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Original Article

Network Lifetime Enhancement by Employing Clustering and Sleep Cycle Scheduling Techniques with Ensemble SVM Learner and Crystal Algorithm

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Abstract - *Clustering wireless sensor networks (WSNs) together is an excellent idea for improved data collection and extending the life of WSNs. When messages are sent among sensor nodes for periodic or sequential clustering, the sensor nodes become overwhelmed. During clustering, there is complex information sharing and instability in energy usage. The main requirements are efficient approaches for extending network lifetime and intra-cluster transmission increases. The main goal of this article is to reduce node energy loss while decreasing message transmission overhead. The network lifetime is increased by upgrading clusters. In this study, we proposed an ensemble SVM learner with a Crystal method to reduce data transmission while applying an appropriate sleep or active schedule to optimise individual sensor node energy consumption. The inputs of residual energy, cluster head distance to sink, and average data rates are applied to ensemble SVM learners with the Crystal algorithm to generate the outputs of both the sleep cycle and the cluster update cycle with the least amount of energy consumption. Based on the experimental investigation, the sensor network lifetime is enhanced, the energy utilisation of cluster heads is optimised, and the proposed method achieves good results than other state-of-art methods.*

Keywords - *Wireless sensor network, Cluster head, Update cycle, Ensemble SVM learner, and Crystal algorithm.*

1. Introduction

The wireless sensor networks [1] collectively gather communication information from the environment and control the network's received user nodes. Thus most of the real-time applications employ the WSN approach. In WSN, so many sensors are distributed around the network to process a massive amount of data. The increase in the number of services provided by the WSNs has increased the need for a number of sensor nodes with non-rechargeable batteries with limited capacity. As a result, achieving energy-efficient sensor nodes and networks becomes challenging. Meanwhile, the life span of the nodes, transmission delay, coverage, and transmission delay rely on the quality of service [2].

Moreover, to accomplish the energy-efficient WSN, it is necessary to enable an optimal routing algorithm [23] or topology for the networks. Also, some networks save energy by sampling rate manipulation. For manipulation, some researchers utilise a numerical approach or swarm-based topology control, localisation, preserving the coverage area, etc.

Meanwhile, the transmission of data through the multi-hop [4] method is effective and thus enhances the balanced loads among the nodes. Some of the limitations of WSN [5] are due to the predefined specifications for the construction of sensor nodes since the effectiveness of the sensor nodes depends on environmental conditions such as climate, position, and time. Thus the environment impacts the QoS. For example, consider the sound sensors; the QoS of the sound sensor depends on the noises around the environment. Meanwhile, the resolution of the light sensor is higher during the day than the night. Hence the predefined WSN will affect due to these facts. Due to this, energy consumption will increase, and the increase in the number of sensor nodes also dramatically affects the energy savings mode of the WSN.

Besides resource management [6] in the WSN is also an important task to provide better connectivity among the nodes. While transmitting the packets to the adjacent nodes consumes more power and thus affects the efficacy of the networks. Thus the energy efficiency in the WSN becomes an important topic, and to address this problem, we proposed a novel hybrid Ensemble SVM-based CSA approach to mitigate energy consumption. This can be achieved by two power-saving methods, which are mentioned below,

- First, our proposed method effectively achieves energy savings at the network level and is called the N1-saving node.

- Meanwhile, to increase the energy-saving capacity, our proposed method manipulates the sampling rate and the transmission period of the sensors that comprise the WSN, known as the N2-saving mode.

The rest of the work is organised as follows: Section 2 delineates the literature survey. Section 3 explains the proposed work and the experimental results investigated in section 4. Finally, section 5 concludes the article.

2. Literature Survey

For energy efficiency in WSN, Bhushan et al. [7] suggested the fuzzy-based data aggregation (FDA) technique. Perform parent node selection depending upon the minimal number of dynamic neighbors with candidate nodes. The parent node examines the minimal sum of each weight, and the equivalent number of dynamic neighbors uses fuzzy logic. The performance evaluation parameters like energy consumption control overhead, overall transmission slots, energy consumption data interval, and average schedule length validate the performance of the FDA, but it met higher execution delay as well as higher computational cost. For energy efficiency in WSN, Gupta et al. [24] suggested machine learning (ML) techniques to create the structured hypercube network. These ML techniques had reliable and effective data communication performance with minimum complexity and higher cost.

The energy efficiency improvement is performed via the Fuzzy-based clustering and secure authentication (FCAS) algorithm, suggested by Sureshkumar et al. [9]. The FCAS avoids the attacks transmitted from the data packets. The simulation of FCAS reduced the energy consumption to utilise a capable routing path. Compared to the existing methods, the FCAS achieves 12% energy values with less data packet delivery ratio than existing methods. There is higher node density with less performance of cluster head selection.

Khan et al. [10] proposed dynamic scheduling and content-based adaptation with energy efficiency improvement in WSN. During data aggregation, dynamically change the content-oriented adaptive and dynamic scheduling (CADS). In the opposite direction, node functions are regulated, and the contents of sensed data packets are probed using base stations. Message-forwarding duplication was avoided, reducing undesired network traffic. This CADS approach was more authentic and had superior statistical analysis while having larger computer difficulties.

Hariharan et al. [11] introduced the Advanced Multi-Hop (AMH) process, which directly interacts with the multi-hops and transmissions. The Dijkstra algorithm was utilised for information packet routing within the movable community. While installing a major media link wireless router, various other nodes' strength was removed via the AMH process. Better community efficiency with reduced community daily life was accomplished using the AMH process. This procedure attained better and improved node degree at a lower cost. Nevertheless, they failed to use any other security models.

A client-side secured dual-TEE (Trusted Execution Environment) based deduplication model (Dual-TEE) for the cloud is presented in [30]. This work is based on different phases such as setup, data outsourcing, PoW protocol initialisation and data updation. This work focuses on security as well. In [29], a clustering model for WSN is proposed for WSN by employing the Coyote optimisation algorithm with fuzzy logic for enhancing energy efficiency and, thereby, network lifetime. This work improves energy efficiency by employing an optimised clustering process.

Motivated by these existing works, this paper intends to bring energy efficiency to improve the network lifetime. The energy efficiency of the existing work can still be improved when another energy-efficient process accompanies the clustering process. Based on this idea, this paper presents a cluster-based sleep cycle scheduling process, and the performance of the work proves better.

3. Proposed Methodology

The clustering process is performed via every network node, thereby detecting the status of both member nodes and cluster heads. Consider the specific node with its communication radius as neighbors. Periodically update the clusters and employs the node's energy parameter. In the center of all network nodes, power consumption is fair. Selecting nodes with higher energy identifies the cluster head. The entire area is examined in detail to optimise clustering. Fig 1 explains the proposed model.

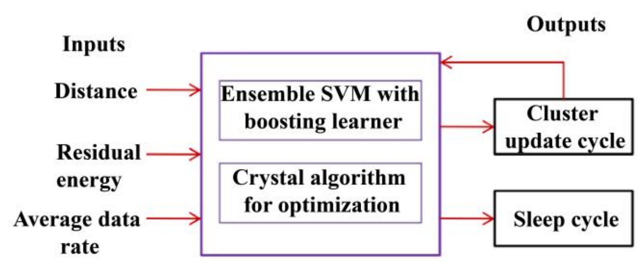

Fig. 1 Proposed workflow diagram

3.1. Clustering Procedure

The initialisation messages with each neighbor node are exchanged by operating each node to begin clustering processes. The residual energy, as well as the node ID, is present in the initialisation message. While comparing the energy to all its neighbors, the major role is identifying the initialisation stage [25]. The neighbor node obtains the message from each node in which each network node stores the neighborhood information. The connect request to node *j* is forwarded via member node when it determines such as node. The requesting node with its member table is included by connecting each cluster head. Create the associated member nodes in which the head nodes with clusters. Reconstruct these clusters and add the proper parameters to the Ensemble SVM boosting learner with optimisation.

The overall network performance is enhanced by applying ensemble SVM-boosting learners with a crystal optimisation algorithm. While supporting routing and data aggregation, the proposed method establishes both cluster head and clustering [13]. For several issues, the most suitable model is ensemble SVM boosting learner with optimisation, which offers robustness and simplicity implementation.

3.2. Update/Sleep Cycle Computation

This section delineates the ensemble SVM boosting learner with optimisation for the computation of both periods of sleep and the update cycle, which is briefly explained in the following section.

3.2.1 Ensemble SVM Boosting Learner

The stacked de-noising auto-encoder trainable extraction tool integrates the sub-learner outputs for SVM ensemble classification, which is expressed as below:

$$R_J(D_{+1(-1)}/r) = \frac{1}{M}\sum_{j=1}^{M} R_j\left(D_{+1(-1)}/r\right) \tag{1}$$

For the sample set $\{r_j\}(j = 1,2,3,\ldots.,m)$, the total hidden layers and probability output of the *j^th^* sub-classifier is$R_J(D_{+1(-1)}/r)$. The stacked de-noising auto-encoder provides the input of ensemble SVM with boosting learner models [14]. The probability of test samples is predicted, and the model is trained using the training samples.

Ensemble Boosting Learning Model

The SVM classifier accuracy is improved via the ensemble-boosting learning model. By assigning some weights, the inputs from the samples are collected. The SVM ensemble performs classification that is applied as the ensemble-boosted SVM classifier. The voting models with SVM perform and improve the classification accuracy. From weak learners created by SVM, the strong learners obtained via boosted ensemble learners.

The following equation assigns the initial weights for the initialisation of samples. From this, $Q_j = \{-1,+1\}$and$(j = 1,2,\ldots,m)$ is for the dataset$DS = \left(P_j^m, Q_j\right)$.

$$E_T = \sum_{j=H_t(R_j)\neq Q_j} DS_t(j) \tag{2}$$

For training round *T*, the base learner on distributionDS_t isH_t. Based on the error determination, update the weight for the next round of *t+1*.

$$\beta_T = \frac{e^T}{1-e^T} \tag{3}$$

The weak learners to strong learners are converted, and the error is reduced by updating weights.

$$G(P) = arg\max_{P_j\in Q} \sum_{T:H_T(P\_=Q} log\frac{1}{\beta_T} \tag{4}$$

This process is continued until a strong learner is achieved. Based on the respective weights, combine the prediction generated. Depending on boosting methods' voting outputs, secure or insecure SVM samples are classified via strong learners.

3.2.2. Crystal Structure Algorithm

This section presents a detailed view of the Crystal structure algorithm [27]. This CSA is based on the structure of crystalline solids, which includes the elements such as molecules, atoms, or ions. These components are repeatedly arranged in three spatial directions and thus form crystals. Moreover, it possesses highly isotropic and diverse properties. Besides, the predefined spaces for the elements are denoted as lattice; nonetheless, it does not indicate the particular locations of the atoms. The location can be identified by 'basis' along with the lattice point. Thus crystals are determined based on the two components, such as lattice and basis.

Lattice defines the overall structure of different geometrical structures, and the basis determines the various configurations of atoms in the defined lattice. The numerical representation of the lattice can be made with the help of the Bravais model. As shown below, a periodic crystal structure is established to represent the lattice point in a vector form.

$$s = \sum n_i b_i \tag{5}$$

Here, the shortest vector present in the principal crystallographic directions is denoted as an integer. The number of corners in the crystals is denoted as *i*.

Numerical Model

The numerical model of adopted CAS is portrayed in this section. The optimised candidate solutions are deemed as single crystals in the lattice space. At first, the number of crystals is determined for iterative purposes.

$$C = \begin{bmatrix} C_1 \\ C_2 \\ \vdots \\ C_3 \\ \vdots \\ C_n \end{bmatrix}$$

$$= \begin{bmatrix} y_1^1 & y_1^2 & \cdots & y_i^j & \cdots & y_1^d \\ y_2^1 & y_2^2 & \cdots & y_2^1 & \cdots & y_2^d \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ y_i^1 & y_i^2 & \cdots & y_i^j & \cdots & y_i^d \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ y_n^1 & y_n^2 & \cdots & y_n^j & \cdots & y_n^d \end{bmatrix},$$

$$\begin{cases} i = 1,2,\ldots.,n \\ j = 1,2,\ldots.,d \end{cases} \tag{6}$$

The problem's dimensionality is denoted as d, and the total number of crystals, i.e., nodes, is determined as n. Initially, the nodes are placed randomly in the search space of the network, as shown below,

$$y_i^j(0) = y_{i,min}^{j\left(y_{i,max}^{j^j_{i,min}},\begin{cases} i=1,2,\ldots,n \\ j=1,2,\ldots,d \end{cases}\right)} \tag{7}$$

The initial location of the nodes is determined as $y_i^j(0)$. The permitted minimum and maximum values are denoted as $y_{i,min}^j$and $y_{i,max}^j$ correspondingly. This is the value for the jth decision variable for the ith candidate solution. The random variable χfalls under the range of 0 to 1.

According to CSA, the nodes that are located in the corner are defined as the base nodes C_B. These nodes are determined randomly with respect to the initially generated crystals. While performing the selection process, the current nodes are neglected, nodes with the best configuration are defined as C_O, and the randomly selected mean values are represented as M_C. The best candidate node from the network search space can be upgraded by considering the lattice principal from the CSA and follows four steps as shown below,

- **Simple Cubicle:**
$$C_{new} = C_{pre} + sC_B \tag{8}$$

- **Cubicle along with the best nodes:**
$$C_{new} = C_{pre} + s1C_B + s2C_O \tag{9}$$

- **Cubile with respect to the mean nodes:**
$$C_{new} = C_{pre} + s1C_B + s2M_C \tag{10}$$

- **Cubicle with respect to the best and mean nodes:**
$$C_{new} = C_{pre} + s1C_B + s2M_C + s3C_O \tag{11}$$

The new updated locations are denoted as C_{new} , and the previous location is indicated as C_{pre}, and the random numbers are denoted as s1, s2, and s3. The two critical features (exploration and exploitation are determined by using equations (8) to (11).

Algorithm 1: Pseudocode using CSA

Initialise the position y_i^j of an initial node using CSA
Estimate the fitness values for each node
While (t<Maximum iterations)
For i=I: number of initial nodes
Generate C_B
Generate new nodes by Eqn. (8)
Generate C_O
Generate new nodes using Eqn. (9)
Generate M_C
Generate new nodes using Eqn. (10)
Generate new nodes using Eqn. (11)
If any nodes break the boundary scenarios, then manage the boundaries of position and neglect them
End if
Estimate the fitness values for the estimated new nodes
The global best node is updated after finding the better solution
End for

$$t = t + 1$$

End while
Return the global best solution
End

3.2.3 Ensemble SVM Boosting Learner with Optimisation Model for the Calculation of Update and Sleep Cycle

Previously we set the best sensor subset sSE_C^* based on the environmental state. This contributes to the N1 energy-saving mode of the determined WSN. The sampling rate and the transmission periods are determined by utilising the subsets, and the optimisation of the approach can be achieved by our proposed method. For global optimisation, our proposed method uses the CSA approach, and the local optima can be obtained by the Ensemble SVM boosting approach. It is arduous to attain the global optima by the ensemble SVM boosting approach due to the noising problems.

However, the power consumed by the $sSE_C^*$is given as,

$$PC = \sum_i^* \left(\frac{SE_{i*}}{\beta_{i*}} + \delta_{i*} TE_{i*}\right) \tag{12}$$

The sampling rate sS_{i*} is given as β_{i*} , and the energy consumption per the sampling is given as SE_{i*}. The transmission period of the node is given as δ_{i*} , and the energy consumption per the transmission is given as TE_{i*}. In order to circumvent the transmission of data from the sensor nodes before collecting needed data, it must require better constraints. This will also prevent the performance degradation of the WSN. Then the constraint is given as,

$$\rho \times min\left(\frac{1}{\beta_{i*}}\right) < minmax(\delta_{i*}), \forall_{i*} \tag{13}$$

Here, ρ_{it} represents the number of sensor nodes to be transmitted. The N1 energy-saving mode can be achieved by mitigating sensor nodes in the WSN. This will result in the degradation of performances when compared to conventional methods. The degradation is overcome by adding the following constraints:

$$A_{ep} \geq \varphi_a \times \partial$$

$$R_{ep} \geq \varphi_r \times \partial \quad (14)$$

The loss of our proposed method can be determined by ∂. Here the accuracy and recall of all the sensor nodes in the WSN can be defined as $A_{ep}$and R_{ep} , respectively. The optimum issues due to the temperature can be solved using the following constraints.

$$DropScenario: \frac{T_{max}}{(T+1+\mu)}$$

$$where \mu = \begin{cases} 1(L_{ep+1}) \\ 0(otherwise) \end{cases} \quad (15)$$

The maximum temperature is indicated as $T_{max}$and T is the normal temperature.

3.3. Hybrid Ensemble Boosting learning and CSA

The following procedure is used to accomplish ensemble BL and CSA hybridisation. First, the parameters of both EBL and CSA are initialised, and then the constraint is used to find the best solution. Then the best solutions are calculated using two levels of multi-balanced EBL and CSA. The best subset nodes are selected using the EBL and the CSA by following the algorithm mentioned above. Henceforth, the ideal solution is calculated based on the priority classification. Select the accurate solution values.

Each cluster head calculates the following update cycle whenever the scheduled clustering activity is finished to tackle the disadvantage. The decision-making is improved for selecting the cluster head nodes by applying an ensemble SVM learner with optimisation. Lower outstanding energy owned by cluster nodes may not be able to govern their operation for an extended period of time. In a longer update cycle, lower average data rate outputs are present in the transmission period. Equation (4) computes cluster nodes that update the cycle UP_j.

Update cycle = Fitness(Averagedatarate$_j$, Distance$_j$, Residualenergy$_j$ (16)

The model stands out because it uses member nodes to identify similarities at regular intervals. An ensemble SVM learner with an optimisation model is created to train the provided data subsets. Finally, recent data samples are identified via machine learning models. Similar sensed readings are determined based on the update cycle, which computes the sleep cycle.

$$Sleepcycle = Fitness\left(Re\,s\,idualenergy_j, updatecycle\right) \quad (17)$$

When the update cycle ends, the node combines the cluster head selection and clustering processes. Sleep cycle and cluster update cycle varied from medium, short, and too long based on varying residual energy.

3.4. Network Lifetime Enhancement and Energy Consumption Modeling for WSN Nodes

Let *L1* be the network lifetime achieved by the network using the Random Update process and *L2* be the network lifetime achieved by the proposed method. In both cases, the nodes are denoted as *x*, these nodes *x* are transferred to the cluster s, and existing nodes after transferring are indicated as y. Communication cost for transferring is represented as $C_{cos\,t}$, energy spending due to data exchanging is represented as E_s, energy decreased due to transferring hello message is represented as E_h.

Let *p* be the probability of restructuring the cluster in the Random Update process. Let E_{ad} be the energy spending on transmitting hello messages in the Random Update process [28]. Node count and modified node count are represented as x_i and y_i. In the Random Update process, the energy consumption during the update is represented by E_{update}.

$$E_{update} = \sum_{i=1}^{r} p y_i (E_s - E_h) \quad (18)$$

$$E_{update} = \sum_{i=1}^{r} \frac{y_i^2}{x_i} (E_s - E_h) \quad (19)$$

Let l_1 and l_2 bits are the packet segment length of the data transfer and announcement. Let t_0 be the threshold of a lower transmission gap.

$$E_{update} = \sum_{i=1}^{r} \frac{y_i^2}{x_i} (l_1 + l_2)\left(E_e + \alpha_g t_0^2\right) \quad (20)$$

The distance of transmission of the join request message in the proposed method is less than the random update method; it is given as follows

$$td_{pro} < td_{RU} \quad (21)$$

The energy dropped by the network E_h is, therefore, substantially decreased in the proposed algorithm, as a join request is sent each time the network is reclustered to the nearest H-Node [20].

$$E_h < E_{ad} \quad (22)$$

The amount of energy used by the WSN during clustering is given by

$$Energy = x(E_s + E_h) \quad (23)$$

$$Energy = rs(E_s + E_h) \quad (24)$$

Where E_h indicates the considerable decrease in energy utilisation of the proposed system. When clustering, the energy utilisation is shown below,

$$Energy = rs(l_1(E_e + \alpha_g t_0^2) + l_2(E_e + \alpha_g d_t^2) \quad (25)$$

The distance taken to transmit join_req messages was reduced and indicated as d_t.
By comparing equations (3) and (8), we get

$$L_2 > L_1 \quad (26)$$

From the above discussion, we get to know that the proposed algorithm shows less energy utilisation compared to the Random Update process. Hence by saving energy, the proposed algorithm achieves enhanced network lifetime. Therefore, the proposed algorithm is also cost-effective when compared to the Random update process.

4. Results and Discussion

We use a dataset of two CASAS smart home sensors from WSN single resident flats to perform a series of experiments to demonstrate the efficacy of our proposed framework. The datasets contain sensor data from many types of sensors deployed in the home for a range of activities such as grooming, sleep, alarm, phone, clothes, and so on. All datasets have the same types of sensor nodes. Even though the types of sensor nodes are the same, the dataset differs in terms of the number of sensor nodes, deployment, and the home's interior layout. Table 1 explains the statistics of the WSN. The performance of the proposed methods is evaluated by doing different experiments using CASAS datasets. The features selected from the datasets are depicted in Table 2.

Table 1. The smart home WSN statistics

Datasets	1	2
Number of sensors	68	73
Number of features	221	240
Number of class	21	23
Sensing time	11 days	5 days

Table 2. Selected features from datasets

Number of features	1	2	3	4
Feature name	Sensing time	Sensor node ID	Similarity	Temperature

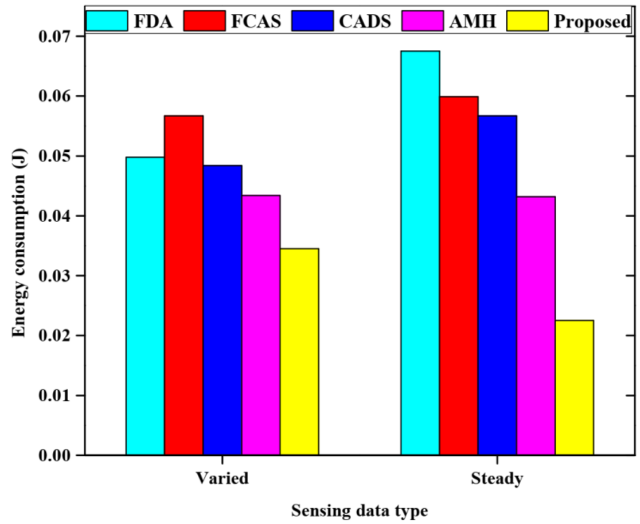

Fig. 2 Comparison concerning Energy Consumption

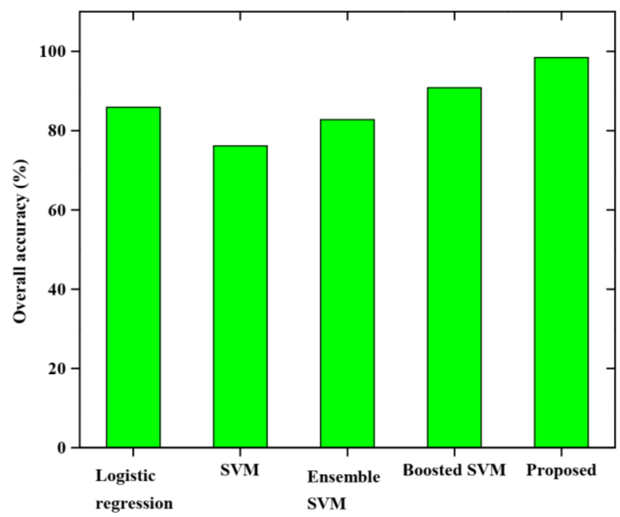

Fig. 3 Comparison concerning the accuracy

Fig 2 explains the comparative analysis of energy consumption by different methods with the proposed method. On comparing, we get to know our proposed method is less energy consuming than other state-of-art methodologies like FDA, FCAS, CADS, and AMH in both varied and steady Sensing data types.

Fig 3 explains the overall accuracy of the proposed method compared with other existing methods. The overall accuracy achieved by Logistic Regression is 83%, SVM is 78%, Ensemble SVM is 81%, Boosted SVM is 90%, and the proposed method is 98%. Thus we conclude the proposed method is highly effective and accurate compared with other state-of-art works.

When compared to ensemble SVM and linear SVM, the performance of the SVM ensemble with booster learning classifier may be evaluated. We used ensemble SVM [16] and linear SVM [17]. The results are reported in table 3.

Table 3. Performance analyses of different classifiers

Different classifiers	Time required for training dataset (sec)	False negative rate (%)	Accuracy (%)
Proposed SVM EBL	6.23	2	99.45
Linear SVM	17.28	85	84.23
Ensemble SVM	11.65	38	94.12

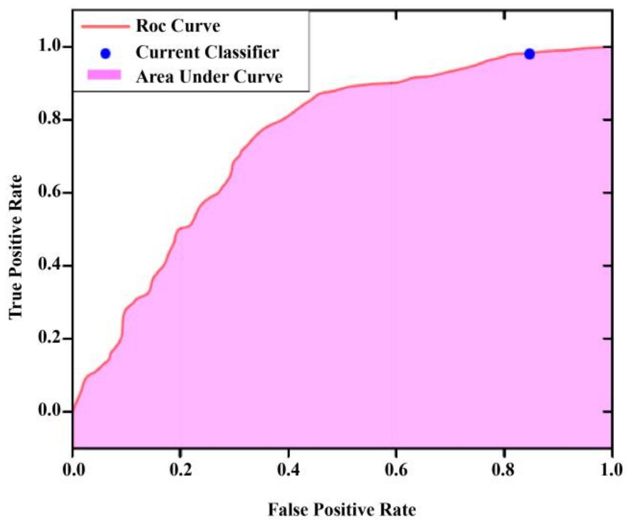

Fig. 4 Linear SVM classifier's Linear SVM

From the table, it is evident that the proposed approach has the fastest training, whereas the linear SVM [18] achieves the longest. Meanwhile, the accuracy of our proposed classifier is higher, that is, 99.45% and the linear SVM achieves the least accuracy at about 84.23%. The booster learning increases the speed of the ensemble SVM. Hence our approach achieves better performance.

4.1. Comparison based on the ROC Curve

ROC curves are used to define the correlation between the false positive rate and the true positive rate. However, the classifier's quality is defined using the AUC curve. It means if the AUC value is higher, then the classifier's quality is maximum. The ROC curve of linear SVM is illustrated in figure 4. The ROC curve of the proposed classifier is illustrated in figure 5.

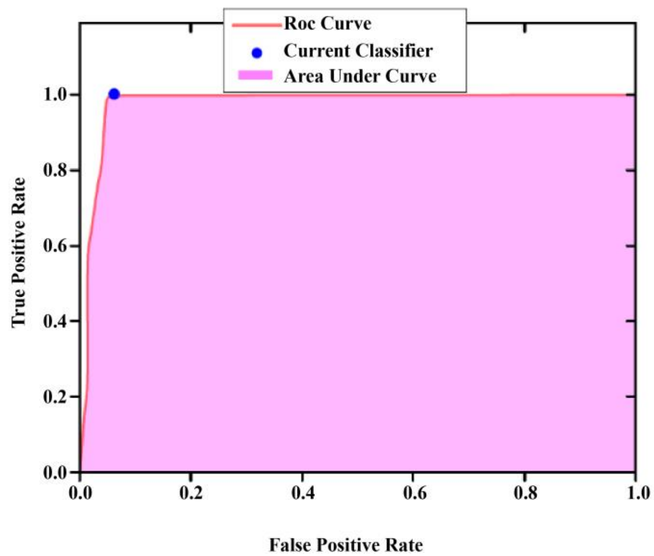

Fig. 5 ROC curve of the proposed classifier

5. Conclusion

The article in this work is based on the CSA algorithm-optimised hybrid SVM ensemble booster learning approach, which reduces the energy consumption of sensor nodes in the WSN. The lifetime of the nodes depends on the environmental condition, and resource allocation is also important in maintaining the nodes in the WSN. The hybrid approach selects the cluster head effectively and increases the data transmission speed. We have taken 2 CASAS smart home sensors-based datasets to analyse the performance. The data's collected over five days. The experimental analysis depicted that the proposed increases the classifier accuracy. Also, the overall consumption of sensor nodes by our proposed method decreased to a great extent. Thus our proposed method provides energy-efficient wireless sensor networks.

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