AN INTELLIGENT POWER ADAPTIVE MODEL USING MACHINE LEARNING TECHNIQUES FOR WSN BASED SMART HEALTH CARE DEVICES

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Abstract-Maximizing the lifetime of wireless sensor networks become a essential objective nowadays. Many traditional approaches achieve this objective by reducing the transmission power that degrades the network performance. To optimize both performance and power, in this paper we designed the intellectual supervised learning predictors known as support vector machine (SVM), Random Forest (RF), Decision Tree (DT) models for wireless sensor networks. The ultimate aim of these model is to decrease the number of chosen sensors for the analysis to achieve maximum energy efficiency while keeping up the specified level of accuracy in the detailed estimation. In this paper, the proposed model is compared with other existing classifiers. From the simulation outcome, it is clear that Linear-SVM selects sensors with higher energy productivity and it outperforms other supervised learning approaches.

Keywords: Energy consumption, Support vector machine, supervised learning, predictor, wireless sensor network.

1 INTRODUCTION

Nowadays Wireless Sensor Networks (WSN) are considered to be well growing application and it needs determined observation of environmental parameters such as humidity, temperature and so on with no human mediation. In WSN, the battery powered small gadgets are known to be sensor hubs and which does not have any micro controller.

Likely, As mentioned like in [1] [2], [3], [4], in many of the applications, sensor hubs are expected to turn out constantly for quite a long time as well as quite a while with no human oversight. So always the battery backup is very important. the battery lifetime is directly relies on battery capacity as well as confidingly identified with its Energy use. always Sensor Hubs are conventionally minimal in measure. Thusly it incorporates an obliged fuel source available for the activity. Thus, it is major to diminish the energy usage as well as wastage in sensor centers for a delayed lifetime.

For the WSN design, the principal energy-burning-through get ready is radio communication. Both transmission as well as reception draw a noteworthy volume of vitality from the source. Inside the instance of radio social occasion, usage of energy increases with the time it spends in get mode. Thusly, by decreasing the get mode time Energy use can be altogether reduced. many techniques [5] are available to reduce the energy utilization [6] during the get mode. Then again, Energy went through by the transmitter is explicitly comparative with the gauge as well as few bundles to be sent and the transmission control level used. For a sensor frameworks, transmission control is difficult task. Despite the way that it is shown that TPC can give energy investment funds, an ineffectually arranged TPC system may be counterproductive.

Since sensor center points use moo control radios which are more disposed to channel assortments and he ideal transmission control for the communication among the couple of hubs can't be consistent all through the lifetime of the hubs. Studies were exhibited that there's an effect of spatial-fleeting boundaries on far off correspondence [7]. A gainful TPC framework should have the option to effectively acclimate to the varieties in the channel with the goal that the interface between the transmitter and the gatherer is strong. Most of the existing works are focused on minimizing the transmission control power to save the lifetime of battery. In recent days, machine learning is become trending in many applications such as computer vision, wireless sensor networks, IoT, etc. To maximize the energy efficiency, we developed a intellectual supervised learning algorithms called SVM, MLP, RF,and DT as energy source predictor for WSN. These learning algorithms are skilled and verified with WSN datasets.

1.1 Significant Contribution

In this work, we developed various learning algorithms as energy source predictors in order to select the best sensor with low-power consumption for each transmission.

(i) **Database Collection:** We initiated with data scrutinizing in terms of No. of hubs, transmission speed, number of packets transmitted, distance between each node, power consumption during transmission, etc. for low-level to high-level WSN.

(ii) **Feature Extraction and reduction:** The profile includes many features in the unstructured format. We analyzed these features and formatted the database with most significant features in a optimized way.

(iii) **Models Development:** In this work, We designed the support vector machine, random forest, MLP supervised learning models for the best sensor prediction in terms of low-power consumption for each packet during transmission on the network.

(iv) **Simulation:** Finally, we developed these algorithms using python IDE and skilled with created WSN database. The observed results enforce that linear-SVM performed with high accuracy compared to MLP, random forest models.

The arrangement of paper is as follows. Section 2 describes the various machine learning (ML) algorithms role in WSN. Proposed framework is presented in section 3. simulation setup and Observed results are explained in section 4. Finally,Work summary is concluded in section 5.

2 RELATED WORKS

D. S. D. Son *et.al* [8] introduced technique for sensor assurance which can help choose the ideal number of sensor center points in the overall network. this framework significantly expands the network lifetime by reducing the no. of sensors without spoiling the decision handle. this strategy adopts Bayesian methodology was used for finding the ideal sensors inside the course of action. Likewise, the 'Self-Organizing Outline'-('SOM') was used as a classifier.

A. Moustapha *et.al* [9], a new methodology was proposed to diminish the energy utilization of WSN. the methodology utilizes Credulous Bayes classification calculation to reduce the energy utilization. here, the sensors were situated from the preeminent to the smallest basic, in view of the meaning of their use inside the WSNs. This methodology was taken a stab at three notable veritable sensor datasets. More Energy is used if more sensors are used and, along these lines, the lifetime of the sensor network is diminished.

Likewise in [10] new scheme was introduced by Y. Wang *et.al* to limit the Energy usage as well as amplify the lifetime of the sensor association. this scheme utilizes K-Nearest Neighbor classifier to upgrade the lifetime of sensor organizations. This is regularly founded on an element/sensor choice that limits the quantity of the used sensors. .

A. Christmann *et.al* [11] introduced knowledge based methodology for multisensor blend and mix. The experts watched out for the keenly sensor combination the structure at the arrangement level to defeat the issue of normal sensor botches and lacks Z. Yang *et.al* [12] proposed a sensor system and its connected banner planning and plan acknowledgment approaches to distinguish times of sustenance confirmations. This examination depended on the checking and characterization of jaw movement. The investigators used the forward assurance technique to pick the most appropriate features, which address sensor signals. Additionally, the SVM was used as the characterization count for biting acknowledgment.

In [13], Y. Chen *et.al* proposed coordinating the centers inside the orchestrate into a reformist level-structures. Inside a particular group, data collection and sending are performed at CH('cluster head') to diminish the measure of data communicating to the BS ('Base Station'). cluster-head arrangement is as a rule dependent on the imperatives of sensor center points and sensors area to group head. Center points other than bunch head select their group head just in the wake of sending and communicate identified information to the group head. The piece of group head, acting naturally a sensor center, is to advance these information and its case data to the BS subsequent to performing information amassing and sending.

3 PROPOSED METHODOLOGY

In this work, three different models termed as RD, MLP, SVM developed for best sensor identification in a large WSNs.

3.1 SVM - Support Vector Machine

SVM is introduced by Boser, Guyon, and Vapnikin the year of 1992 in COLT-92. it is a set of learning strategies for classification [14]. SVM forecast instrument that has ML speculation to amplify insightful exactness though normally keeping an essential separation from over-fit to the data. It can be portrayed as frameworks that use the theory space of direct work in a tall dimensional incorporate space, arranged with a taking in estimation from improvement speculation that executes a taking in tendency gathered from genuine learning speculation. RSSI means that the "Received Signal Strength", it isn't dependable in channels with high obstruction and commotion. It may increment or lessening dependent on the idea of impedance present in the channel. Productive obstruction can cause an expansion in it and we may get a high RSSI esteem regardless of whether the connection is powerless. Then again, damaging impedance can prompt a decreased RSSI esteem. Additionally, RSSI has a transient and spatial part connected with it. Hence the utilization of RSSI alone for transmission power change can bring about incorrect force level settings prompting unwanted network conditions.The greater part of the extraordinary low power radios have a measurement known to be "Link Quality Indicator" ("LQI") added to the got parcel notwithstanding RSSI. It can can give a note on how solid is the communication connect between two hubs. It is determined dependent on the 'RSSI' and the quantity of mistakes got. Accordingly, by utilizing both "LQI" and "RSSI" we can improve the exhibition of the DTPC plot. The upside of "LQI" over "RSSI" is that it tends to be utilized as a sign of commotion or impedance present in the channel. The LQI is a dimensionless seller explicit amount . For instance, for CC2420[14], Zigbee viable RF handset from Texas Instruments, "LQI" is consistently appropriated somewhere in the range of 0 and 255, with 1 addressing the most noticeably terrible connection and 255 addressing the best connection [15-21]. While for CC2500, a restrictive 2.4 GHZ RF handset from a similar maker LQI is characterized somewhere in the range of 0 and 128 [22-26].

Based on the RSSI and LQI features, we trained and tested the SVM algorithm in order to predict the best senosr with low-power during transmission.

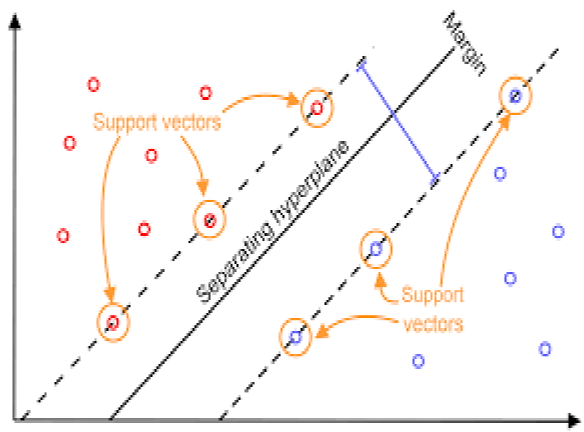

Figure 1 SVM Working procedure

4 EXPERIMENTAL SETUP

We simulated the proposed SVM based power controller on Python IDE. Hubs are permitted to differ transmission power from 1 to 12 dBm in strides of ±1 dBm. Force esteems beneath - 12 dBm are disregarded since the current utilization doesn't follow dropping request, relatively, some low power esteems show an expansion in energy utilization. Added substance obstruction model is utilized in the reenactment.

Parameters Analyzed

$$Accuracy = \frac{DR}{TN_i} * 100 \quad (1)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+TN}} \text{x100} \quad (2)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TP+TN}} \text{x100} \quad (3)$$

Table 2: Notations and Meanings

Notations	Meaning
TP	True Positive
TN	True Negative
TNi	Total number of iterations
DR	Detected results

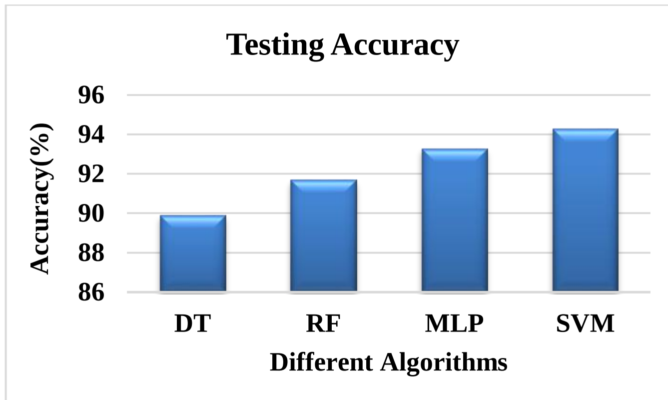

Figure 2 Prediction Accuracy Analysis

Figure 2 to 4 illustrates the prediction accuracy, sensitivity, and specificity parameters observed using the proposed SVM sensor predictor and also results are compared with traditional learning approaches such as DT, RF, MLP. As per the observed results, SVM achieved better results in an average of 95.6% in accuracy.

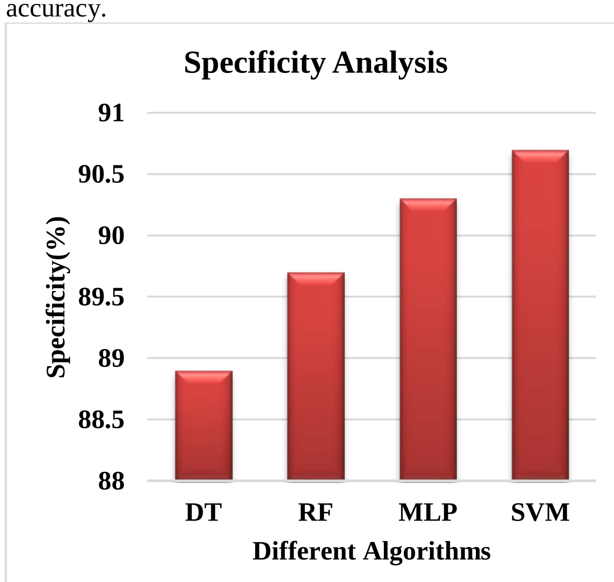

Figure 3 Specificity Analysis

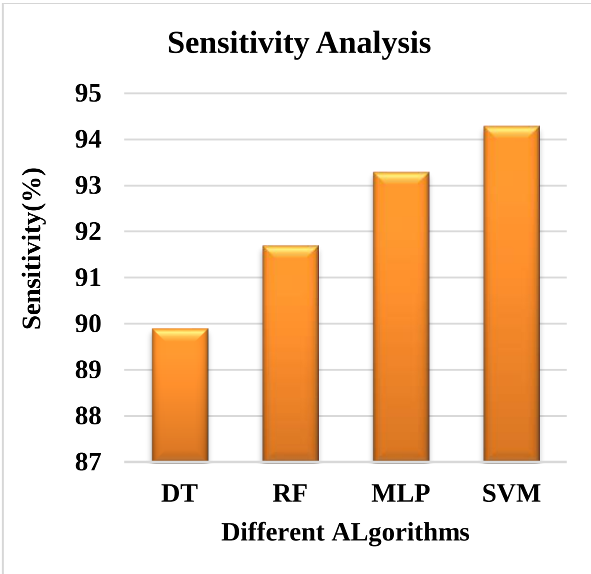

Figure 4 Sensitivity Analysis

5 CONCLUSION

In this paper, we developed a SVM learning algorithm to detect the best sensor for each transmission. The proposed algorithm is trained with RSSI and LQI values. Various parameters are analysed for the proposed algorithm. Accuracy, specificity and sensitivity are observed using the calculations. The accuracy achieved as 95.6% for the proposed algorithm, 93% for specificity and 94% for sensitivity in an average when compared with decision tree,random forest, and MLP algorithm. In the future, we planned to implement the deep learning algorithms for large-size WSN networks.

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