



ANOMALY DETECTION FOR HEALTHCARE WIRELESS SENSOR NETWORK

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ABSTRACT - Wireless Sensor Networks are helpless against a plenty of various fault types and outer attacks after their organization. Wireless sensor networks utilized in healthcare applications for essential sign assortment from remotely monitored patients. These kinds of individual region networks should be vigorous and strong to sensor disappointments as their capacities include exceptionally basic systems. In this paper proposes an anomaly detection algorithm for Healthcare wireless sensor networks. The proposed approach first and foremost detects cases of detected patient credits as ordinary and unusual. Once distinguish a strange occurrence, use regression prediction to perceive between a faulty sensor reading and a patient going into a basic state. The experimental results on genuine patient datasets shows the proposed approach can rapidly identify patient anomalies and sensor faults with high detection accuracy while keeping a low false alarm ratio.

Keywords: [Wireless sensor networks, Wearable sensors, Healthcare applications, Anomaly detection, Decision tree, Regression.]

1. INTRODUCTION

Wireless sensor organization (WSN) technologies can possibly change our way of life with various applications in fields like healthcare, entertainment, travel, retail, industry, dependent care and emergency management, notwithstanding numerous different areas. The mix of wireless sensors and sensor networks with processing and man-made brainpower research have created a cross-disciplinary thought of surrounding knowledge to beat the difficulties face in regular day to day existence. One of the principal challenges confronting the World as of late has been the expansion in the older populace in created nations. As per the Population Reference Bureau, throughout the following 20 years, the 65-and over populace in the created nations will turn out to be practically 20% of the complete populace. Consequently the need to give quality care and administration in these nations for a quickly developing populace of older individuals, while decreasing the healthcare costs is a significant issue for governments and health specialist co-ops in such nations. Wearable and implantable body sensor network frameworks are one gadget to achieve this objective, as an observable application here is the joining of recognizing and buyer electronics technologies which would permit individuals to be monitored during all their ordinary exercises. As the

expense and size of sensor gadgets are diminishing quickly, the application areas of wireless sensor networks have additionally extended quickly. The significant application domains are home and office, control and mechanization, coordinated operations and transportation, natural monitoring, healthcare, security and reconnaissance, the travel industry and recreation, instruction and preparing and entertainment. Common conceivable application situations might incorporate carefully prepared homes, producing process monitoring, vehicle following and detection, and monitoring stock control.

Wireless sensor gadgets that can be utilized to effectively screen human exercises have earned extraordinary examination premium as of late. Request of wearable wireless gadgets has been on the ascent as of late. Another idea of 'individuals driven' and 'metropolitan' wireless sensor organizing has been a hot examination area. Sensor networks are being explored and sent in extensive variety of applications in healthcare. Average application situations could be monitoring of heart beats, body temperature, body positions, location of the individual, generally monitoring of sick patients in the medical clinic and at home, etc. Here and there this space area is alluded to as wireless body area sensor networks or Wireless Body Area Networks (WBAN).

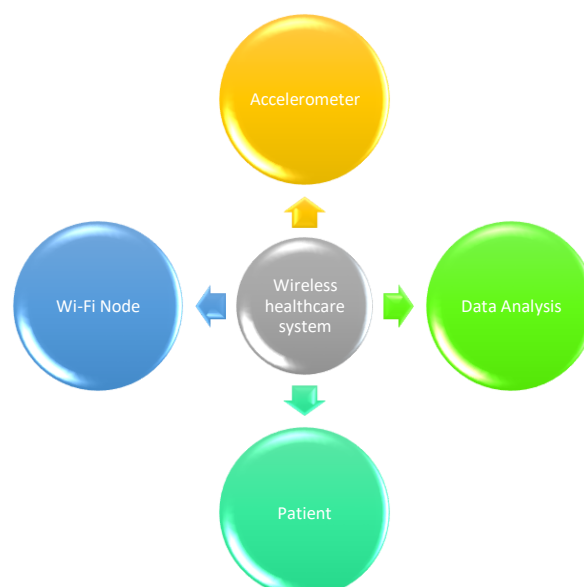


Figure 1. Wireless Healthcare System

In this paper center around anomaly detection in clinical wireless sensor readings, and propose another methodology in light of machine learning algorithms to recognize abnormal values. First we use J48 decision tree algorithm to perceive strange records, and when recognized, we apply straight regression to pinpoint unusual sensor assessments in an abnormal record. In any case, physiological attributes are vigorously corresponded, and changes happen regularly in something like at least two boundaries, for example in Atrial Fibrillation (AF) and Asthma disease, the heart rate and respiration ratio increment at the same time. Our proposed arrangement is expected to give dependability in clinical WSNs utilized for continuous patient monitoring, where we recognize anomalies in a patient's health, and separate between the singular entering a basic health state and faulty readings (or sensor equipment). Try to diminish the false alarm rate set off by conflicting sensors readings.

2. EXISTING METHODOLOGIES

2.1 Rozeha A. Rashid et.al proposed Home healthcare via Wireless Biomedical Sensor Network. The present home healthcare movement is turning into a transcendent type of healthcare delivery. In spite of the fact that there have been numerous new advances in biomedical sensors, low-power radio communication and implanted calculation, there doesn't yet exist an adaptable, hearty communication foundation to coordinate these gadgets into a crisis care setting. Quick information recovery is turn of clinical forward leap to offer quality clinical types of assistance. The fundamental goal of this exploration is to deliver a functioning model of genuine home healthcare monitoring system over wireless sensor network with productive power and data transmission and solid home-care-sensor network. Right now, we had examined the reasonable steering protocol and fostered a fundamental WBSN stage for home healthcare application and mix of RTLD directing protocol and our created hardware stage.

2.2 Joseph Chuma et.al proposed Healthcare Cloud Computing for Underground Wireless Sensor Networks. Wireless Sensor Networks (WSNs) are spatially dissipated networks furnished with incalculable hubs for checking and recording different regular conditions. These networks are controlled as far as their handling power, capacity assets, and battery duration. At the end of the day, they are not themselves capable in performing such different assignment set like limitation of nodes, data handling and so on. Cloud computing (CC) offers on-request access of the assets like networks, servers, and information stockpiling. Guaranteeing this touchy information security, availability and scalability are a central point in the cloud computing climate. In this paper, we proposed a numerical model for estimating the availability of data and machines (nodes). We likewise present a proposed system known as Self Encryption System (SES) that will scramble data before it is being shipped off the cloud. The paper presents the moves toward accomplish the proposed system and furthermore an example of encrypted and decrypted record.

2.3 W. Fang et.al proposed Binomial Distribution-based Trust Management Scheme for Healthcare-oriented Wireless Sensor Network (HWSN). It in addition to the fact that better accomplish the physiological information of individuals, yet additionally more proficiently diminish the Latency in regards to information assortment and transmission.

Nonetheless, like other conveyed networks, it additionally faces huge security challenges, particularly from inward attacks. Recognizing many assault ways of behaving from obstruction in the complicated healthcare situations, for example, On-Off attack is troublesome. In this paper, we propose a Binomial Distribution-based Trust Management Scheme (BDTMS) for HWSN. The proposed strategy can quickly recognize and actually protect against On-Off attacks. Moreover, the proposed strategy is additionally appropriate to safeguarding against castigating attacks in guarding against On-Off assault under hindrance development, particularly with higher detection accuracy.

3. PROPOSED METHODOLOGY

3.1 Wireless Sensor Networks

Wireless sensor networks have arisen as a practical technology for a bunch of applications, including various health care applications. WSN technology can be adjusted for the plan of pragmatic Health Care WSNs (HCWSNs) that help the key system engineering prerequisites of dependable communication, node mobility support, multicast technology, energy productivity, and the opportune delivery of data. The use of the Wireless Sensor Networks in healthcare systems can be isolated into three classes: 1. monitoring of patients in clinical settings 2. Home and old care community monitoring for persistent and old patients 3. Assortment of longterm databases of clinical data

3.2 Healthcare

Wireless sensor networks used in healthcare systems have received significant attention from the research community, and the corresponding applications. In vital status monitoring applications, patients wear sensors that supervise their vital parameters in order to identify emergency situations and allow caregivers to respond effectively. Applications include mass-casualty disaster monitoring, vital sign monitoring in hospitals, and sudden fall or epilepsy seizure detection.

3.3 Anomaly detection in Healthcare wireless sensor networks

Consider a general situation for far off quiet monitoring, where numerous wireless bits with limited assets are utilized to gather data, and a compact assortment gadget (for example advanced mobile phone) with higher assets and higher transmission capacities than bits, is utilized to dissect gathered data, and to raise cautions for crisis group when unusual patterns are recognized. Try to identify unusual values; to decrease misleading problems came about because of broken estimations, while separating shortcomings from patient health debasement.

The proposed approach depends on decision tree and linear regression. It fabricates a decision tree and searches for linear coefficients from ordinary indispensable signs that fall inside confined stretch scope of observed attributes. To recognize strange values, we use decision tree algorithm (J48) to arrange records (or line) as typical or unusual. Linear regression is a measurable technique which models dependent variable y_{ik} utilizing a vector of free factors x_{ik} called repressors. In the remainder of this paper, we center just around the accompanying imperative signs: HR \in [80–120], beat \in [80 – 120], breath rate \in [12 – 30], SpO2 \in [90 – 100], T ° \in [36.5 – 37.5]. Attributes values that fall

outside these (confined) typical spans are viewed as strange. HR and heartbeat mirror similar attribute from various sensors, where heartbeat is gotten from the beat oximeter and HR is estimated as the quantity of interbeat spans (R) in ECG signal.

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Algorithm 1 Detection Algorithm
1: for each received record  $R_i$  during T do
2: Classify  $R_i$  using J48;
3: if  $\text{Class}(R_i) == \text{'ABNORMAL'}$  then
4: for each  $x_{ik}$  do
5:  $\hat{x}_{ik} = \sum_{j=1, j \neq k}^n C_j x_{ij}$ 
6:  $\text{ctr} += (|x_{ik} - \hat{x}_{ik}| \geq 0.1 * \hat{x}_{ik}) ? 1 : 0$ 
7: end for
8: if  $\text{ctr} \geq 2$  then
9: Raise alarm for healthcare;
10: end if
11: end if
12: end for
    
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Below equation shows the residual threshold used to detect abnormal measurement:

$$e_i = |x_{ik} - \hat{x}_{ik}| \geq 0.1 * \hat{x}_{ik}$$

The proposed approach depends on two stages: training and detection. In the training stage, AI techniques create a model to classify data, and in the testing stage, inputs are classified as abnormal in the event that they stray from laid out model. The J48 decision tree model (fabricated utilizing training data inside confined spans) is utilized in our way to deal with classify each got record as normal or abnormal. In our experiments, the decision tree was the most productive classification algorithm. The tree model is a bunch of rules (on the off chance that) which is economical to fabricate, hearty, and quick in processing as it depends on mathematical correlations for classification. Besides, abnormal occasions distinguished by J48 will just trigger the forecasting with linear regression, and for this reason we utilize confined little stretches for checked attributes in the training stage.

Assuming that a record is classified as abnormal by J48, we recursively expect that an attribute(x_{ik}) is missing, and the coefficients of linear regression are utilized to gauge the ongoing value for this attribute (\hat{x}_{ik}) with respect to the others ($x_{ij} | j \neq k$) as given in equation for heart rate assessment;

$$\widehat{HR}_i = C_0 + C_1 \text{Pulse}_i + C_1 \text{RESP}_i + \dots + C_5 T_i$$

If the Euclidian distance between current (HR_i) and estimated (\widehat{HR}_i) values is bigger than the predefined limit (10% of assessed value) for only one attribute, the estimation is viewed as broken and supplanted by assessed value with linear regression. Be that as it may, in the event that no less than two readings are higher than the edge, trigger an alert for reaction caregiver emergency group to respond, for example weighty changes in the HR and diminished pace of SpO2 are side effects of patient health debasement and requires quick clinical mediation. Accept that the likelihood of many attributes (2 in our experiments) being broken is extremely low.

The J48 is utilized to decrease the calculation complexity, and to forestall the assessment of each attribute for each occurrence on the base station. Sliding window isn't utilized in that frame of mind to lessen the complexity. At the point when the model is all around indicated with the training

data, updating or revamping the model requires extra complexity (temporal and spatial) without huge effect on the performance.

4. EXPERIMENT RESULTS

4.1 False Alarm Rate

No of Nodes	SES	BDTMS	Proposed DTLR-AD
2	0.95	0.80	0.73
4	0.96	0.83	0.74
6	0.97	0.85	0.76
8	0.98	0.87	0.77
10	0.99	0.88	0.79

Table 1.Comparison of False Alarm Rate

The table 1 Comparison of False Alarm Rate values explain the different values of existing algorithms (SES, BDTMS) and proposed DTLR-AD. While comparing the Existing algorithm (SES, BDTMS) and proposed DTLR-AD, provides the better results. The existing algorithm values start from 0.95 to 0.99, 0.80 to 0.88 and proposed a DTLR-AD value starts from 0.73 to 0.79.

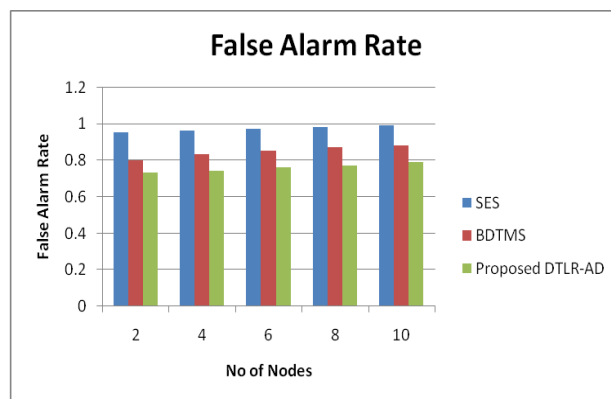


Figure 1.Comparison of chart False Alarm Rate

The figure 1 Comparison of False Alarm Rate values explain the different values of existing algorithms (SES, BDTMS) and proposed DTLR-AD. X axis denote the No of Nodes and y axis denotes the False Alarm Rate. While comparing the Existing algorithm (SES, BDTMS) and proposed DTLR-AD, provides the better results. The existing algorithm values start from 0.95 to 0.99, 0.80 to 0.88 and proposed a DTLR-AD value starts from 0.73 to 0.79.

4.2 Accuracy

No of Nodes	SES	BDTMS	Proposed DTLR-AD
2	70	80	93
4	74	83	96
6	76	85	97
8	77	87	98
10	80	95	99

Table 2.Comparison of Accuracy

The table 2 Comparison of Accuracy values explain the different values of existing algorithms (SES, BDTMS) and proposed DTLR-AD. While comparing the Existing algorithm (SES, BDTMS) and proposed DTLR-AD, provides the better results. The existing algorithm values start from 70

to 80, 80 to 95 and proposed a DTLR-AD value starts from 93 to 99.

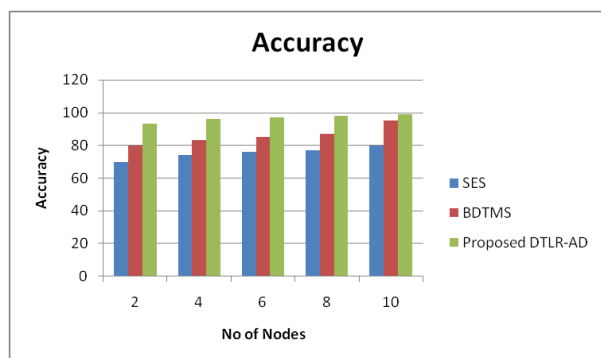


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CONCLUSION

In this paper proposed another system which integrates decision tree and linear regression for anomaly detection (DTLR-DA) in Healthcare WSNs. The proposed approach accomplishes both spatial and temporal investigation for anomaly detection. Assessed our methodology on genuine clinical data set with many (genuine and engineered) peculiarities and trial results demonstrated the capacity of the proposed way to deal with accomplish low false alarm rate with a high detection accuracy. They are as of now researching the exhibition of the proposed approach on genuine clinical wireless sensor traffic utilizing Shimmer platinum development kit.

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