Machine Learning Against Statistics to Detect Faults in WBANs(Wireless Body Area Networks) in Healthcare

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***Abstract*—The WBAN (Wireless Body Area Network), is a subset of WSN (Wireless Sensor Network), where the fusion between, sensing, pervasive computing, intelligent information processing, and wireless communication is used, healthcare is one of the most important application domains, where a numbered body sensor nodes implanted on, in or around the Hyman body to supervise their vital signs, the limited software and hardware resources lets these body sensor nodes, exposed to faults, statistics, and machine learning techniques are a good choice for fault handling in WBANs, in this paper, we aim to achieve an efficiency comparison between these two techniques.**

***Index Terms*—Fault,machine learning, statistics, WBAN**

I. Introduction

WBANs, this kind of networks is developed to implanted on the human body, where the target is to use in different domains like health, sport,..., the figure(1) shows the application of WBANs in the healthcare where a miniaturized body sensor nodes are deployed on the human body to supervise their vital signs.

These tiny sized nodes have limited resources (energy, computation, and communication), these limitations create several challenges that would hinder this network and cause faults, theses challenges must be taken into consideration when designing and implanting a WBAN, among them :

- Interoperability: this means that the data can exchange and without interruption between different wireless technologies and standards such as Zigbee (IEEE 802.15.4), Bluetooth (IEEE 802.15.1), and Wi-Fi (IEEE 802.11) [1]
- Energy: is also a big challenge especially when the battery is dead, this fault may cause the death of a patient.
- Reliability: The low transmission power and tiny sized antenna of wireless sensor devices will affect the signal to noise ratio that causes a higher bit error rate and decrease the reliable coverage area.
- Interference: There are chances of collision and packet loss due to Body Area Networks sensors come in each other‘s range.

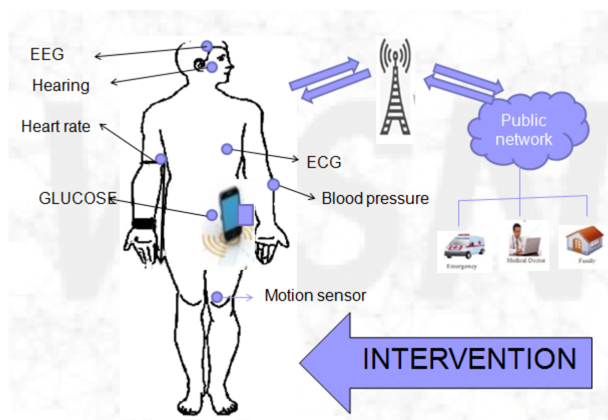

Fig. 1. WBAN architecture.

These are a few challenges that may exist and cause faults in our WBAN, these faults may appear to falsify the health care intervention, that may cause a degradation state of the patient or its dead, so it was necessary to establish an efficient mechanism to detect such faults when designing or implanting a WBAN.

Statistics and machine learning are a good choice for fault detection in WBANs, in this work, we have tried to achieve a comparison between these two techniques.

The remainder of the paper is structured as follows. In Section II, we present a related work, where we focus only

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on statistical, and machine learning techniques. In section III, we present the two approaches to be compared. In section IV, we present the experimentation results. Finally, we conclude our paper in Section V.

II. Related Works

In this our paper we have focused only on statistical-based, and machine learning-based techniques used to detect faults in WBANs, where a plethora of techniques are proposed, concerning the statistical-based techniques, authors in [2] combine between median absolute deviation and majority voting algorithm, for detecting outliers values, then identify false alarms. Markov Chain Model is used also in [3], where the authors proposed a three-model system, the forecasting model, root mean square of errors, and the Markov model. In [4], [5], the authors used Hidden Markov Model (HMM) as a method for fault diagnosis of ECG sensor data, where they used the Baum-welch algorithm to estimate HMM parameters, then Viterbi algorithm to check if a new sensor reading is faulty. In [6], authors used queue management as a technique for reserving the channel bandwidth.

Concerning the machine learning-based techniques, several approaches have been proposed using different tools such as decision tree, linear regression, support vector machine, and wavelets, in [7] [8] [9], the authors used a decision tree to classify the measurements as normal and abnormal, and if abnormal instances are located, they apply regression, for prediction, to distinct between a faulty value, and the emergency state of the patient. The support vector machine also is combined with the linear regression In [10], to classify data stored in a data set source, and when an abnormal class is detected, the linear regression is applied for prediction to achieve the comparison. In [11], [12], the authors proposed a detection system which has three components: Discrete Haar Wavelet transform, Hampel filter, and Boxplot to distinguish between fault measurements and medical emergencies.

III. approaches

A. SVM with linear regression

- Support Vector Machine (SVM): is a binary classification tool, used to construct the classification model, using training data, considered as a supervised classification method.

  The main concept behind linear SVM is to maximize the distance between two parallel boundaries or hyperplanes which are defined by support vectors see the following equations:

  $$W^T X_i + W_0 = +1 \tag{1}$$

  and

  $$W^T X_i + W_0 = -1 \tag{2}$$

  as shown by the figure(2) the objective is to construct a separating hyperplane that achieves maximum separation between the two classes. [10]

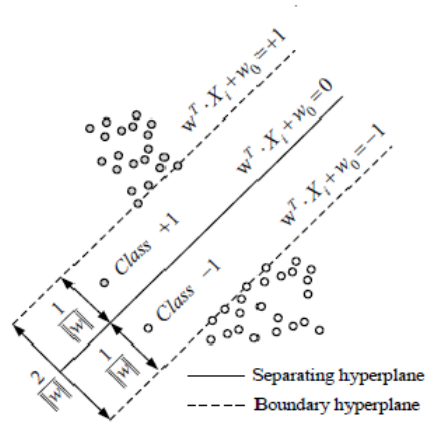

Fig. 2. Linear SVM and data separation [10]

- Linear Regression: The linear regression is a statistical method used to predict, value for a specific attribute from other attributes exploiting the spatial correlation between these attributes, according to the following equation:

  $$pred_{ij} = \beta_0 + \beta_1 attr_{i1} + \beta_2 attr_{i2} + ... \tag{3}$$

  where the coefficients of the linear regression computed during the training phase.

The proposed approach has two phases, training phase, and detection phase, in the training phase both the SVM classification model and the linear regression are constructed. In the detection phase, each input data, injected on the SVM classification model, if this received value is abnormal, then the prediction model is activated, to predict value, then a comparison is achieved between the actual and the predicted values if the difference is greater than a specific threshold, then the received value is considered as faulty otherwise, an alert should be triggered.

B. Median Absolute Deviation with Majority Voting

This study combines Median Absolute Deviation (MAD), that is outlier detection method with Majority Voting (MV) algorithm, the MAD for abnormal data detection, and MV algorithm to identify and signal false alarm.

- Median Absolute Deviation (MAD) : the MAD is defined as the median of the absolution deviation from the median of the data set, and it is calculated using the following equation:

  $$MAD = median(|X_i - median(X)|) \tag{4}$$

- The Majority Voting algorithm: If the MAD determines the data point is outside the dynamic range, a majority voting algorithm is initiated to vote on sensor values. In this case, the MV algorithm votes on the subject attribute [2], the fault detection process is described by the figure(3)

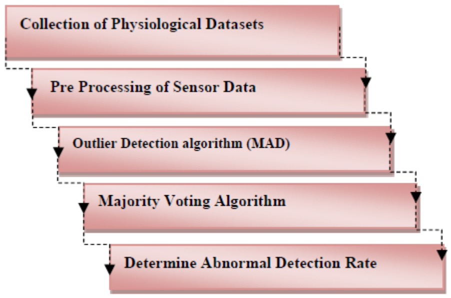

Fig. 3. Detection process [2]

IV. Experimentation Results

Our experimentation has been conducted to evaluate the efficiency of two approaches, a machine learning-based technique based on the support vector machine and the linear regression [10], from one side, and a statistical-based technique used the median absolute deviation and the majority voting algorithm [2], from another side, we have used WEKA [13], and the real medical dataset physionet [14] Where we used the record 221 which has contained 07 vital signs (ABPmean ABPsys ABPdias HR PULSE RESP SpO2).

About the detection accuracy presented by the figure(4), we find that the machine learning technique (SVM with linear regression), achieves 88.6234% is more accurate than the statistical technique(median absolute deviation with the majority voting algorithm), that achieves 51.8203%. the accuracy is described by the following equation:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \qquad (5)$$

where, TP (True Positive), TN (True Negative), FP (False Positive), FN (False Negative).

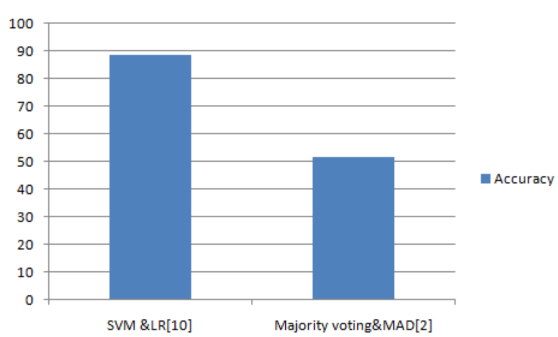

Fig. 4. Accuracy detection.

Concerning the MAE(Mean Absolute Error), which described by the following equation:

$$MEA = \frac{\sum_{i=1}^{n} \mid pred_i - act_i \mid}{n} \qquad (6)$$

shown by the figures(5), we observe that the machine learning technique has the lowest errors 2.803% comparing with the statistical technique which has 49.93%

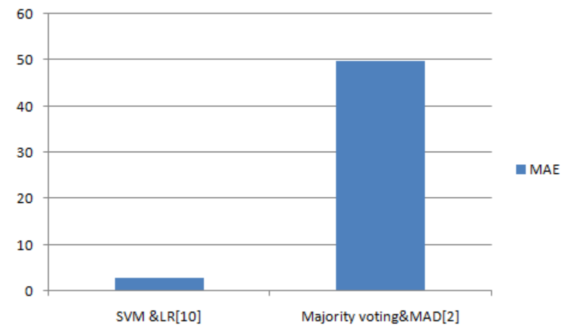

Fig. 5. Mean Absolute Error.

The figures(6,7) show the ROC(Receiver Operating Characteristic) curves of each technique, which represents the true positive rate against the false positive rate, we notice that the SVM with linear regression has the largest area, in other words, most accurate than the second.

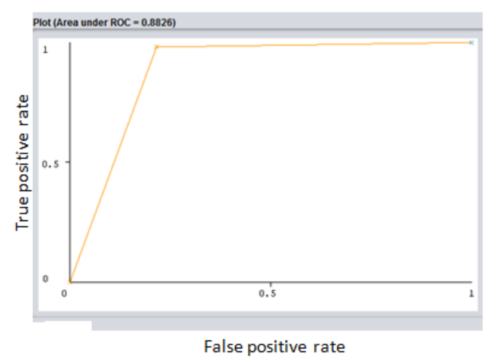

Fig. 6. ROC curve[10].

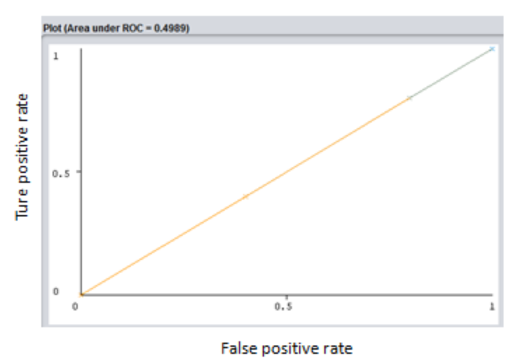

Fig. 7. ROC curve[2].

V. Conclusion

The WBAN is a specific kind of WSN, where it shares some specifications, but there are also some differences, where

WBANs characterized by their limited resources, faults are one of the popular challenges of this type of networks, machine learning and statistics are a good choice for the fault handling in WBANs, we try in this paper to present the efficiency of the machine learning against statistics where an experimentation on a real medical dataset is achieved for this goal, and we have concluded that the machine learning techniques are more accurate and deal better than the statistical methods, for fault detection in WBANs.

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