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Original Article

Chimp optimization algorithm based support vector machine for congestion control in WSN-IoT

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Abstract

The Wireless sensor network (WSN) has huge part in Internet of Things (IoT), as it is used in different applications, for example, detecting climate and sending information by means of the Internet. In any case, the issue of heavy congestion, may affect the performance of WSN-IoT. Despite the fact that machine learning calculations have been introduced by analysts for distinguishing the congested data, accuracy of detection needs to be further enhanced. To control the congestion, Chimp Optimization Algorithm (ChOA) based Support Vector Machine (SVM) is proposed in this paper. To enhance on the execution of SVM, the tuning parameters of SVM are improved utilizing ChOA algorithm. Simulation results indicate that the SVM-ChOA outranks other models, for example, SVM with Genetic Algorithm (SVM-GA), SVM and TCP, based on throughput, energy utilization, delivery ratio, and overhead. Also, the detection accuracy of SVM-CHOA has increased to 92%.

Keywords: WSN, IoT, congestion control, SVM, chimp optimization algorithm (ChOA)

1. Introduction

WSN is a significant part of the IoT that involves sensors in an engaged zone (Bagdadee, Hoque, & Zhang, 2020; Kuo, Li, Jhang, & Lin, 2018). It is used to give steady remote observations, zeroing in on errands in risky or restricted regions where an individual could be exposed to hazards. The idea behind this sensing is commonly to assemble critical information concerning some specific event for explicit applications. WSN relies on a many-to-one data driven approach where every hub can forward the sensed data to a destination node (Singh, Amin, Imam, Sachan, & Choudhary, 2018).

IoT helps in various human life applications, improving their world (Medina, Perez, & Trujillo, 2017). Because of the help of IoT, the metropolitan zone can be upgraded at different levels by redesigning the designs, improving public vehicles, lessening congestion of traffic, and protecting inhabitants. In a particular case, a tremendous proportion of IoT gadgets can suffer from low capacity and less speedy communications due to traffic congestion when many such gadgets simultaneously interface. The information packets forwarded by the connected gadget in the IoT framework have less payload, and a while later in view of the congestion, the lost packets cause expensive retransmissions provoking postponements and huge overheads (Alghamdi, 2020; Bt Halim, Yaakob, & Bin Awang Md Isa, 2016; Haas, & Tian, 2019).

The sections of this article are arranged as follows. Section 2 studies some new studies that introduced congestion control in WSN-IoT. Section 3 proposes a ChOA based SVM for detecting congested data. Consequences of the work are portrayed in section 4. Section 5 concludes summarizing the effects of the approach.

2. Related Prior Work

Kuppusamy, Kalpana, & Venkateswara Rao (2018) had the goal to diminish the activity season of traffic signals in IoT. To achieve the goal, they introduced an inventive

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framework for traffic control with a remote traffic keen server. As a result of the proposed plot, the creators had decreased the activity season of the traffic signal. Qu, Zhao, & Xiong. (2020) had expected to upgrade the throughput by diminishing the issue of congestion. To accomplish this, they proposed a fuzzy sliding mode congestion control algorithm, for short an FSMC, which accomplished improved throughput.

Hussain, Manikanthan, Padmapriya, & Nagalingam (2019) planned to accomplish reduced delays and traffic management among the population of IoT gadgets. To accomplish this, they proposed a versatile off-stacking based on a GA, labelling this GA-OA. Utilizing this offloading plan, delays during the time spent requests were avoided. On account of this proposed strategy, they achieved a superior ratio of request achievement. Swarna, & Godhavari (2021) targeted dealing with the congestion of network. As CoAP is the successful information convention for manifesting congestion, the authors utilized it in their work. The congestion control plot utilized various edges completed using CoAP. Because of this proposed strategy, power utilization and latency were reduced.

Gheisari & Tahavori (2019) expanded the level knowledge of IoT for manifesting congestion. Utilizing intellectual frameworks relying on learning automata, perception was combined to IoT. Then, an inventive intellectual strategy named Cognitive Congestion Control with a round of Learning Automata was proposed. The proposed method accomplished better throughput and dependability. Naeem, Srivastava, & Tariq (2020) worked on the execution of the Multipath TCP as congestion control dependent on MPTCP, accomplishing better throughput.

3. ChOA based SVM for congestion control in WSN- IoT

3.1 Overview

To solve the issue of heavy congestion, an effective strategy is to be introduced in our exploratory work. So, an improved SVM is proposed in this study. Based on the input data, the proposed decision model concludes whether to offload every gadget errand to the server. To upgrade the SVM accuracy, a ChOA algorithm is introduced. Utilizing the algorithm, tuning of the SVM is optimized. The proposed decision construction is prepared based upon the information elements, for example, congestion window size denoted by cwnd, packet loss denoted by pkt loss, queue size denoted by que, and throughput denoted by throu. Figure 1 shows the design of the scheme.

3.2. Description of WSN based IoT

IoT expects to connect smart gadgets through the Internet. The interconnection of gadgets and the information created needs considerably more coordination of correspondence, the board, occasions tracking, and control. Additionally, WSN can assume a significant role by gathering encompassing setting and ecological information. WSN is continuously run in the IoT environment for information processing and changes in real time. Figure 2 shows an instance of congestion in WSN based IoT. As seen in the figure, two source nodes forward the collected data to the destination via 6 intermediate nodes. At the same time, a second intermediate node receives data from one source node and the first intermediate node. Because of incoming packets from different nodes at the same time, the second node is congested. Thus, congestion is a major issue and it occurs in networks collecting information regardless of how these networks are set up, on the grounds that there are numerous small smart gadgets, allowing huge data generation, cleaning and preprocessing for sending appropriate data to the end client. Eventually this creates tremendous traffic in the network, which essentially diminishes network performance in QoS parameters. So, to solve the congestion, an efficient scheme is presented in this work, and the following section describes the proposed scheme.

3.3 SVM-ChOA

3.3.1 SVM

It is intended for the classification of data into two classes according to special regions separated by a hyperplane. The gap from data to the hyperplane is maximized. The capacity of the SVM is upgraded to nonlinear separation by utilizing the kernel trick, which embeds the input attributes to a high dimensional space, while originally it could not be separated linearly with a hyperplane. Here, SVM is utilized for offloading the errand with every gadget to lessen congestion.

The gathered and estimated attributes are given as inputs to the SVM. These attributes are addressed in equation (1),

$$S_t = \{(q_1, r_1), (q_2, r_2), \ldots.., (q_n, r_n)\} \tag{1}$$

Here, q_i represents the training samples that include class labels $r_i \in \{+1, -1\}$ and other data as in equation (2),

$$q_i = \{cwnd,\ throu, que, pkt\,loss\}_i \tag{2}$$

The input attributes of SVM are mapped into a large dimensional space of attributes when not linearly separable. The meanings of the kernel functions of SVM are defined below.

The radial basis kernel function is given in (3),

$$k(q_i, q_j) = \exp\left(-\gamma \left\| q_i - q_j \right\|^2\right) \tag{3}$$

The function of the hyperplane is given in (4),

$$H(q) = b + u * w^T \tag{4}$$

Here, b represents the bias vector while w represents an m-dimensional vector.

An ideal hyperplane is attained by minimizing the goal function in equation (5).

$$Q(b, w, \vartheta) = \frac{1}{2}||w||^2 + C\sum_{i=1}^{n} \vartheta_i \tag{5}$$

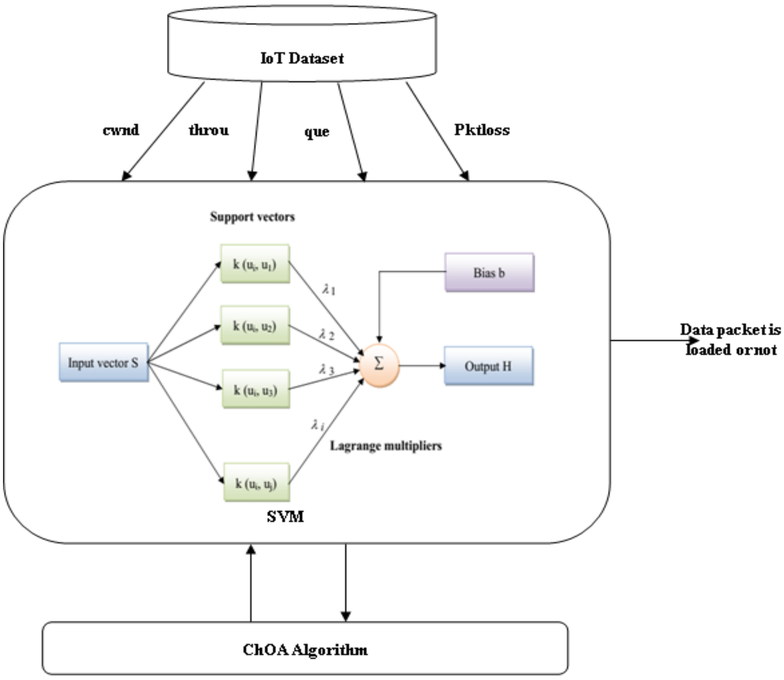

Figure 1. Flow diagram of the proposed scheme

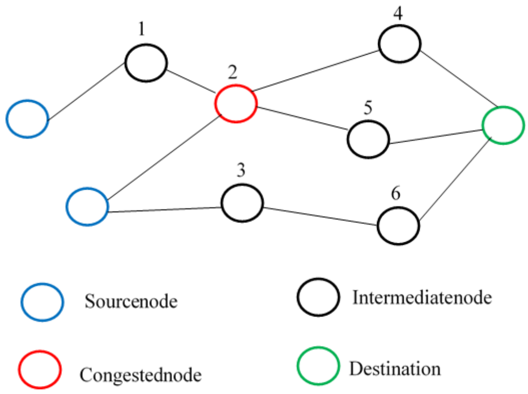

Figure 2. An instance of congestion in WSN based IoT

subject to the conditions (6)

$$r_i\left(b+q_i w^T\right)\geq 1-\vartheta_i \qquad for\ i=1,\ldots..,n \tag{6}$$

Here, ϑ_i denote nonnegative slack variables, C is a penalty parameter, and w is represented as the soft-margin.

Because of (5) including $\|w\|$, it is difficult to obtain the solution. Thus, equation (5) is converted to the Lagrangian for the optimization problem, in (7),

$$\max_{\lambda,\rho}\min_{w,b,\vartheta}\left\{\frac{1}{2}\|w\|^2+C\sum_{i=1}^{n}\vartheta_i-\sum_{i=1}^{n}\lambda_i\left[q_i\left(r_i*w-b\right)-1+\vartheta_i\right]-\sum_{i=1}^{n}\rho_i\vartheta_i\right\} \quad \lambda_i,\rho_i\geq 0 \tag{7}$$

Here, λ_i and ρ_i denote the nonnegative Lagrange multipliers.

The optimum is subject to the conditions (8)

$$\sum_{i=1}^{n}\lambda_i r_i=0, \qquad C\geq\lambda_i\geq 0 \qquad for\ i=1,\ldots.,n \tag{8}$$

Finally, an ideal decision hyperplane is shown in (9),

$$H(q)=\sum_{i\in Q} v_i\lambda_i k\left(q_i,q_j\right)+b \tag{9}$$

In this approach, the radial basis kernel function $k\left(q_i,q_j\right)$ is utilized. U denotes a vector associated to the nonzero Lagrange multipliers λ_i termed as support vector. Figure 3 illustrates the structure of the SVM.

Utilizing this SVM, data from gadget are either stacked or not to offload the data packets to the server. To improve the characterization execution of SVM, the penalty (C) and kernel (γ) parameters are to be tuned. To improve these the ChOA is utilized. This algorithm is introduced as follows.

In this section, the performance of SVM is improved by optimizing the tuning parameters of it using the ChOA algorithm. Chimps are an African species of great apes and are also known as Chimpanzees. In a chimp colony, every group of the chimps autonomously endeavours to find the hunting space with its own technique. In every group, chimps are not exactly comparable as far as ability and knowledge; however, they are all performing their responsibilities as an individual from the colony. The ability of every individual can be helpful in a specific circumstance.

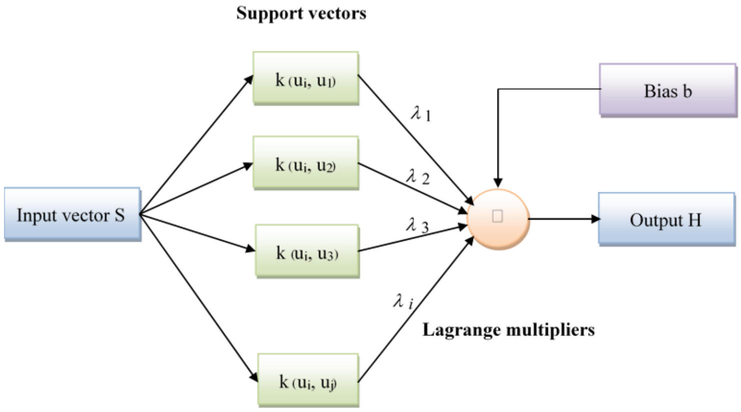

Figure 3. Schematic diagram of the SVM

Besides, chimp colony has four kinds of chimps described as follows.

- Drivers*:* They only pursue the prey but not try to catch it*.*
- Barriers*:* They place themselves in a tree to make a barrier blocking the movement of the prey*.*
- Chasers*:* They follow quickly after the prey to hunt it
- Attackers*:* They guess the prey's breakout route to turn it back towards the chasers or down into the lower shelter.

In general, chimps' hunting process is partitioned into two fundamental stages: "Exploration" which comprises driving, impeding, and pursuing the prey; and "Exploitation" which comprises assaulting the prey.

3.3.2 Initialization

In this approach, the parameters C and γ of SVM are considered as solutions. The population of the solutions is initialized as follows,

$$P_N = \{y_1, y_2, \ldots, y_N\} \tag{10}$$

Where, y_N can be defined as follows,

$$y_N = (C, \gamma)_N \tag{11}$$

3.3.3 Fitness calculation

During this stage, the fitness of each and every solution is evaluated. The fitness calculation is given by,

$$Fit = Max(CR_i(t)) \tag{12}$$

Here, CR represents the rate of correct classification of the ith set of training samples.

According to (12), the solution or the tuning parameters with maximum fitness is chosen as optimal features. In this algorithm, position of optimal solution denotes the position of the prey. If the desired fitness is not obtained, the solution is updated based on the hunting behaviour of chimps.

3.3.4 Update the solution

The following phases explain the hunting process of chimps for updating the solution.

Driving and chasing the prey*:* The mathematical expressions of driving and chasing the prey are defined in equations (13) and (14).

$$z = \left| y_{prey}(t) * c - y_{chimp}(t) * n \right| \tag{13}$$

$$y_{chimp}(t+1) = y_{prey}(t) - b * z \tag{14}$$

Here, t denotes the current iteration counter, position of prey is denoted by y_{prey} and position of chimp is denoted by y_{chimp}. b, c and n denote the coefficient vectors and are determined as follows,

$$b = 2 * f * rand_1 - f \tag{15}$$

$$c = 2 * rand_2 \tag{16}$$

$$n = Chaotic\_value \tag{17}$$

Here, $rand_1$ and $rand_2$ denote random values within [0, 1], and f denotes the coefficient vector that is decreased non-linearly from 2.5 to 0 via the process of iteration. n denotes a chaotic vector which is estimated from different chaotic maps, and it denotes the impact of the sexual motivation of chimps in the process of hunting.

Exploitation or attacking stage*:* In the hunting process, driver, barrier and chaser chimps support the attacker chimps to hunt the prey. Generally, the process of hunting is executed by the attacker chimps. In the mathematical expression, the location of the prey is identified from the best solution or first attacker, driver, barrier and chaser. The attained four best solutions are stored. Then, depending on the location of best chimps, positions of the other chimps are updated. This is defined by equations (18), (19) and (20).

$$Z_{Attacker} = \left| y_{Attacker} * c_1 - y * n_1 \right|, \qquad Z_{Barrier} = \left| y_{Barrier} * c_2 - y * n_2 \right|$$

$$Z_{Chaser} = \left| y_{Chaser} * c_3 - y * n_3 \right| \qquad Z_{Driver} = \left| y_{Driver} * c_4 - y * n_4 \right| \tag{18}$$

$$y_1 = y_{Attacker} - Z_{Attacker} * b_1 \qquad y_2 = y_{Barrier} - Z_{Barrier} * b_2$$

$$y_3 = y_{Chaser} - Z_{Chaser} * b_3 \qquad y_2 = y_{Driver} - Z_{Driver} * b_4 \tag{19}$$

$$y(t+1) = \frac{y_1 + y_2 + y_3 + y_4}{4} \tag{20}$$

Prey attacking stage*:* In this stage, the prey will be attacked by the chimps and the hunting process is stopped as the prey has stopped moving. A chimp chooses its next position between the prey's position and its current position when the value of b lies within [-1, 1]. The chimps are forced to attack the prey if $|b| < 1$.

Exploration stage*:* In this stage, the chimps are diverged from the prey and forced to search for best prey. The chimps are forced to find the best prey when $|b| > 1$. Besides, to avoid local minima in this algorithm, c factor is used within [0, 2]. Also, this factor assigns random weights to prey.

Social motivation*:* In this stage, the chaotic maps have been utilized to enhance the execution of ChOA. These chaotic maps are deterministic cycles which appear to have random behaviours. To demonstrate this concurrent behaviour, we expect that there is a likelihood of half to pick between either the ordinary updating position method or the chaotic model to update the chimps' positions. The mathematical expression of the behaviour is defined in equation (21).

$$y_{Chimp}(t+1) = \begin{cases} y_{prey}(t) - b * z & if\ \eta < 0.5 \\ Chaotic\_value & if\ \eta > 0.5 \end{cases} \tag{21}$$

Here, η denotes a random number within [0, 1].

Termination: The solutions are updated based on the hunting behaviour of chimps until attaining the optimal solution or best tuning parameters of SVM. Once the solution is obtained, the algorithm will be terminated.

4. Results and Discussion

Simulation of SVM-ChOA was executed in NS2. 250 IoT nodes were placed in 1000m×1000m of search space. Transmit and receive power of each node were 0.66W and 0.395, respectively. Transmission range was 250m. AODV routing protocol was utilized for routing the data packets. Besides, 802.11 standard MAC protocol was utilized. Also, in this work, along with the SVM-ChOA, also SVM-GA, SVM and TCP were simulated. In SVM-GA, GA was used to optimize the tuning parameters of SVM. Besides, without any optimization algorithm, the traditional SVM algorithm was simulated. Further, the existing transmission control protocol (TCP) was also simulated for a baseline comparison. Simulation was executed for 100 seconds. Table 1 summarizes the values of simulation parameters.

Table 1. Simulation parameters

Parameter	Value
Packet size	512bytes
Area size	1000m×1000m
Antenna	Omni Antenna
Routing protocol	AODV
Initial receiving power	0.395W
Initial energy	10.3J
Initial transmitting power	0.660W
Simulation time	100secs
MAC	802_11
Nodes	250

4.1 Performance analysis

The approach SVM-ChOA's input measurements are evaluated for fluctuating nodes. Figure 4 portrays the yield of the various methods as far as throughput. Due to the determination of advanced SVM parameters utilizing ChOA, the forecast of blocked packets is enhanced precisely. This prompts an increment in the throughput. Likewise, contrasted with SVM-GA, SVM and TCP, the throughput of the SVM-ChOA was superior by 6%, 24% and 48% separately.

Figure 5 portrays the correlation between delivery ratio for various strategies with changing count of IoT gadgets. As displayed in the figure, when the count of IoT gadgets builds, the delivery ratio gets diminished. Nonetheless, the delivery ratio of SVM-ChOA is superior by 11%, 19% and 28% to those of SVM-GA, SVM and TCP separately. By recognizing the congestion utilizing the SVM-ChOA, the blocked packets are offloaded, therefore, the source node forwards the sensed data to the server with less drops. In this way, the delivery ratio of the SVM-ChOA is amplified from those achieved with SVM-GA and SVM.

The examination of the energy utilization of the distinctive decision models for the fluctuating count of IoT gadgets is portrayed in Figure 6. Energy utilization is amplified when the count of IoT gadgets increases. By and by, contrasted with existing SVM-GA, SVM and TCP, the energy utilization of SVM-ChOA is diminished to 80%, 87% and 93% of these separately. As the congestion is diminished by offloading the data packets, retransmission of bombed packets is likewise diminished. Along these lines, the energy utilization of the network is diminished.

The correlation of the delay of different decision models with changing quantity of IoT gadgets is shown in Figure 7. By keeping away from the blocked packets, the delay in data transmission is diminished. Thus, the delay of the proposed SVM-ChOA is 63%, 68% and 72% of those with SVM-GA, SVM and TCP separately. In Figure 8 and Table 2, the correlation of the overhead of the different decision models for the shifting count of IoT gadgets is shown. As portrayed in the figure, overhead is boosted when the quantity of IoT gadgets increases. Be that as it may, the overhead of SVM-is smaller by 40%, 47% and 52% than those of SVM-GA, SVM and TCP separately. The accuracy of the diverse

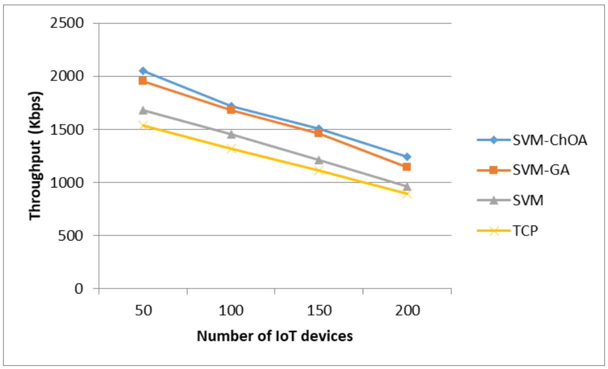

Figure 4. Comparison of throughput of different models

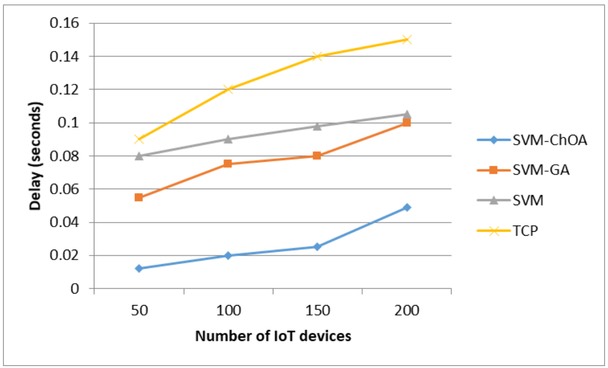

Figure 5. Comparison of delay of different models

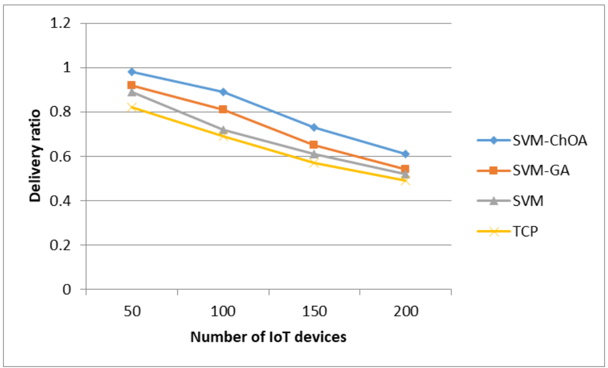

Figure 6. Comparison of delivery ratio of different models

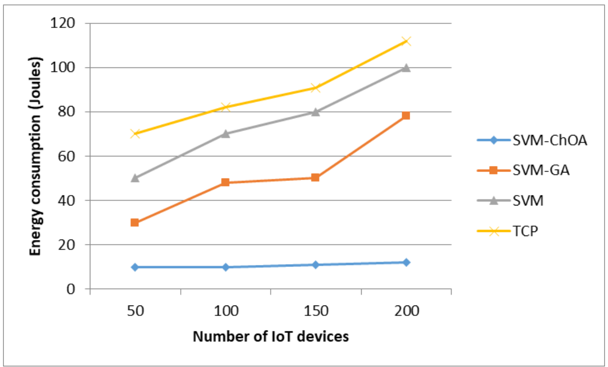

Figure 7. Comparison of Energy consumption of different models

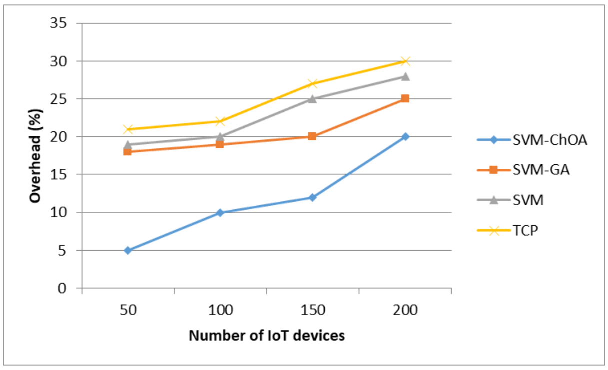

Figure 8. Comparison of Overhead of different models

forecast models is portrayed in Figure 9. As seen in the figure, the proposed decision model SVM-ChOA gets 92% accuracy while SVM-GA, SVM and TCP achieve 89%, 78% and 70% accuracies, respectively.

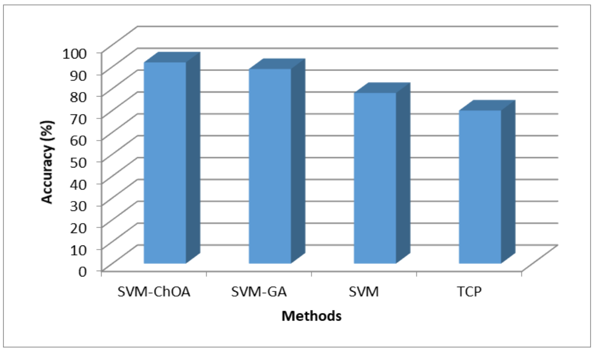

Figure 9. Accuracy of different techniques

5. Conclusions

For controlling the congestion in WSN-IoT, ChOA based SVM has been introduced. The SVM's performance has been enhanced by ideally choosing the penalty and kernel weights of SVM utilizing the ChOA algorithm. To this improved SVM, the input elements, for example, que, pkt loss, cwnd, and throu have been given in both training and testing stages. By using these input measures, congested packet traffic could be anticipated. The performance of the SVM-ChOA was contrasted those of SVM-GA and a regular SVM. As seen in the outcomes, the call accuracy of the SVM-ChOA was 92% and superior to those with SVM-GA and SVM. However, computational complexity of the proposed scheme needs to be further reduced. In the future, we focus to develop an efficient security algorithm for improving the security of WSN based IoT network.

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