct spot for optimum readings is a tedious task. The synchronization of data at the sensor and the output level for visualization purposes is difficult as it requires fine-tuning the hyperparameters to get the appropriate reading. While executing the MQTT protocol in the code and visualizing the data over Ubidots, there was a communication issue between Arduino with Wifi Module. The model requires voltage conversion as the Arduino usually operates at 5 Volt, whereas the wifi Module esp8266 esp-01 works at 3 Volt. A possible reason would be we don't have the voltage regulator for conversion from 5V to 3V. Thus, the proposed model still requires an additional resources - voltage converter device or the NodeMCU Module for its best execution.

XI. Conclusion

The proposed system's main target is to implement a Remote Patient Monitoring System using IoT. It demonstrates a portable, low-cost, versatile, light, and easy-to-operate ECG monitoring system and a predictive Con-1D ECG classification model. The model achieves 95.21 percent testing accuracy. This is a robust model to classify ECG readings from the cloud to classify the heartbeats into five primary attributes mentioned in the pre-processed dataset. In addition to that, the hardware module can send any alert messages in case of larger deviations from the normal values. This model is mainly focused on cardiac health patients.

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