Patient Health Monitoring and Inferencing Arrhythmia Using ECG_Data

Siddhant Thakur Thakur (siddhant.thakur2018@vitstudent.ac.in)
Vellore Institute of Technology University
Devarshi Patel Patel
Vellore Institute of Technology University

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Abstract

Health and Fitness is becoming more of an integral part of human life. Being Healthy is crucial in the present fast-growing world. Most difficult aspect to maintaining health is keeping track of it especially for old people. So, we turn to technology, again, and came out with concept of 'Smart Health Care'. It monitors patient health via IOT devices. It keeps track of EEG rate, Body Temperature, Bpm rate etc. This will not only help patient but also doctors to study their patients on daily basis with daily streaming data. Whenever a patient visits her/his doctors, the doctors would have data of ups and down or any uneven changes, anomalies and observed trends pertaining to the patient. IOT in many ways has transformed the Health Sector immensely. The tracking will be continuous with WIFI module correspondence. The proposed system will used WIFI module and will be constantly uploading patient's data to cloud and keep track of ECG Rate. It will detect type of arrhythmia on bases ECG rate by CNN Deep Learning model. Data generated from this can be also used for research purposes for better and reliable future.

1 Introduction

IoT- The Internet of Things has enhanced the quality, reliability, attainability of the health care industry. Health care is of the utmost importance considering the present scenario. Keeping track of your health and observing on daily basis will be beneficial for the individual, their families, and even doctors. So, to have tracking of your health with a simple device on your hand and data being collected in your phone, laptop, tablet, etc. IoT applications are hugely involved in the health sector and it can truly benefit the rural areas as well. The medical facility is not at a hand's reach for rural inhabitants. The world is full of many unpredictable diseases and coupled with such a huge population there is a shear amount of pressure developed on the health care industry and the adding demand for hospital facilities just keeps adding up. The potential solution directs us towards technology sectors like IoT which has really been the focus in the recent years and has been upgrading and upscaling the health care sector.

Thanks to IoT technology, mutual information sharing among various smart devices has been facilitated anywhere in the world. In this environment, studies on smart health services, which can provide a remote diagnosis of the disease, are also accelerated. Thanks to low cost, low power consumption and high performance, devices that can collect patient heart data can be sent to the patient's family or doctor by smartphone applications.

Continuous monitoring of a person's health through wearable biomedical devices is now possible with many wearable health kits. However, real-time analysis, estimates, warnings, and alarms on health hazards are not adequately addressed and are still in development in these devices.

The data collected by IoT devices for health can be used for research purposes for predicting disease-related factors via Machine learning, AI Technology and Deep Learning. This will help in further advancement and improving the IoT devices and implementation will be more accurate. Machine learning techniques have been widely adopted in a number of massive and complex data-intensive fields such as medicine, astronomy, biology, and so on. These techniques provide possible solutions to extract the information hidden in the data. Similarly, it will help in the development of smart IoT systems for the health care industry.

As we are truly inspired by this, we attempt to propose an innovative system that puts forward smart patient health tracking a system that uses sensors to track patient vital parameters and uses the internet to update the doctors so that they can help in case of any issues at the earliest preventing death rates.

The First one is a temperature sensor, the second is a Heartbeat. This project is very useful since the doctor can monitor patient health parameters just by visiting the website or URL and if there is possibility of presence of any type of arrhythmia it will alert the stakeholders and cardiologists in charge. It will even go further to analyze the type of arrhythmia detected so medical health professionals will have the insight and direction to take aim their first steps which can prove vital and potentially lifesaving. To operate an IOT based health monitoring system project, you need a Wi-Fi connection. The microcontroller or a microprocessor of your choice given that connects to the Wi-Fi network using a Wi-Fi module. Furthermore, the real smartness of IOT system lies in the data analysis sections hence we will need to train a Machine Learning or Deep Learning model for classification of arrhythmia and its types. So, the objective of work will be to build a demo of a device that helps a patient tracking its Body Temperature and Electrocardiogram and further involves arrhythmia detection models using IoT knowledge, architecture and applications.

The current section introduced you to the technologies being used in the domain of smart health care. The distribution of the research paper will in the following sections. We will conduct a literature survey relating to the domain to depict the principles adopted and applied in the domain of smart healthcare using IOT in our system and how the system is scaled up using data processing and deep learning. In the methodology we will discuss the implementation of our system from scratch with hardware and software. Further, in results and analysis we will discuss the results and model performance on the agreed upon evaluation metrics.

2 Related Work And Context

2.1 Related work

Note

[x] denotes reserch paper number in reference section

[1] Mehmet Tastan proposed a wireless patient monitoring system is developed that allows patients to be mobile in their social areas. The developed system continuously measures the heart rate and body temperature of the patient and provides monitoring and tracking through an android based interface. When the patient's vital data reaches a predetermined limit value, the mobile application alerts the patient and the people in the vicinity. This warning is made at a volume level that people near the patient can

hear. If there is nobody in the vicinity of the patient who can help him, the patient's heart rate, body temperature, and coordination information are sent to family members and the doctor as e-mail and twitter notifications.

[2] Prajoona Valsalan, Tariq Ahmed Barham Baomar, Ali Hussain, and Omar Baabood developed a system monitored body temperature, pulse rate, and room humidity and temperature using sensors, which are also displayed on an LCD. These sensor values are then sent to a medical server using wireless communication. These data are then received in an authorized personal smartphone with an IoT platform. With the values received the doctor then diagnoses the disease and the state of health of the patient.

[3] Saed Tarapiah, Kahtan Aziz, Shadi Atalla, and Salah Haj Ismail studied, designed, and experimented system, can significantly improve the quality of health services and reduce the total cost in healthcare by avoiding unnecessary hospitalizations and ensuring that those who need urgent care to get it sooner.

[4]D.M. Jeya Priyadharsan, K. Kabin Sanjay, S. Kathiresan, K. Kiran Karthik, and K. Siva Prasath studied related to Statistical analysis is performed from data accumulated into the cloud from IoT device to estimate the accuracy in prediction percentage. For this kind of IoT platform based continuous monitoring of human health parameters, machine learning algorithms had played a significant role.

[5]C. Senthamilarasi, J.Jansi Rani, B.Vidhya, and H.Aritha concluded patient health monitoring can be highly used in emergency situations as it can be daily monitored, recorded, and stored as a database. In the future, the IoT device can be combined with cloud computing so that the database can be shared in all the hospitals for intensive care and treatment.

[6] Aleksandar Kotevski, Natasa Koceska and Saso Koceski concluded will be used for monitoring of patients’ vital physiological data. It is composed of three modules: web, mobile and Smart TV module, which cover the essential features for a remote monitoring healthcare system. The system can collect required vital data and make them visible to doctors. Doctors can act upon them. Additional functionalities like generating and displaying a group overview chart having one data point for each patient, are also implemented.

[7] R. Andrew Swartz, Deokwoo Jung, Jerome P. Lynch Yang Wang, Dan Shi, Michael P. Flynn concluded new wireless sensing unit design that balances the competing requirements for low power consumption, long transmission ranges, and the ability to calculate complicated structural engineering algorithms on-board.

[8] Priyanka Kakria N. K. Tripathi and Peerapong Kitipawang concluded the advancements in wireless communications and wearable sensor technology open up the opportunity of realtime healthcare monitoring systems. In this study a realtime heart monitoring system for heart patients located in remote areas has been proposed.

[9] Md. Milon Islam, Ashikur Rahaman and Md. Rashedul Islam concluded that the system introduced smart healthcare to monitor the basic important signs of patients like heart rate, body temperature, and some measures of hospital room's condition such as room humidity, the level of CO and CO2 gases.

[10] Mohammad Dawood, Babakerkhell and Nitin Pandey concluded that proposed framework can be set-up in the healing centers and a huge amount of information can be acquired and put away in the online database. It will be possible to access the patient record through smartphone.

2.2 Context of the project

To implement a hardware model for measuring a patient's ECG signals and transmit it to a Cloud IoT database. The data collected here will be exported in required formats to be analyzed for presence of any type of arrythmia. If any, the patient, his/her cardiologist and a family member will be notified through the web interface.

A. Domain Description

An [19]arrhythmia is a problem with the rate or rhythm of the heartbeat. During an arrhythmia, the heart can beat too fast, too slowly, or with an irregular rhythm. When a heart beats too fast, the condition is called tachycardia. When a heart beats too slowly, the condition is called bradycardia. Arrhythmia is caused by changes in heart tissue and activity or in the electrical signals that control your heartbeat. These changes can be caused by damage from disease, injury, or genetics. Often there are no symptoms, but some people feel an irregular heartbeat. You may feel faint or dizzy or have difficulty breathing. The following conditions may cause arrhythmia:

- Changes to the heart's anatomy
- Reduced blood flow to the heart or damage to the heart's electrical system
- Restoring blood flow as part of treating a heart attack
- Stiffening of the heart tissue, known as fibrosis, or scarring.

Arrhythmias differ from normal heartbeats in speed or rhythm. Arrhythmias are also grouped by where they occur—in the upper chambers of the heart, in its lower chambers, or between the chambers. The main types of arrhythmia are brady arrhythmias; premature, or extra, beats; supraventricular arrhythmias; and ventricular arrhythmias

- Normal Heartbeat
- Non-Normal Heartbeat
- L-Left branch block beat: In this condition, activation of the left ventricle of the heart is delayed, which causes the left ventricle to contract later than the right ventricle
- A- premature atrial contraction occurs when a focus in the atrium (not the sinoatrial node) generates an action potential before the next scheduled SA node action potential.

- R-Right bundle branch block beat: Electrical impulses that cause your heart to beat (contract) start in the heart's upper right chamber (right atrium) and travel to the lower chambers (ventricles). In bundle branch block, the pathway these impulses follow is delayed or blocked.
- V-Ventricular contraction: Premature ventricular contractions (PVCs) are extra heartbeats that begin in one of your heart's two lower pumping chambers (ventricles). These extra beats disrupt your regular heart rhythm, sometimes causing you to feel a fluttering or a skipped beat in your chest.

Sudden cardiac death (SCD) and arrhythmia represent a major worldwide public health problem, accounting for 15– 20 % of all deaths. An estimated 180,000–300,000 sudden cardiac deaths (SCD) occur in the US annually[1, 2]. Worldwide, sudden, and unexpected cardiac death is the most common cause of death,[2] accounting for 17 million deaths every year with SCD accounting for 25 % of these.

B. System Description

Here, the patient is regularly under analysis with respect to her/his ECG rate and body temperature so as to monitor the health at each instance of time. The data can be used as a smart way to develop systems which can never overlook any occurred red flags that can be certainly overlooked in a real life scenario with lack of skill availability, lack of presence at each instant or presence of trends which statistical analysis can see while the professionals may not. Using these IOT systems regularly we can create a type of self-awareness for the patient which develops faith and confidence in the system, promotes and more so enforces transparency and gives useful insights for future decision making. These factors when all working together in a chain reaction can be potentially life- saving due to the available insights with faster and consistent insights provided by the data analysis. So, We will implement an Deep Learning model to detect arrhythmia on the basis of patient ECG rate and further detect the arrhythmia type that is present in that particular patient in consideration.

3 Proposed Solution

3.1 Architecture

The architecture of the IoT-based [20]ECG monitoring system is illustrated in Fig. 1, which mainly consists of three parts, i.e., the ECG sensing network, IoT cloud, and GUI.

- **ECG Sensing Network**

The ECG sensing network is the foundation of the entire system, which is responsible for collecting physiological data from the body surface and transmitting these data to the IoT cloud through a wireless channel. Wearable ECG sensors are usually adopted in this system, which have little impact on the user’s daily life. Through this means, ECG data can be recorded over long hours or even days. Then, the ECG value will be tested in DL model to detect arrythmia and its type.

We will be alerting Patient on the basis of ECG rate, whether they have arrhythmia or not and further its Type.

♣ Data storage

ECG data plays a vital role in the diagnosis of heart diseases. Thus, historical data is needed to be stored in the database for further analysis. The ECG data often includes the time and digitized signal amplitude. In addition, at least one copy of the data needs to be stored for disaster recovery. The ECG data is high dimensional and requires high memory for storage. Having a streaming data due to continuous monitoring poses a big challenge for a nearly unbound data. Using the new technologies of Data Engineering and Management we will prioritize the storage of such highly bulky but sensitive data either in on premise Hadoop systems or a cloud IOT database service.

♣ Data analysis

Data is one of the most important parts of the IoT system. Therefore, the IoT cloud often provides a facility to export the data to be analyzed which then will be used to extract useful information from the ECG signal. Here we will be using Convolutional Neural Networks to detect arrhythmia and its type.

♣ Disease Warning

Detect arrhythmia on the basis of patient ECG rate and further detect the arrhythmia type that is present in that particular patient in consideration.

We will be alerting Patient on the basis of ECG rate, whether they have arrhythmia or not and further its Type.

- **GUI**

The GUI is responsible for data visualization, management and alerts. It alerts the Health professionals and other key stakeholders, if arrhythmia is detected. It collects data which can be analyzed, visualized and tracked daily to keep patient and his family aware as well as to not overlook any key fluctuations in the ECG signals.

3.2 Hardware Description

1. Arduino Uno: The Arduino Uno is an open-source microcontroller board based on the Microchip ATmega328P microcontroller and developed by Arduino.cc. The board is equipped with sets of digital and analog input/output (I/O) pins that may be interfaced to various expansion boards (shields) and other circuits.
2. LCD: A liquid-crystal display (LCD) is a flat-panel display or other electronically modulated optical device that uses the light-modulating properties of liquid crystals combined with polarizers. Liquid

crystals do not emit light directly, instead using a backlight or reflector to produce images in color or monochrome.

3. ECG Sensor: The electrocardiography or ECG is a technique for gathering electrical signals which are generated from the human heart So an AD8232 sensor is used to calculate the electrical activity of the heart. This is a small chip and the electrical action of this can be charted like an Electrocardiogram (ECG).
4. Lm35 Temperature Sensor: The LM35 series are precision integrated-circuit temperature devices with an output voltage linearly- proportional to the Centigrade temperature The LM35 device is rated to operate over a − 55°C to 150°C temperature range, while the LM35C device is rated for a − 40°C to 110°C range (− 10° with improved accuracy).
5. [17]ESP8266 Wi-Fi Module: The ESP8266 is a low-cost Wi- Fi microchip, with a full TCP/IP stack and microcontroller capability, produced by Espressif Systems in Shanghai, China. The chip first came to the attention of Western makers in August 2014 with the ESP-01 module, made by a third-party manufacturer Ai-Thinker.
6. Arduino Cable, Jumper wires, Potentiometer, Resistor, Light Emitting Diodes.

3.3 IoT Cloud Platform Syncing

Arduino will collect the ECG Rate and it will transmit the data to [11][12]Thingspeak.com an IOT cloud Database service over the internet via a Wi-Fi Module.

ThingSpeak is an open-source Internet of Things (IoT) application and API to store and retrieve data from things using the HTTP and MQTT protocol over the Internet or via a Local Area Network.

ThingSpeak enables the creation of sensor logging applications, location tracking applications, and a social network of things with status updates".

3.4 Neural Networks

A neural network is a series of algorithms that endeavours to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. In this sense, neural networks refer to systems of neurons, either organic or artificial in nature.

3.5 Convolutional Neural Network

A [18]Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

Convolutional Neural Networks, or CNNs, were designed to map image data to an output variable. They have proven to be so effective that they are the go-to method for any type of prediction problem involving image data as an input. The benefit of using CNNs is their ability to develop an internal representation of a two-dimensional image. This allows the model to learn position and scale in variant structures in the data, which is important when working with images. The CNN input is traditionally two-dimensional, a field or matrix, but can also be changed to be one- dimensional, allowing it to develop an internal representation of a one-dimensional sequence. This allows the CNN to be used more generally on other types of data that has a spatial relationship. For example, there is an order relationship between words in a document of text. There is an ordered relationship in the time steps of a time series. Although not specifically developed for non-image data, CNNs achieve state-of-the-art results on problems such as document classification used in sentiment analysis and related problems.

3.6 Model Preparation Dataset Description

The MIT-BIH Arrhythmia Database contains 48 half- hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample.

The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Two or more cardiologists independently annotated each record; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110,000 annotations in all) included with the database.

3.7 Data Visualizations

Re-sampling is done to avoid domination of any class over any other which may affect model's accuracy and effectiveness in classifying the classes being dominated upon.

3.8 Convolutional Neural Network Architecture

We will split the dataset into train and test sets accordingly. Encoding Target variables which will help in going forward with our classification.

Now, to build the best model we applied Convolutional Neural Networks with 6 Hidden Layers with 5 Convolutional Layers applying different concepts like DropOut, Batch- Normalization, Pooling - (Max, Min, Average) which gives 1 Output Layer.

The output layer comprising of an image of some resolution has been flattened out as the purpose of the output is to perform classification and not the general CNN tasks like object detection, face detection, etc. Applying SoftMax activation function as the activation function of the output layer is for the reason as the requirement for our model is multiclass classification. Using an Adam Optimizer for gradient descent implementation because it is known to converge faster and less probability to converge at a local minima. As the data size grows the ability to increase the model building efficiency goes a long way in creating and tuning the best possible models.

For 5 convolution layers we used layers and activation function are as follow:

1st Layer - Convolution1D with 'elu' activation function with Batch Normalization along and MaxPool1D.

2nd Layer - Convolution1D with 'elu' activation function with Batch Normalization.

3rd Layer - Convolution1D with 'elu' activation function with Batch Normalization.

4th Layer - Convolution1D with 'elu' activation function with Batch Normalization.

5th Layer - Convolution1D with 'elu' activation function with Batch Normalization and MaxPool1D.

Above "elu" stands for Exponential Linear Unit.

Output Layer - Now for Output Layer after trying various the best result came out with dense layer which is then flattened and then in the last layer with SoftMax activation function gives out the final probabilities, all the above trained using then Adam optimizer. To evaluate the training errors, we used various epoch iterations. We found out with more iterations data was overfitting the training set. So, the optimum number of epochs turned out to be around 10.

3.9 Evaluation Metrics

[13]Precision quantifies the number of positive class predictions that actually belong to the positive class. Precision should ideally be 1 (high) for a good classifier. Precision becomes 1 only when the numerator and denominator are equal i.e TP = TP + FP, this also means FP is zero. As FP increases the value of denominator becomes greater than the numerator and precision value decreases (which we don't want).

[14]Recall quantifies the number of positive class predictions made out of all positive examples in the dataset. Recall should ideally be 1 (high) for a good classifier. Recall becomes 1 only when the numerator and denominator are equal i.e TP = TP + FN, this also means FN is zero. As FN increases the value of denominator becomes greater than the numerator and recall value decreases (which we don't want).

So ideally in a good classifier, we want both precision and recall to be one which also means FP and FN are zero. Therefore we need a metric that takes into account both precision and recall. F1-score is a metric which takes into account both precision and recall.

[15]F-Measure provides a single score that balances both the concerns of precision and recall in one number. F1 Score becomes 1 only when precision and recall are both 1. F1 score becomes high only when both precision and recall are high. F1 score is the harmonic mean of precision and recall and is a better measure than accuracy. F1 score means that you have low false positives and low false negatives, so you're correctly identifying real threats and you are not disturbed by false alarms. An F1 score is considered perfect when it's 1, while the model is a total failure when it's 0.

In the field of machine learning and specifically the problem of statistical classification, a [16]confusion matrix, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one (in unsupervised learning it is usually called a matching matrix). Each row of the matrix represents the instances in a predicted class, while each column represents the instances in an actual class (or vice versa).The name stems from the fact that it makes it easy to see whether the system is confusing two classes (i.e. commonly mislabeling one as another).

4 Results And Analysis

For analyzing the test error which will in turn be the real determinant of the model performance in the real world we used Classification accuracy rate as our single number evaluation metric coupled with satisfying metrics like precision, recall and f1 score for each respective class to analyze the skewness of the results. We plotted the confusion matrix with colour scale to analyze the distribution of classifications into their correct as well as incorrect classes. We also implemented a normalized confusion matrix to analyze the actual proportions of correct and incorrect classifications in each class. The following figures are the results of the same.

As we can clearly see from the Fig. 10 when implementing gradient descent with Adam Optimizer, we are more likely to converge sooner and hence we should consider training for lesser epochs. Hence, we will also use early stopping to prevent any overfitting that may be caused by the extra training iterations.

Table 1
Class wise Classification Results

Class Name	Correctly Classified	Wrongly Classified	Correctly Classified %age
Normal	1033	11	98.946%
Left branch block beat	1002	6	99.404%
Right branch block beat	977	2	99.795%
premature atrial contraction	931	38	96.078%
Ventricular contraction	979	8	99.189%
Paced beat	1012	1	99.901%

To observe the classifications with respect to the total examples in the class we implement the normalized classification matrix as in the Fig. 13.

Table 2
Precision, Recall and F1-Score

Class Name	Precision	Recall	F1-Score
Normal	0.98381%	0.98946%	0.98662%
Left branch block beat	0.99701%	0.99404%	0.99552%
Right branch block beat	0.96541%	0.99795%	0.98141%
premature atrial contraction	0.99785%	0.96078%	0.97897%
Ventricular contraction	0.99189%	0.99189%	0.99189%
Paced beat	0.99901%	0.99901%	0.99901%

5. Conclusion And Future Work

The proposed work and model is implemented successfully. The proposed model for classification of arrhythmia presence and its type if present works in competence with human level performance in the respective field of operation but consumes lesser time. On implementation we were able to execute a model with 95%+ accuracy and satisfying metrics like precision and recall on the dataset. This shows it will provide instant and accurate result in alignment to the human level performance and arguably even better due to subtracting the human error and the recognizing the consistency of the results that this system promises to provide all of which may be potentially life- saving in some-cases.

We can upgrade hardware which can be made more compact and portable and with emerging smart watch technologies can be made more common and affordable for even daily usage. With the development in large number of smart Watch operating systems and on chip sensor integration technologies and cloud and analytics platforms like google cloud platform the system can be revolutionized with low latency, Highly manageable, Scalable and reliable results that will be a very positive transformation of Health Care Industries.

Declarations

Funding – Not Applicable

Conflicts of Interests – Not Applicable

Data Availability[21] – The data that support the findings of this study are available from Moody GB, Mark RG. The impact of the MIT-BIH Arrhythmia Database. IEEE Eng in Med and Biol 20(3):45-50 (May-June 2001). (PMID: 11446209). Data are however available on the https://archive.physionet.org/physiobank/database/mitdb/

Code Availability - All the Hardware and software code files and model will be available in following repository.

Author's Contribution – Hardware & Software Design – Devarshi Patel

Model Design – Siddhant Thakur

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Figures

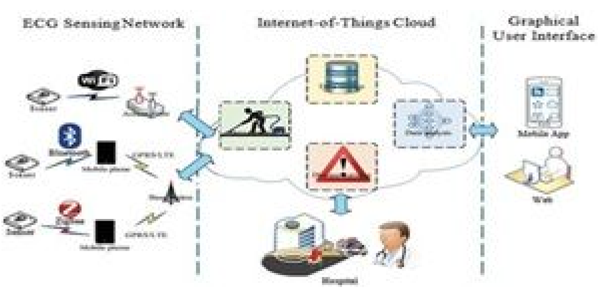

Figure 1

IoT System Architecture

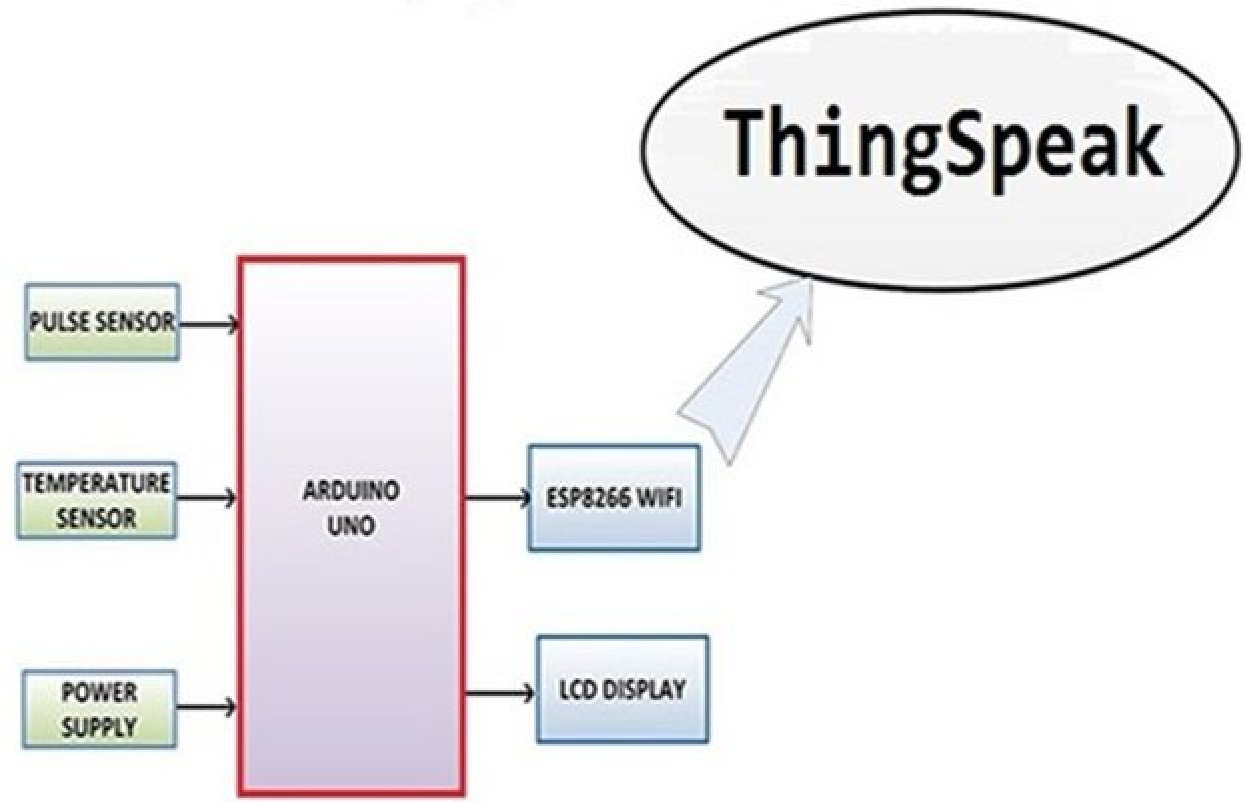

Figure 2

IoT Proposed System Scheme

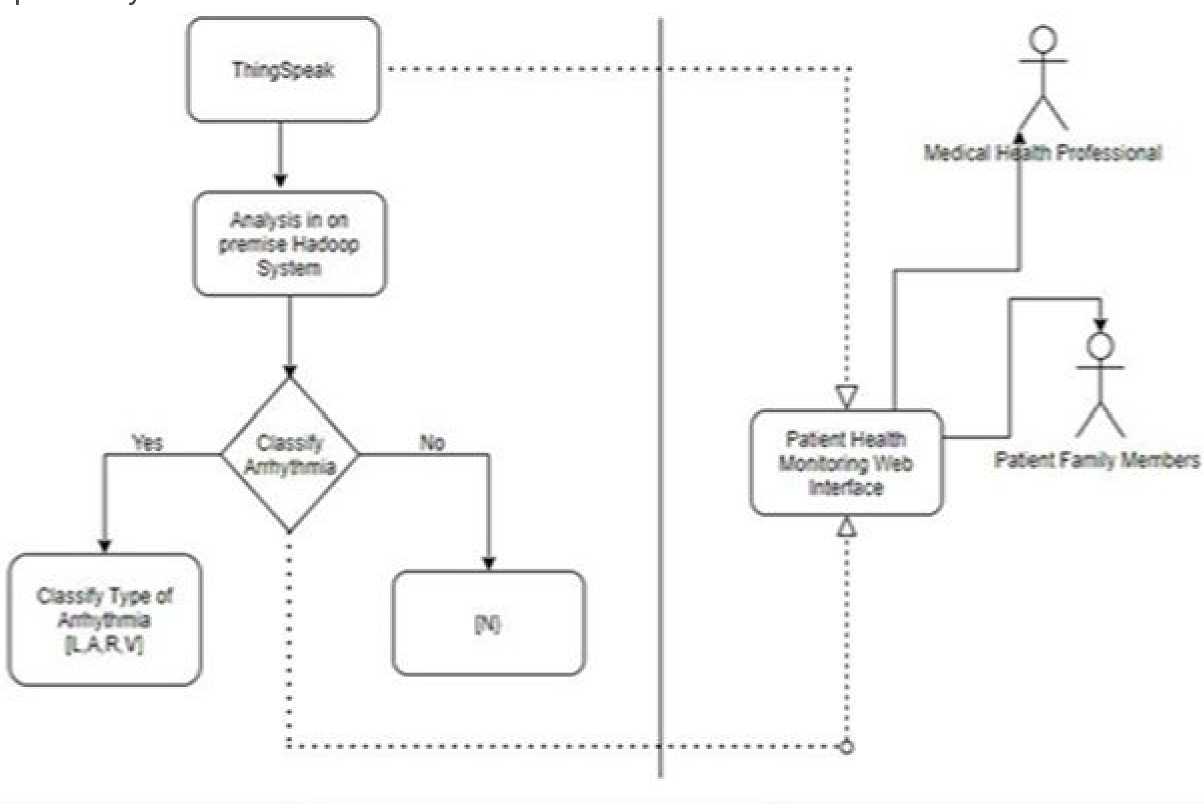

Figure 3

IoT Proposed System Data Flow Block Figure

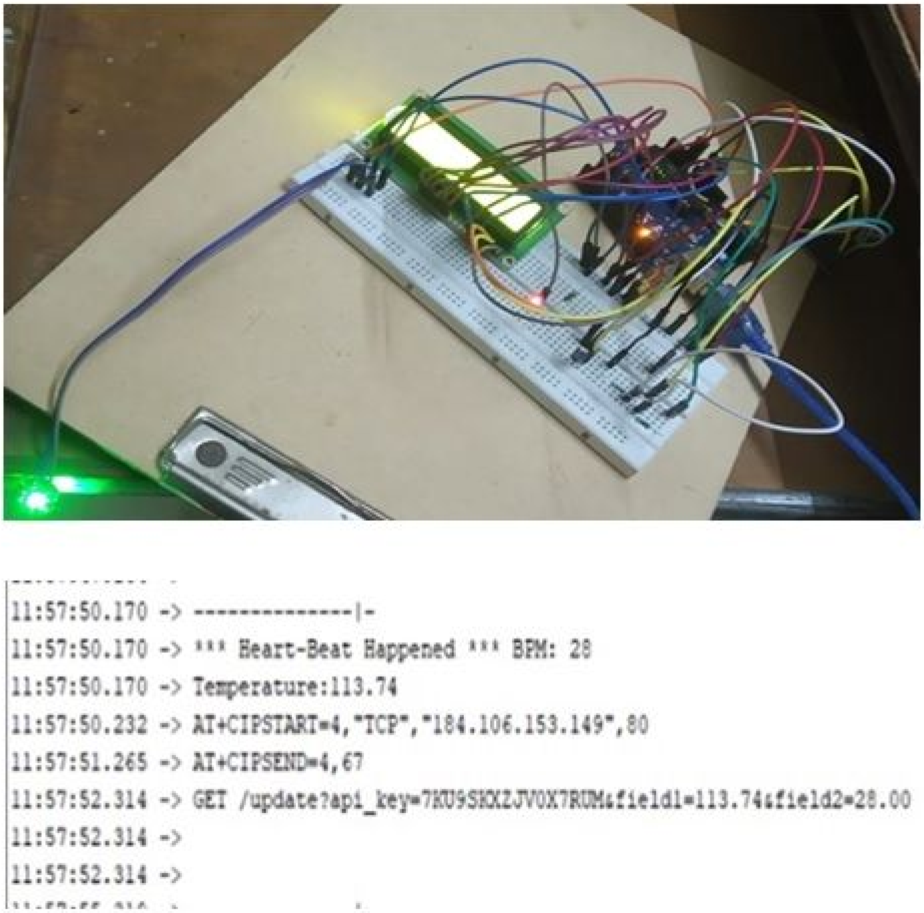

Figure 4

Hardware Implementation and Serial Window

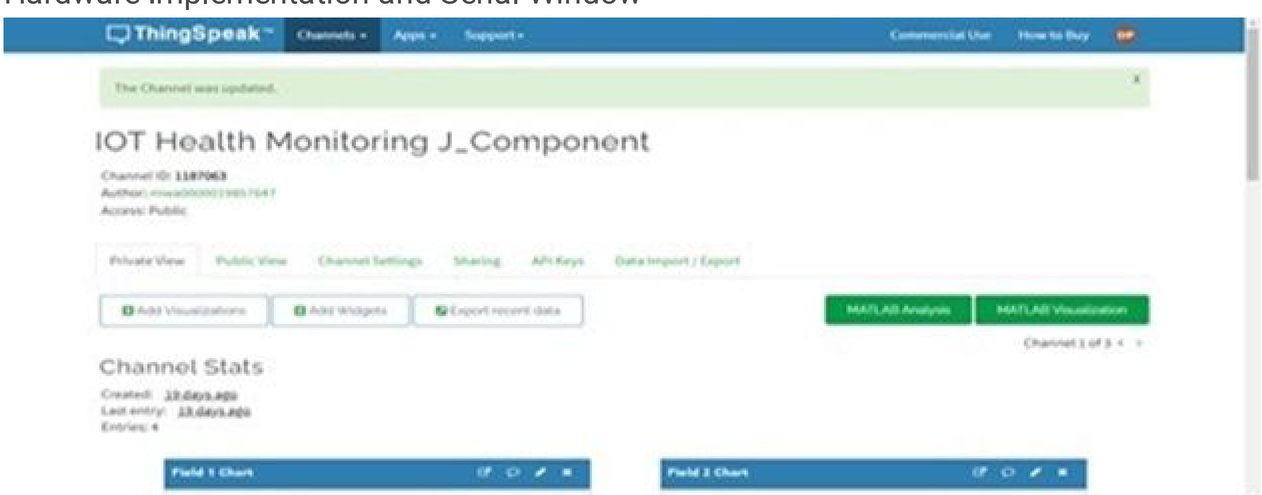

Figure 5

IoT Cloud Platform Project Dashboard

Figure 6

Auto plot Pulse Rate on IoT Cloud Platform

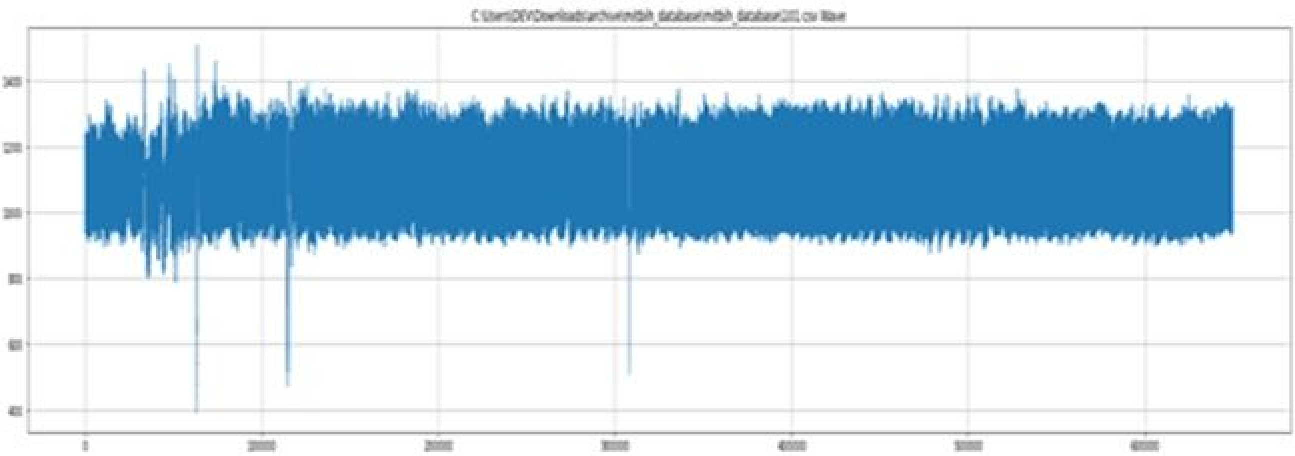

Figure 7

ECG values associated with one Patient.

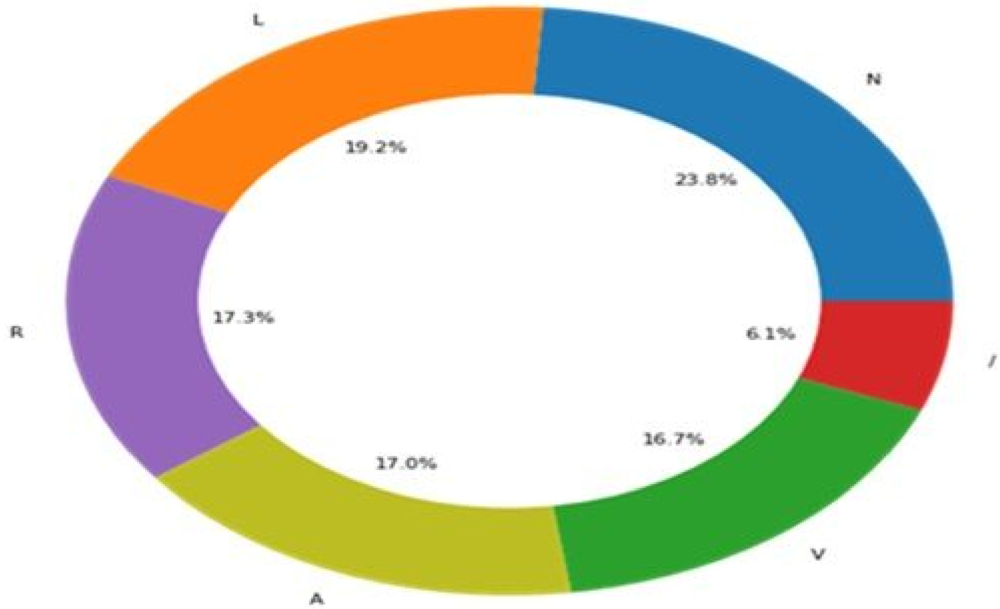

Figure 8

Distribution of data in classes before Resampling

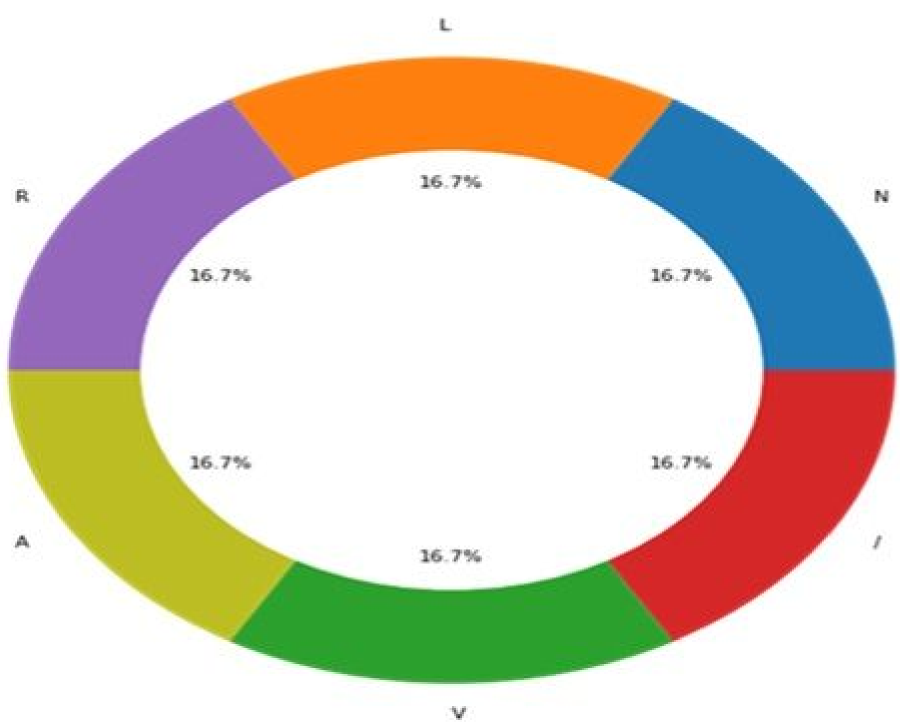

Figure 9

Class Distribution after Resampling

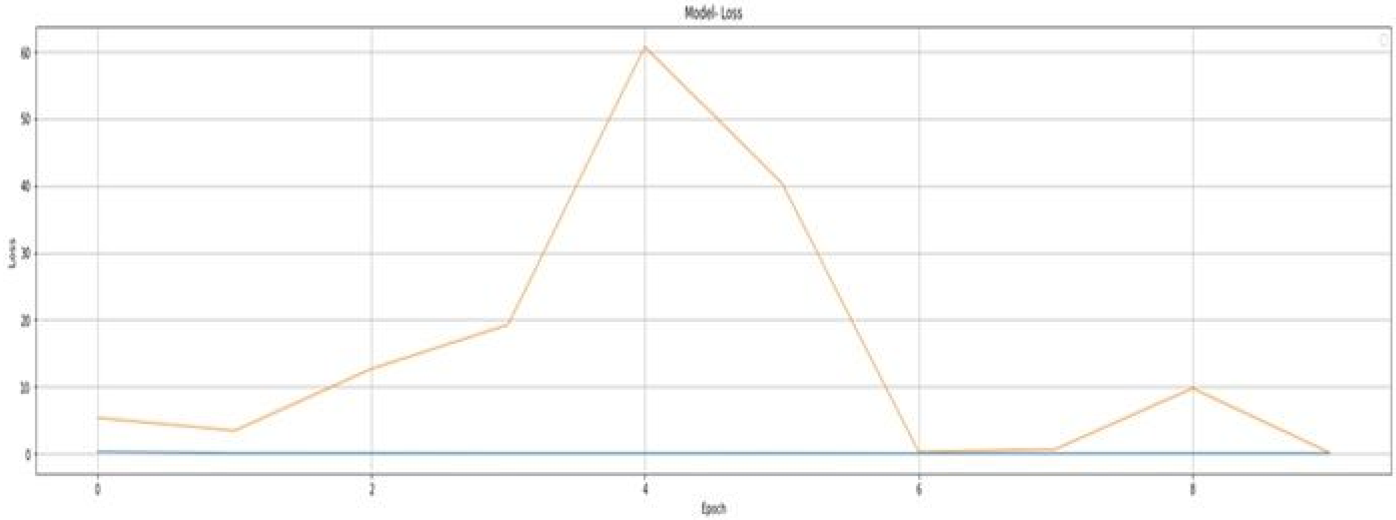

Figure 10

Gradient Descent Loss Function (Training) Plot

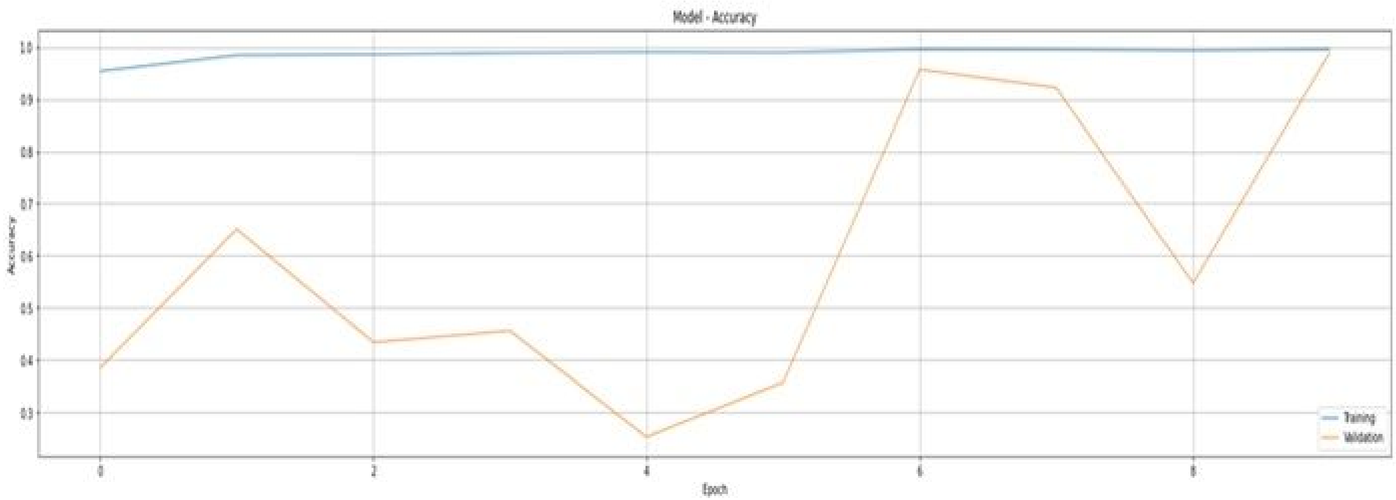

Figure 11

Training and Validation Set Accuracy Plot

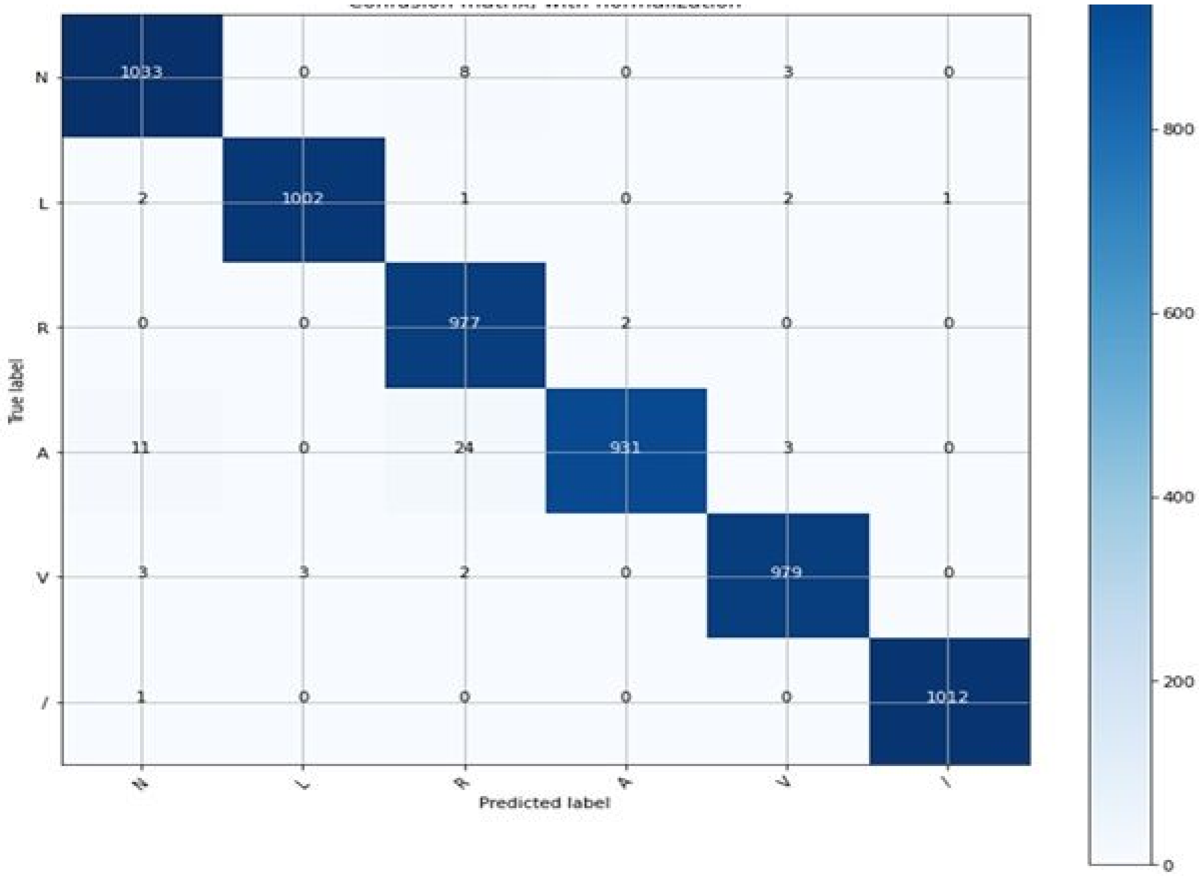

Figure 12

Per Class Confusion Matrix

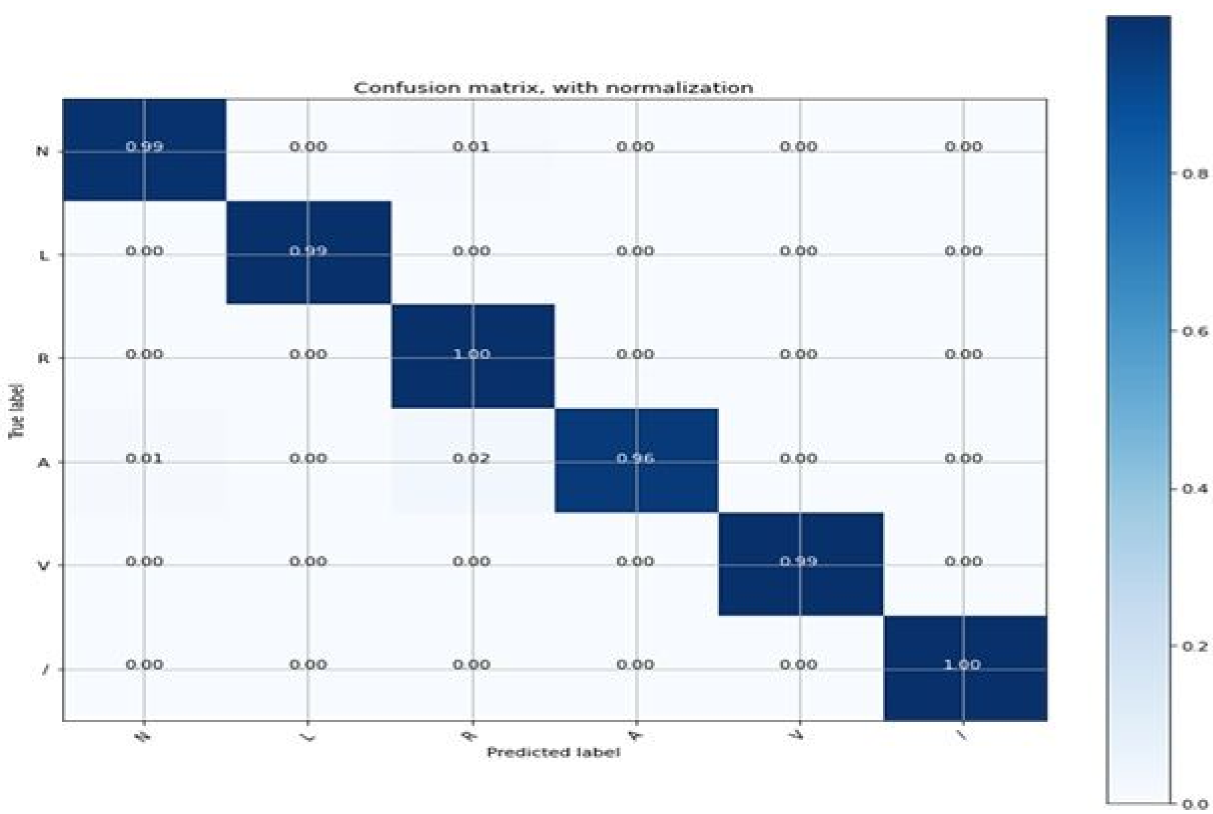

Figure 13

Normalized Confusion Matrix