Intelligent remote health monitoring using evident-based DSS for automated assistance

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Abstract — **the shift from common diagnosis practices to continuous monitoring based on body sensors has transformed healthcare from hospital-centric to patient-centric. Continuous monitoring generates huge and continuous amount of data revealing changing insights. Existing approaches to analyze streams of data in order to produce validated decisions relied mostly on static learning and analytics techniques. In this paper, we propose an incremental learning and adaptive analytics scheme relying on evident data and rule-based Decision Support System (DSS). The later continuously enriches its knowledge base with incremental learning information impacting the decision and proposing up-to-date recommendations. Some intelligent features augmented the monitoring scheme with data pre-processing and cleansing support, which helped empowering data analytics efficiency. Generated assistances are viewable to users on their mobile devices and to physician via a portal. We evaluate our incremental learning and analytics scheme using seven well-known learning techniques. The set of experimental scenarios of continuous heart rate and ECG monitoring demonstrated that the incremental learning combined with rule-based DSS afforded high classification accuracy, evidenced decision, and validated assistance.**

I. INTRODUCTION AND RELATED WORK

Home healthcare services have been proposed as a potential approach for an efficient use of healthcare resources to accommodate a growing number of patients in aging societies, mainly those with chronic diseases [1]. In this range of home telehealth care systems, mobile health monitoring is the most promising. Such systems are built around body sensors to get vital signs readings and mobile applications to communicate any valuable information to patients and physicians. M-health application are of less pragmatic use if they are not intelligent enough to automatically propose customized and appropriate therapies based on vital signs readings.

Decision Support System (DSS) is a well-known concept that has been largely used to help in decision taking ([2], [3], [4], [5], [6]). Although their use in healthcare and critical care systems have been proposed a while ago ([7]), they did not see that much development in healthcare until recently. In fact, they are seen as a very promising approach to help physicians and healthcare personnel. Such systems can also be vital to outpatients who require expert decision while out of hospitals or out of reach of a physician.

The authors in [8] presents a telehealth system where received clinical measurements from remote patients are analyzed to search for trends and shifts in parameters values that might exceed thresholds. A system to determine carbohydrate intake for diabetes is presented in [9] with the main purpose of providing valuable food intake and suggesting appropriate therapies. A similar DSS for chronic and complex diseases is presented in [10] to analyze medical data acquired from subjects at their place of residence and work. The authors in [11] propose a DSS system to enhance m-health applications used by rural populations where access to healthcare experts is limited. The efficiency of such an application depends on its ability to independently take accurate decisions.

The authors in [12] compares the use of fuzzy expert systems and Neuro Fuzzy systems for hypertension diagnosis. For hypertension as well, [13] proposes a system for monitoring patients in a comorbid conditions. Using statistical reasoning and fuzzy inference, authors in [14] propose a generic transparent decision support system with application for heart diseases.

While the works cited above are interesting, they have some known weaknesses. The most notable limitation is their inability to consider continuous streams of large readings values. More limitations include one or a combination of the following:

- No support for mobile continuous monitoring
- No consideration of dynamic data
- Accuracy of readings
- Accuracy of proposed decision

In this paper, we propose to address some of the above challenges and we propose an incremental leaning and event-based DSS that support continuous mobile monitoring. The later consider dynamicity of collected data, pre-process data for higher data accuracy, efficient data analytics, and better-proven decisions.

II. EVIDENT-BASED AND RULE-DRIVEN DSS

A. System Design

Figure 1 shows an overview of the architecture and its components for continuous monitoring and automated assistance.

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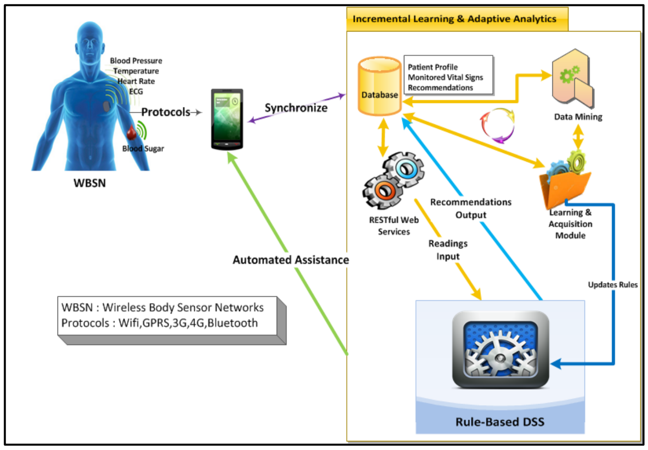


Figure 1. Architecture for intelligent monitoring based incremental

The first phase starts with data acquisition and storage, which consists of retrieving data using biosensors, attached to the human body and relaying data to mobile devices via communication protocols (e.g. Wi-Fi, 4G, Bluetooth); then synchronize the collected data with a database. When needed, readings are retrieved from the database using Restful web services, and then passed to the DSS. The later processes the readings and applies a set of rules to generate automated assistance to the patient under monitoring; generated advices can be displayed on his/her mobile device. A continuous intelligent process is continuously running on the background and consists of incremental mining of gathered data (vital signs and generated advices) and incremental learning of and from these data. Finally, rules are enhanced using the knowledge acquired from learning and continuous data collection and enriched with new sets of rules.

B. *Sensory data collection*

Wearable sensors are used to continuously record vital signs, sent readings to the specified storage and processing device (e.g. mobile device). During this activity, some challenges might be encountered such as data loss, network bandwidth, and battery drainage in case a mobile device is used to retrieve and process data. We have developed some intelligent features to cope with these issues at both ends. At the sensor, we implemented some pre-processing and filtering (e.g. remove noise, eliminate redundant and insignificant data). At the mobile device, we implemented intelligent agents that wisely consider the resource scarcity and network condition to process and/or communicate data.

C. *Feature extraction and classification*

Feature extraction is an important process used to extract features from the collected data such as ECG signal, in order to be used for diagnosing some diseases such as cardiac diseases. Extracted features for an ECG signal include for example QRS duration, RR interval, QT, and ST segment. Prior to features extraction, the signal is filtered and noise is removed.

D. *Incremental learning*

The incremental property of our monitoring and diagnosis system is continuously enriched as new data are learned and new knowledge is developed. This is done through data slicing, which makes it flexible to delimit the data to be processed and allows shrinking and expanding the data window size when needed (e.g. data urgency). Incremental learning and classification allow continuous enhancement of the overall monitoring cycle since it nourishes the DSS with up-to-date knowledge.

E. *Automated Assistance based DSS*

Automated guidance are generated by the DSS and sent to patient's mobile. The later uses the output generated from learning and classification of collected data in addition to the knowledge acquired from all past experiences. Advices are validated and stored in the database and automatic assistance are sent to the patient's mobile device. Afterwards, they are used to check whether these have impacted the subject's health condition in future monitoring round.

III. EVALUATION

A. *Environment Setup*

To implement the monitoring system, we have used the following:

- Sensors: Zephyr HxM heart Rate/ BioHarness 3
- Mobile devices: Android tablet running KitKat 4.4.2.
- Database server: MySQL server 5.6.
- Restful Web Services to retrieve readings from the mobile phone.
- Rapid Miner for data mining and learning [15].
- Matlab 2012.

B. *Dataset*

We have used a combination of datasets retrieved from (1) continuous monitoring of Heart Rate (HR) and the Electrocardiogram (ECG) of a number of patients and (2) an arrhythmia dataset from UCI Machine Learning Repository [16]. Another dataset considers heartbeats and ECG features of 452 patients as well as other parameters such as age, gender, etc.

The following table describes the main class distribution:

TABLE 1. DATA DISTRIBUTION PER CLASS OF DISEASE

Class Name	No Of Instances
PVC – Premature Ventricular Contraction	3
AMI - Anterior Myocardial Infarction	15
SPVC - Supraventricular Premature Contraction	2
SB - Sinus Bradycardy	25
LVH - Left Ventricule Hypertrophy	4
CAD - Coronary Artery Disease	44
IMI - Inferior Myocardial Infarction	15
ST - Sinus Tachycardy	13
AF - Atrial Fibrillation	5
LBBB - Left bundle branch block	9
RBBB - Right bundle branch block	50
Others	22

C. *Real time Mobile Data Collection implementation*

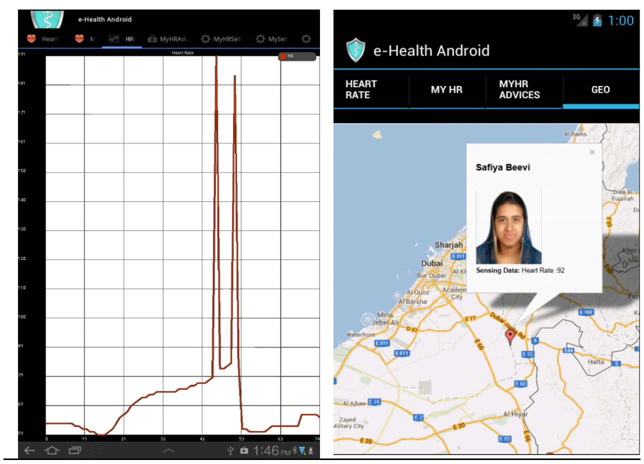
We developed an Android mobile application to retrieve the sensed data and synchronize it with the backend via Restful Web Services. Initial settings include setting the age of the patient via the application as well as the permission to use the current locations. Current location information is used to send patient geographic locations in case of emergency to the nearest hospitals and emergency authorities. The below figure shows a sample snapshot of the application we have developed, this includes an interface for data visualization (Figure 2.a) and geo-location determination (Figure 2.b).

We also implemented a couple of components that include a set of restful Web services, rule-based DSS, and visualization module:

Restful Web services: Web services provide interfaces to create, read, update, and delete readings. These operations help in the pre-processing of collected readings.

DSS implementation: the DSS is developed using Java.

Visualization Interface: advices are visualized through an E-health portal where patients have read-only access and physicians have read-write authorizations.



(a) Data visualization (b) Geo-Location

Figure 2. Snapshot of online monitoring using Android mobile App

D. *Feature extraction*

The figure below shows the result we have obtained from the execution of ECG signal pre-processing and feature extraction. As illustrated in the graph, different signal's picks and waves are detected and classified.

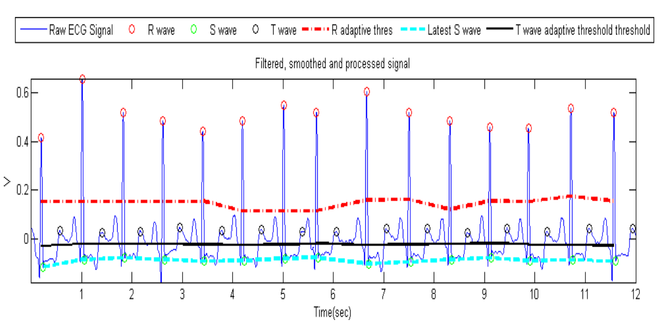


Figure 3. Sample of a pre-processed ECG signal P-QRS-T feature detection

E. *Continuous learning*

To learn from the collected data, we have first evaluated the accuracy and the execution time of seven learning models using the same dataset. These models include: Neural network, decision tree, AutoMLP, W-OneR, NaiveBayes, RuleModel, and J48graft. A set of induction rules was generated for the purpose of learning and classification. The followings are examples of J48graft pruned rules.

```
HR <= 57
|   QRSDuration <= 96: Sinus bradycardy
|   QRSDuration > 96: RBBB
HR > 57
|   QRSDuration <= 113
|   |   HR <= 101: Normal
|   |   HR > 101: Sinus tachycardy
|   QRSDuration > 113
|   |   QRSDuration <= 123
|   |   |   HR <= 69.5: Normal
|   |   |   HR > 69.5: RBBB
|   |   QRSDuration > 123: LBBB
```

The above rules relied on two vital signs Heart Rate and ECG to decide about the class (e.g. bradycardy) for each patient based on the data given as input.

F. *Test Scenarios*

The following are the scenarios we have selected to evaluate our monitoring and analytics scheme while considering the following parameters: learning accuracy, execution time, and recommendations appropriateness.

<u>Scenario 1</u>: In this scenario, we consider monitoring HR only using the dataset we described above. The objective of this scenario is to evaluate the accuracy and the execution time of our monitoring and analytics scheme using different learning models. We also measured in this scenario the execution time recorded to learn and classify data by each of the seven models. The results obtained from the execution of this scenario are reported in Figure 4.

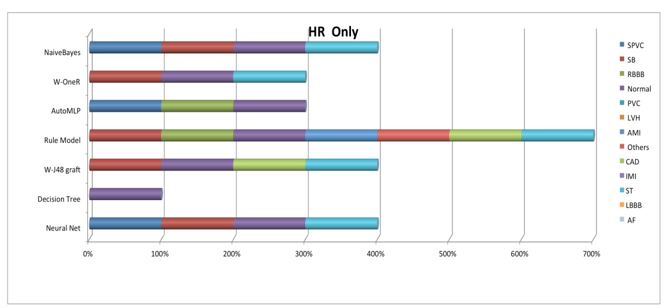


Figure 4. Data Analytics based HR

<u>Scenario 2</u>: In this scenario, we enhanced the HR dataset with additional ECG data considered in scenario 1. We also measured in this scenario the execution time recorded to learn and classify data by each of the seven models. The objective is to test if this extension will impact the learning accuracy, classification, and/or analytics. The results of this scenario are reported in Figure 5.

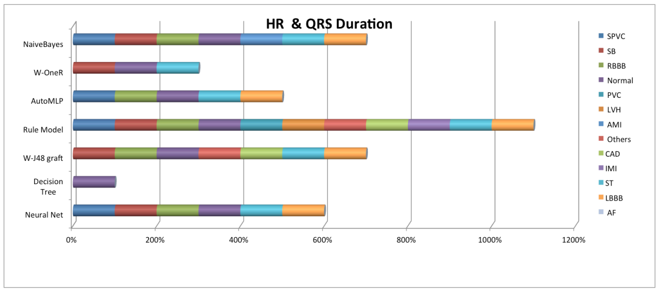


Figure 5. Data analytics based ECG and HR

IV. Results and Discussion

Figure 4 illustrates the results of analyzing and classifying the learned HR data using the seven learning models. These models have detected only few classes. The *RuleModel* detected 7 classes out of a total of 12 classes, which exhibits accuracy around 60%.

Figure 5 illustrates the results of analyzing and classifying the learned HR and ECG data using the seven learning models. These models now detected at least 25% more classes compared to the experiments conducted in scenario 1. The *RuleModel* in this experiment offers also the highest accuracy (90%) compared to the other learning models. This confirms that the incremental learning and analytics scheme is a very appropriate learning solution that adequately matches the continuous monitoring where data are continuously collected.

The results of recording the execution time showed that the *AutoMLP* learning model required the highest execution time, the neural network model comes the second. However, the other learning models required negligible execution time.

Finally, the overall results proved that our monitoring and analytics system is able to provide a better accuracy while applying incremental learning and classification techniques combined with an evidence-based DSS.

V. Conclusion

Continuous monitoring based sensing has changed the way healthcare systems support people's wellbeing. It generates a large amount of data, which makes it challenging to collect, process, classify, analyze, and generate appropriate decisions from this data. In this paper, we proposed a monitoring based incremental learning and adaptive analytics. This scheme evaluated the classification accuracy of seven learning models while considering new data and new parameters. The learning process is continuously enriched with new knowledge learned by incremental learning. This will impact the diagnosis decision and validate the possible advices. Users can view advices via their mobile devices. The experiment we have conducted demonstrated that our monitoring scheme combined with the incremental learning afforded high classification accuracy, thus evidenced decision and validated assistance.

References

[1] S. Koch, "Home telehealth—current state and future trends," International journal of medical informatics, vol. 75, pp. 565-576, 2006.

[2] C. W. Holsapple and A. B. Whinston, Decision support systems : theory and application. Berlin ; New York: Springer-Verlag, 1987.

[3] G. Fick and R. H. Sprague, Decision support systems : issues and challenges : proceedings of an international task force meeting, June 23-25, 1980. Oxford ; New York: Pergamon Press, 1980.

[4] R. H. Sprague and E. D. Carlson, Building effective decision support systems. Englewood Cliffs, N.J.: Prentice-Hall, 1982.

[5] R. H. Sprague and H. J. Watson, Decision support systems : putting theory into practice. Englewood Cliffs, N.J.: Prentice-Hall, 1986.

[6] E. R. McLean and H. G. Sol, Decision support systems : a decade in perspective : proceedings of the IFIP WG 8.3 Working Conference on Decision Support Systems: a Decade in Perspective, Noordwijkerhout, the Netherlands, 16-18 June 1986. New York, U.S.A: Elsevier Science, 1986.

[7] M. M. Shabot and R. M. Gardner, Decision support systems in critical care. New York: Springer-Verlag, 1994.

[8] J. Basilakis, N. H. Lovell, S. J. Redmond, and B. G. Celler, "Design of a decision-support architecture for management of remotely monitored patients," IEEE Transactions on Information Technology in Biomedicine, vol. 14, pp. 1216-1226, 2010.

[9] P. Pintér, L. Vajda, and L. Kovács, "Developing a decision support system to determine carbohydrate intake of diabetic patients," in IEEE 10th International Symposium on Applied Machine Intelligence and Informatics, ed: IEEE, 2012, pp. 427-430.

[10] J. Basilakis, N. H. Lovell, and B. G. Celler, "A decision support architecture for telecare patient management of chronic and complex disease," in 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, ed: IEEE, 2007, pp. 4335-4338.

[11] M. V. Ramesh, T. Anu, and H. Thirugnanam, "An intelligent decision support system for enhancing an m-health application," in Ninth International Conference on Wireless and Optical Communications Networks (WOCN), ed: IEEE, 2012, pp. 1-5.

[12] S. Das, P. K. Ghosh, and S. Kar, "Hypertension diagnosis: a comparative study using fuzzy expert system and neuro fuzzy system," in 2013 IEEE International Conference on Fuzzy Systems, ed: IEEE, 2013, pp. 1-7.

[13] D. Lin, F. Labeau, and G. Kang, "Decision support system for monitoring hypertensive patients in a comorbid condition," in IEEE Conference on Prognostics and Health Management ed: IEEE, 2013, pp. 1-7.

[14] A. Hamilton-Wright and D. W. Stashuk, "Transparent decision support using statistical reasoning and fuzzy inference," IEEE Transactions on Knowledge and Data Engineering, vol. 18, pp. 1125-1137, 2006.

[15] RapidMiner. (2014, June). Predictive Analytics, Data Mining, Self-Serve, Open Source. Available: http://rapidminer.com

[16] K. Bache and M. Lichman. (2013, June). UCI Machine Learning Repository. Available: http://archive.ics.uci.edu/ml/datasets/Arrhythmia