ECG Classification and Prognostic Approach towards Personalized Healthcare

Wearable Systems for Real-time ECG Classification and Prognosis

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Abstract— **A very important aspect of personalized health-care is to continuously monitor an individual's health using wearable biomedical devices and essentially to analyse and if possible to predict potential health hazards that may prove fatal if not treated in time. The prediction aspect embedded in the system helps in avoiding delays in providing timely medical treatment, even before an individual reaches a critical condition. Despite of the availability of modern wearable health monitoring devices, the real-time analyses and prediction component seems to be missing with these devices. The research work illustrated in this paper, at an outset, focussed on constantly monitoring an individual's ECG readings using a wearable 3-lead ECG kit and more importantly focussed on performing real-time analyses to detect arrhythmia to be able to identify and predict heart risk. Also, current research shows extensive use of heart rate variability (HRV) analysis and machine learning for arrhythmia classification, which however depends on the morphology of the ECG waveforms and the sensitivity of the ECG equipment. Since a wearable 3-lead ECG kit was used, the accuracy of classification had to be dealt with at the machine learning phase, so a unique feature extraction method was developed to increase the accuracy of classification. As a case study a very widely used Arrhythmia database (MIT-BIH, Physionet) was used to develop learning, classification and prediction models. Neuralnet fitting models on the extracted features showed mean-squared error of as low as 0.0085 and regression value as high as 0.99. Current experiments show 99.4% accuracy using k-NN Classification models and show values of Cross-Entropy Error of 7.6 and misclassification error value of 1.2 on test data using scaled conjugate gradient pattern matching algorithms. Software components were developed for wearable devices that took ECG readings from a 3-Lead ECG data acquisition kit in real time, de-noised, filtered and relayed the sample readings to the telehealth analytical server. The analytical server performed the classification and prediction tasks based on the trained classification models and could raise appropriate alarms if ECG abnormalities of V (Premature Ventricular Contraction: PVC), A (Atrial Premature Beat: APB), L (Left bundle branch block beat), R (Right bundle branch block beat) type annotations in MITDB were detected. The instruments were networked using IoT (Internet of Things) devices and abnormal ECG events related to arrhythmia, from analytical server could be logged using an FHIR web service implementation, according to a SNOMED coding system and could be accessed in Electronic Health Record by the concerned medic to take appropriate and timely decisions. The system focussed on 'preventive care rather than remedial cure' which has become a major focus of all the health care and cure institutions across the globe.**

Keywords- ECG classification; Wearable IoT; preventive health-care; real-time ECG; arrhythmia detection; arrhythmia Neural-Net; MITDB, Physionet; GP Connect; HL7; FHIR

I. INTRODUCTION

"*Keeping your heart healthy, whatever your age, is the most important thing you can do to help prevent and manage heart disease. There are many different heart conditions and problems, which include angina, heart attack, heart failure and abnormal heart rhythms - as well as many other conditions including congenital heart disease and inherited heart conditions.*"

- The British Heart Foundation

So, any heart related ailment could be caused by a mix of conditions that are complex to measure and monitor. The research activity demonstrated in this paper, at an outset, focused on the classification and prediction problems whereby an arrhythmia could be electronically detected 'before' the heart condition would start to deteriorate. The research focused on identifying patterns of heart rhythms, and on classifying heart beats into a categories of ECG abnormalities. MITDB (MIT-BIH Database) records were used to generate learning and prediction models using MATLAB WFDB (Waveform Database) software package [5] [6] [7] [8]. The research paper first presents a review on current state of the research and examples of existing smart systems for ECG monitoring. These systems, however, do not have a predictive analysis component that can detect or alert individuals of ECG abnormalities well in time and before it's too late for treatment. Moreover, some of these devices have been implemented on hardware that restrict mobility, so cannot be used by patients whilst engaged in their day to day activities, which is when they are most likely to suffer a cardiac arrest or a heart attack. The paper then describes the methods used to train ECG classifiers and their predictive aspect. For a case study, a real-time smart IoT (Internet of Things) system has been proposed which could be integrated with the GP Connect infrastructure provided by NHS, UK and which is based on a widely accepted HL7 FHIR standard [40]. Such infrastructure is now also becoming available in many countries across the globe and the proposed system could be easily integrated to relay patient health status to the General Practitioner (GP) or Physician in real time.

II. BACKGROUND LITERATURE, RELEVANT RESEARCH PROBLEMS AND TECHNOLOGY

A. ECG Analysis

The heart comprises of a muscle called myocardium that is rhythmically driven to contract and drives the circulation of blood throughout the body. Before every normal heartbeat, a wave of electrical current passes through the entire heart and triggers a contraction. The pattern of this electrical current and its propagation is not random and spreads over the entire structure of the heart in a coordinated pattern and leads to an effective flow of blood in and out of the heart. This results in a measurable change in potential difference (voltage) on the human body surface. The resultant amplified (and filtered) signal is known as an electrocardiogram (ECG, or EKG). [1] A broad number of factors affect the ECG, which are, but not limited to: abnormalities in cardiac muscles, metabolic abnormalities of the myocardium and the geometry of the heart. ECG analysis is a routine part of a complete medical check-up, due to the heart's essential role in human health, and the recording and analysis of the ECG in a non-invasive manner is quite essential in patient health monitoring. The term tachycardia is used to describe a heart rate greater than 100 beats/min. A bradycardia is defined as a rate less than 60 beats/ min (or < 50 beats/min during sleep). [1][2] The ECG measurements show that the heart rhythms follow a distinctive pattern of progression and the sub-waves can be identified as the P, QRS and the T sub-waves and each of these have a time duration in humans with some degree of relative variation. As a result of the electrical activity of the heart cells, the current flows within the body and potential differences are established on the surface of the skin, which can be measured using suitable equipment, which is the ECG kit. The graphical recording of these body surface potentials as a function of time produces the electrocardiogram [3] [4].

B. MIT-BIH Arrhythmia Database

For the analyses presented in this paper, MITDB i.e. MIT BIH ECG database maintained and annotated at MIT, is being extensively used for data analysis and it is widely used in industry and academia for ECG related research. Several researchers have used MITDB to derive feature sets based on ECG morphology and heartbeat intervals, and have developed supervised algorithms for detection and classification of arrhythmia [5]. The database consists of ECG recordings that has wide range and variety of waveforms that could possibly cover most of the abnormal beat waveforms and which can be used to build a machine learning model and test it. [6] The MIT-BIH Arrhythmia Database contains 48 half-hour two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. [6][7] Two or more cardiologists independently annotated each record to obtain the computerized reference annotations for each beat (approximately 110,000 annotations in all). The database also happens to be widely used, referenced and cited, and is considered to be a gold standard for ECG data analysis. The distribution of the records according to the ages of the subjects is shown in Figure 1 and age along with the frequency of occurrence was used to calculate the impact factor of a record on the analyses. MITDB WFDB also provide ECG analyzers that could be used to test trained models.[8] The trained models were then used on acquired data samples in real-time in order to classify arrhythmia.

ECG QRS detection is an important aspect in ECG analysis and techniques such as K-Means, PCA (Principal Component Analysis), K-Nearest Neighbours (K-NN) and Probabilistic Neural Network (PNN) have been successfully used recently yielding over 99% classification accuracy [11][12][28]. The drawback however is that these models tend to accept test data in large samples and perform analysis on entire dataset in a single execution cycle instead of beat-by-beat samples in real-time. Although, this may help to develop analytical models, they remain isolated from monitoring equipment and can't be used in real-time monitoring in order to generate alarms and alerts related to arrhythmia. In methods section an illustration to overcome this limitation has been demonstrated by combining the data acquisition with machine learning servers in real time. By transmitting the JSON (JavaScript Object Notation) encapsulated ECG readings in real time to the server that is already trained on ECG data from MITDB the analytical server performs the analyses and classification tasks. There also exists a high degree of correlation between Heart Rate Variability (HRV) and arrhythmia. To determine the correlation k-Nearest Neighbours (k-NN) and Multilayer Perceptron Neural Network (MLP) have been previously used with some success to predict sudden cardiac deaths with a high degree of accuracy (about 99.73%, 95%. .96.52%) [13] The problem however is that HRV analysis depends on the morphology of the ECG waveform and QRS detection [10] [29], which depends on the accuracy of the ECG equipment and accurate 12-lead ECG equipment may not be portable and certainly not wearable. In order to not base classification accuracy on ECG morphology, a unique feature extraction method was developed as explained in ECG Waveform dataset preparation sub-section (Methodology and Data Analysis) of this paper. The same features and machine learning models could be used with other databases from Physionet MIT-BIH: Creighton University ventricular tachycardia database, MIT-BIH atrial fibrillation database and Holter database which are records of patients who suffered sudden cardiac death during recordings and can be used for ECG pattern recognition of extreme conditions [15] [16]. It is worth noting that an arrhythmia is non-linearly dependent on P, T, QRS waves and on individual features like RR interval, heart rate, signal strength and arterial blood pressure, or a combination of these, so a Principal Component Analysis was used to reduce the dimensionality in such a way that the variance of data in lower dimensions could be maximized to visualize the data in lower dimensional space.

C. *Wearable ECG Kits and Signal processing*

There are commercially available wearable 3 Lead ECG kits which can take ECG sample readings while the person under observation is engaged in day to day activities. However, many of these kits focus only on data-acquisition and monitoring and provide no analysis or prognosis information in real time. Furthermore, with these kits intelligent aspect of prediction and raising appropriate alarms, before the health hazard occurs, has not been adequately addressed. The system proposed in this paper consists of a software implemented on the wearable device which encapsulates the sample readings in a standard JSON format [23][24] and transmits the samples to the analytical server that implements the classification and prediction algorithms using the utilities provided by MITDB WFDB database. Such algorithms can be implemented on IoT (Internet of Things) devices and can be networked in a peer-to-peer mode. [20]

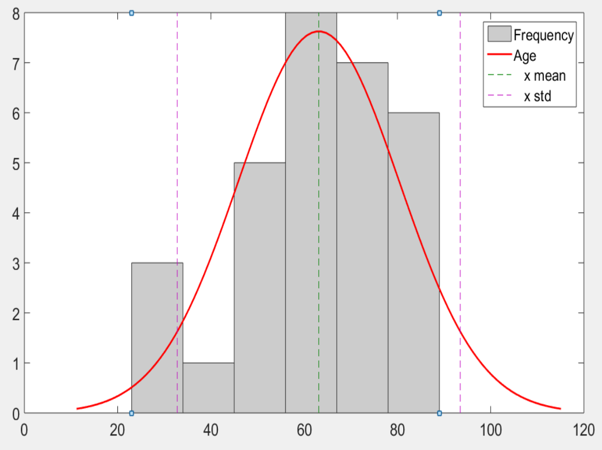

Figure 1. *Distribution of Age in the 48 records of MITDB database used to extract the 'impact factor' feature of each record on the classification algorithm*

With the advent of wearable devices and Internet of Things (IoT) technologies several SoC (Systems on Chip) integrated circuits vendors have started providing system software to enable these devices operate on low power and with high up-time operation (24/7 hours). With Bluetooth 4.0 Low Energy modules the devices can exchange data efficiently without needing excessive power to operate on 24/7 basis with miniaturization. The research involved developing software components that performed data-acquisition, signal conditioning and calibration using appropriate filtering techniques as illustrated in Real-time data acquisition sub-section (Methodology and Data Analysis section) of this paper. The data preparation subsection (Methodology and Data Analysis) section of the research paper focuses on prediction and inference model generation to alert the patient whilst engaged in day to day activities. Multi-Agent systems have been recently used in monitoring patients and since the system requires high uptime, i.e. 24/7 operation, the power consumption, load balancing and fault tolerance aspects have to be taken care of and agent based systems can best handle these scenarios [18][25]. The agent software responds to heart rhythm pattern events based on the beliefs and goals programmed into it and can classify specific type of arrhythmia.

III. METHODOLOGY AND DATA ANALYSIS

A. *ECG waveform dataset preparation and analysis*

In this section, methods to combine real time ECG samples acquisition with real-time analyses and arrhythmia classification have been demonstrated. Taking this a step ahead, trained machine learning models have also been used to predict arrhythmia and raise appropriate alerts and alarms whilst the individuals under monitoring remain engaged in day to day activities. The Class 1 MITDB waveform database is considered gold standard in ECG analysis and is widely used, referenced and more importantly it is manually annotated by medics and is quite reliable as there is least noise in the dataset. [21] [22]. In order to classify arrhythmic beats, MITDB WFDB waveform records were used to prepare datasets to train classifiers. The most essential aspect of data analysis is feature identification and extraction and cleaner and accurate the features the easier it is for the data analysis models to learn and perform pattern recognition, regression, prediction and classification. Initially, the *'RDSAMP'* utility was used to convert the samples to WFDB compatible format in MATLAB [6] [7]. Normal beats were removed from the samples and only the abnormal beats that were annotated according to the WFDB annotation files, were read by the *'RDANN'*. The '*RDANN*' utility was used for this purpose, as the utility uses MIT BIH database's own annotation file, and since this file was manually annotated by ECG experts, correct results could be obtained. For all the records, the feature vectors that attributed to abnormal heart rhythm were identified. The important features were: Age, Gender, the ECG signal amplitude for each sample (millivolts), RR interval (inter-beat interval in milliseconds), WABP (arterial blood pressure in millivolts) and instantaneous heart rate measured at the 'instance' when the abnormal heart beat annotation occurred in ECG recording. These feature vectors were derived for 4 annotation types: V (Premature Ventricular Contraction: PVC), A (Atrial Premature Beat: APB), L (Left bundle branch block beat), R (Right bundle branch block beat) [6] [7] [29]. It has been observed that these 4 annotation types do occur in ECG recordings of healthy subjects as well and can go unnoticed without showing any symptoms [30]. It may take as many as three consecutive PVCs before a ventricular tachycardia is detected or confirmed [31] [32] [33]. Similar argument could be made for 'A' type annotation which refers to Premature

Atrial Complexes (PAC) and though it can go undetected without showing any symptoms, it may lead to atrial fibrillation [32][34].

MITDB database from MIT-BIH repository is an ECG waveform samples database for 47 subjects of various age groups for both the genders. An impact factor was calculated from age and frequency of distribution information (Figure 1) so as to associate weights to the recordings and to determine how much an individual's ECG recording impacted the overall classification process. Classification algorithms were initially trained on the feature vectors with 70% training set, 15% validation set and 15% test set, however, other combinations of percentage values have also been experimented with results shown in Table 2. From each of the 47 records in MITDB database about 650,000 samples per record were used to train the classifiers in order to classify a heartbeat sample as belonging to a category (or label) of an abnormal beat type. From the experiments performed using several classifiers, k-NN classifiers with 6 principal components yielded 99.4% accuracy as shown in Figure 2 and Table 1. The figure shows 4 different annotation types representing 4 different types of arrhythmia denoted by V, A, L, R annotation types. Table 1 shows classification accuracy scores using Tree and k-NN classifiers which remains fairly consistent with or without principal components and with 10-fold cross validation. Figure 3 shows the prediction accuracy across the 4 classes corresponding to V, A, L, R annotations.

In addition to the classification based on regression approach, classification based on fitting and pattern recognition using neural networks was also experimented with. Similar experiments have been performed in the past where patterns of ECG recordings were analysed in order to extract patterns using artificial neural net models and QRS wave characteristics of abnormal beats were compared with normal beats to classify and predict arrhythmia. [35] The accuracy of classification however, depends on the features extracted from the datasets. Table 2 and Figure 4 show pattern recognition accuracy over several combinations of percentages of training-validation-test data showing no bias or over-fit.

Other techniques do exist which use multi-layer feed-forward perceptron models to analyze the waveform for prediction and analysis [36]. Many of these and other techniques consider the morphological structure of the ECG waveform and RR interval is commonly used for analysis, however, the morphological structure of the QRS waveform using individual's own ECG waveform pattern, over a period of time, for a comparison to detect abnormal from normal waveform may present challenges. Furthermore, the QRS waveforms and ECG recordings are relative to an individual and the HRV (Heart Rate Variability) analyses and the risks inferred from the readings are influenced by gender and age information [37]. The MATLAB Neural Net Fitting models with 10 hidden layers and Levenberg-Marquardt training algorithm yielded the values as presented in Table 2.

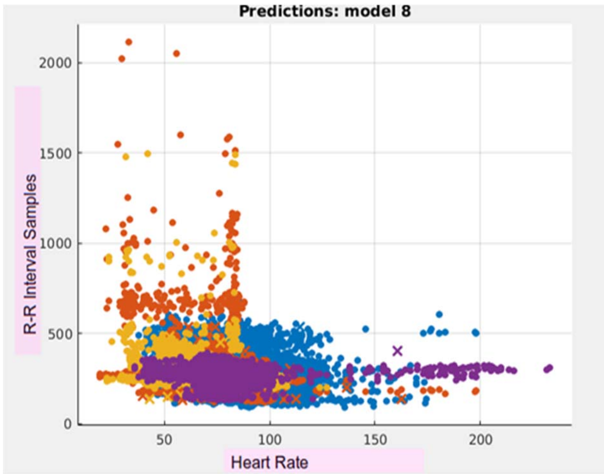

Figure 2. *k-NN classifier with Number of neighbors: 10; Distance metric: Euclidean; Distance weight: Squared inverse; Principal Components:4 out of 6 yielding Accuracy of 97.1% for classifying 4 predictor annotation classes of Arrhythmia in MITDB database. Ensemble Bagged Tree classifier produced classification accuracy of 97.4% without PCA (Principal Component Analysis) and 95.4% with 3 Principal Components. The MATLAB classification learner was set to cross-validate at 10- fold validation and 25% hold-out validation.*

TABLE 1. : ACCURACY RESULTS FOR CLASSIFICATION MODELS USING 10-FOLD CROSS VALIDATION

Classifier	**Accuracy**
Bagged Trees classifier Ensemble method: Bag Learner Type: Decision tree Number of learners: 30 10-fold cross-validation	97.4% without principal components selected. 97.0% with 4 out of 6 principal components selected. 95.0% with 3 out of 6 principal components selected.
Weighted KNN classifier Number of neighbours: 10 Distance metric: Euclidean Weight: Squared inverse Standardize data: true 10-fold cross-validation	99.4% without principal components selected. 97.1% with 4 out of 6 principal components selected. 95.4% with 3 out of 6 principal components selected.
Accuracy scores obtained with Bagged Decision Trees and kNN classification models using 10-fold cross validation in MATLAB Classification Learner tool.	

TABLE 2. NEURALNET PATTERN RECOGNITION RESULTS FOR VARIOUS PERCENTAGE OF TRAINING VALIDATION AND TEST DATA

Type of Neural Network	**Percentage (%) Training- Validation- Test data**	**Mean-squared error (MSE) and Regression R for test data.**
Neuralnet Fitting	70-15-15	MSE= 0.0085 and R= 0.99
	60-20-20	MSE=0.0017 and R=0.99
	60-15-25	MSE=0.0012 and R= 0.99
Neuralnet Pattern Recognition	70-15-15	Cross-Entropy Error for test data: 7.6 Misclassification Error: 1.2%
	60-20-20	Cross-Entropy Error for test data: 9.9 and Misclassification Error: 2.1%
	60-15-25	Cross-Entropy Error for test data: 8.7 and Misclassification Error: 1.7%
MATLAB Neural Net Pattern Recognition tool was used to obtain results for various percentage values for training, validation and test dataset.		

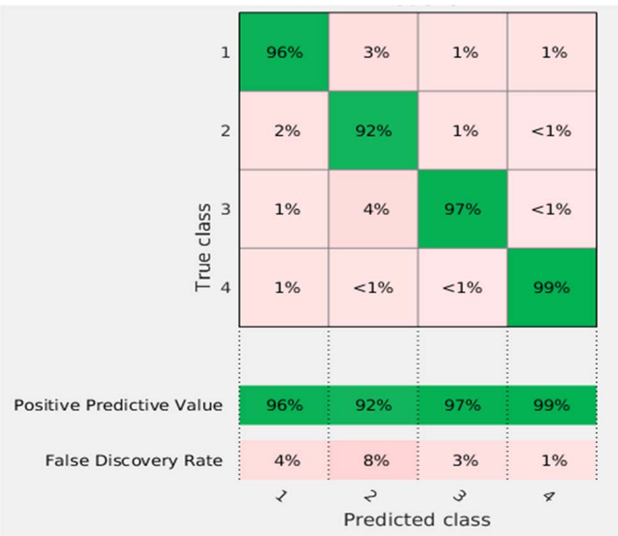

Figure 3. *Confusion matrix for Ensemble Bagged Trees method for classifying from a total of 24190 samples across all 47 MITDB records where all the feature vector elements (age, gender, signal strength, RR interval, heart rate, impact factor) were used for classifying (1,2,3,4) corresponding to (V, A, L, R) type of annotations.*

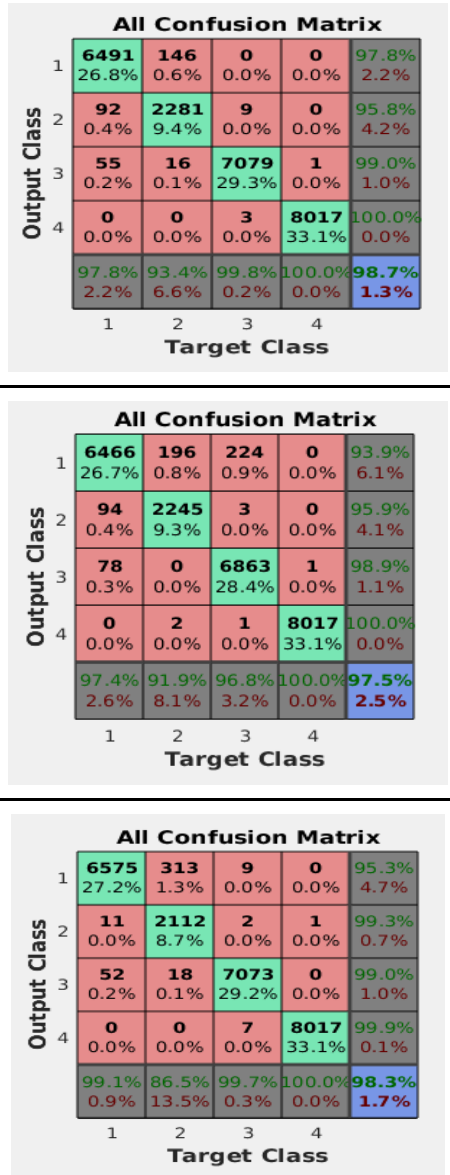

Figure 4. *Confusion matrices for MATLAB Neural Net Pattern Recognition yielded 1.3%, 2.5% and 1.7% classification error for training, validation, test data sets in following configuration: training (70%,15%,15%), validation (60%,20%,20%) and test (60%,15%,25%) datasets. Scaled Conjugate Gradient back-propagation algorithm was used as available default in MATLAB pattern recognition tool with the network depth set to 10.*

B. Real-time data acquisition and Web-services

Once the data analysis model was ready, a 3 Lead ECG kit from Olimex [38] was used to take samples from human subject. The ECG readings obtained from the Olimex 3-electrode ECG kit [38] were sampled at 250 Hz with 12 bit resolution followed by low pass anti-aliasing filter, as required by MITDB WFDB database, in a format called 'Format 212' [6]. The raw waveform samples were passed through the '*WRSAMP*' utility followed by QRS detectors to generate annotation files. *'WABP'* utility was used to generate Arterial Blood Pressure (ABP) annotations. The *'WRANN'* utility in WFDB toolkit annotated the waveform as required by the MITDB database for further analysis. The '*TACH*' utility was used to obtain the instantaneous heart rate from the samples. The 3-lead ECG Olimex device was interfaced to an Arduino micro-controller which transmitted the samples to the Linux system with WFDB/MATLAB through a serial port. The analytical server software on Linux system collected the samples and passed the samples to WFDB component for Arrhythmia detection and classification. A prototype that could collect the readings from ECG kit and microcontroller and to transmit the samples to the analytical server over Wi-Fi connection was also developed. A JSON (JavaScript Object Notation) structure that encapsulated the sample readings was adopted which passed the samples to the analytical server running Node.js [24] using Websockets [23] for further processing as shown in Figure 5. The readings encapsulated with JSON data structures were transmitted containing ECG samples spread over a 10 seconds interval as ECG rhythm strips are generally for a 10 seconds duration [2][3]. The user-agent software running on the wearable device was configured and modelled as a P2P (peer-to-peer) agent software and ECG readings conformed to HL7 and FHIR standards specification [26] [27]. The protocol used to deliver data in real time used HTTP for transport, which makes the technology ubiquitous and platform independent over the internet. The P2P user agent running on the wearable device however, connected to the data analysis software using a RESTful Web-Service. [41][42]

The data analysis software developed using GCC WFDB libraries provided by MITDB BIH arrhythmia has been hosted on a Linux IoT (Internet of Things) device, the Raspberry Pi and the Beaglebone Black from Texas Instruments. Once abnormal beats or waveforms are detected appropriate alarms are raised and passed to the health-care agency entrusted with the patient care.

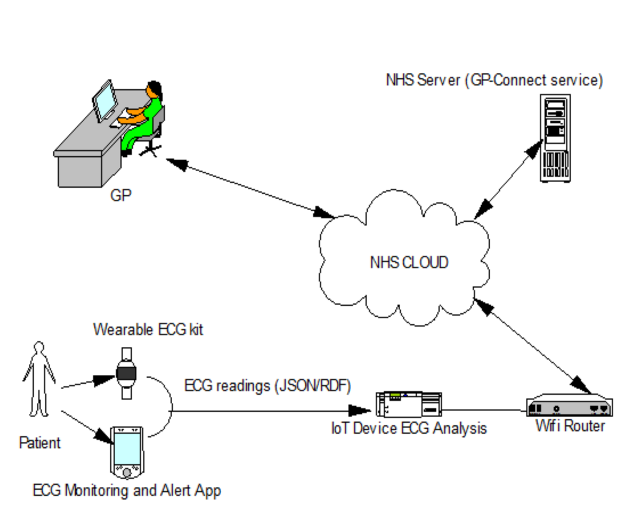

Figure 5. *ECG Real-time Monitoring IoT network set-up.*

The NHS (National Health Services, UK) have an informatics facility in the form of a Developer network hosted by the NHS Digital that provide the specification for data and services interoperability [39] The GP Connect Ecosystem have defined standards and web-services that can be used to upload data to the NHS data centres (offered by NHS GPSoC - GP System of Choice or GP Connect) so the real-time data can be uploaded to NHS cloud and monitored by the patients' General Practitioners. FHIR is a well-known HL7 standard used by health services in several countries across the globe to enable web-services upload and host patient records in Electronic Health Records (EHR) [40]. In order to demonstrate gathering of samples, passing the same to the analytical server and logging these to EHR in a standard recognized format, a publicly available FHIR server instance was identified and a RESTful web-service was hosted in an HSPC sandbox [41][42]. The ECG recording and analyses could then be coded according to SNOMED-CT [43] coding system (code: 428803005 for 3-lead ECG monitoring) [44] and be potentially logged to EHR repository. One of the vital and essential component in any cloud based service is security and whether the EHR records could be accessed or modified using appropriate authentication and authorization schemes. NHS Digital GP Connect, for example, relies on Spine Security Proxy (SSP) and would be exposed as FHIR RESTful APIs and the consumer system can connect using GP organisational identifier. [49] Since a large number of EHR systems have adopted FHIR standards these systems would rely on TLS/SSL (Transport Layer Security) for RESTful API calls. The FHIR specification on security also supports OAuth authentication and authorization service which the consumer services can embed in their FHIR servers. [50] [51]

IV. CONCLUSIONS AND DISCUSSION

The motivation behind the research was to combine a wearable ECG monitoring kit with real-time arrhythmia classification and prediction server, raise appropriate alarms and at the same time upload and log the events to electronics health records database using HL7 and FHIR standards. The learning models trained using MITDB arrhythmia database and MATLAB WFDB library yielded 97.5% and higher percentage of accurate results in classification and prediction. Initially it was anticipated that unsupervised learning algorithms may present a solution by recognizing abnormal ECG patterns in an individual, however supervised learning models based on 6 features (Table 1, Figure 2 and Figure 3) yielded more accurate results in classification and prediction of 4 types of arrhythmia (V, A, L, R annotations in MITDB). Along with regression based classification fitting and pattern recognition using neural networks was also experimented with and Table 2 and Figure 4 show pattern recognition accuracy over several combinations of percentages of training-validation-test data showing no bias or overfit. In currently available systems as mentioned in Background Literature and Problems section and despite of the availability of accurate classification [11] [12] [13] [47] algorithms these could not be put to practical and beneficial use to raise alarms due to size constraints of the accurate 12-lead ECG equipment and non-real time batch processing nature of the algorithms. Traditionally, ECG arrhythmia classification relied on QRS detection and HRV analysis which produced accurate results [10] [29] [45] [46] [47] [48] though it relied on accurate ECG equipment which is not portable or wearable. The feature extraction method (explained in Methodology and Data Analysis section) illustrated in this paper that did not solely rely on morphology of ECG waveforms and ECG equipment noise sensitivity, produced almost as accurate results as produced by machine learning and feature extraction models that relied on HRV analysis and ECG morphology. Furthermore HRV analysis is susceptible to be influenced by the physical state of the individual like running, climbing and dormant and sleeping states. [52] [53]. These modifications would have to be factored in the data acquisition, de-noising and filtering mechanisms and an area of further instrumentation research. By combining the real-time data acquisition, filtering and signal processing mechanisms with asynchronous JSON based transmission in burst intervals of 10 seconds each, the classification server could analyse and classify arrhythmia continuously in real time and could raise appropriate alarms. The encapsulation of samples according to FHIR [41] [42] specifications enabled demonstrating the logging of events to electronics health records repository for further analysis by the general practitioners and medics. This should enable and immensely assist incident response medical health-care teams to prepare for an emergency for heart related patients ahead of time and may prevent or reduce emergent situations and related trauma. With further consolidation of EHR and other ubiquitous platforms the model could be extended to monitor and respond to emergencies related to health monitoring of individuals whilst they remain engaged in day to day activities.

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