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# Gradient Descent Float Boost Serial Correlated Autoregressive Model for Target Object Detection and Tracking in WSN

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**Abstract**

WSN is scheme of spatially allocated SN which collect as well as transmit information about physical or environmental conditions, namely temperature, and so on. These nodes, equipped by sensors, for communiqué capabilities, work collaboratively to monitor specific areas and relay information to a central sink node or base station. When a target object enters a WSN during communication, it initiates a dynamic series of events that significantly impact data collection and system functionality. This scenario is critical in applications of forest fire detection, where timely detection and response are essential. Machine learning-based target detection in WSNs is used to identify and track objects of interest based on data collected from SN. In this manuscript, new method called the Gradient Descent Float Boost Serial Correlated Autoregressive (GDFBSCA) model is developed for efficient target location recognition as well as tracking in WSNs with higher accuracy and reduced time consumption. This approach enhances accuracy and efficiency of detection processes, creating it suitable for various relevances, from surveillance to environmental monitoring. Initially, number of SN is provided as input. After target object penetrate network, every SN begin sensing information as well as transmit it to base station for location detection in the WSN. The base station utilizes the Float Boost Classifier to identify the target object's location through the Multiplicative Upper Bound Winnow (MUBW) method. The MUBW technique uses ToA to calculate distance among SN, applying triangulation to detect the target node's location. Censored regression is also employed to find weak learners with minimal error. Finally, accurate location detection with minimal error is selected through gradient descent, providing a strong learner as the final output. Next, Serial Correlated Autoregressive Analysis is conducted to examine the target object's location and predict its trajectory, specifically for forest fire detection in WSNs. Experimental assessment is conducted on various factors. The performance outcomes demonstrate GDFBSCA model effectively enhances target tracking accuracy while reducing time compared to conventional methods.

***Keywords***: WSN, target object tracking, Float Boost classifier, Multiplicative Upper Bound Winnow method, Censored regression, Serial Correlated Autoregressive Analysis

## 1. Introduction

WSN is wireless network of spatially dispersed SN which communicate wirelessly to observe as well as record environmental situations, namely temperature and so on. These networks commonly used in applications like environmental monitoring, industrial automation, healthcare, military, and disaster management, forest fire detection where they collect, transmit, and process data autonomously. In case of forest fire detection, WSNs are particularly valuable because they enable real-time monitoring and tracking of fire across large and often inaccessible areas, allowing for timely detection and response. Target tracking in forest fire detection refers to the continuous monitoring and localization of fire outbreaks. In this application, WSNs play a vital role by using strategically distributing the sensor nodes to detect temperature, smoke, or other indicators of fire presence. These nodes communicate and transmit information to base station systems, allowing for the tracking of fire movement and intensity.

The Particle Filter with a Support Vector Machine (PF-SVM) was developed in [1] to address target tracking and localization problems with reduced energy consumption. But, achieving higher accuracy in target tracking remained a significant challenge. An adaptive dynamic programming model was designed in [2] for energy-efficient cooperative target tracking to effectively enhance constancy related to convergence of the NN. Although model minimizes error, it did not reduce the time consumption associated with target tracking.

An improved early forest fire detection model was designed in [3] based on a deformable transformer to achieve high detection accuracy for end-to-end object recognition of smoke at dissimilar scales. But, processing speed for object detection was low. Combined learning-based forest fire recognition method was developed in [4] to attain elevated accuracy in detecting huge as well as little forest fire targets. But, time complexity associated with forest fire detection was not minimized. A mobile target tracking algorithm was designed in [5]. But, complexity of the algorithm was not minimized, and it was unable to apply in large-scale environments. A motorized target tracking approach was developed in [6] based on a convolutional BiLSTM NN. But, it failed to focus on reducing method difficulty as sustaining elevated positioning accuracy.

An energy-efficient coverage model was designed in [7]. But, it was not applied to scenarios involving large-scale networks. The Local Greedy Threshold Algorithm and Overall Greedy Search Algorithm were developed in [8] to enhance the performance of target tracking while maintaining minimal complexity. But, error rate associated with target tracking was not reduced.Multi-objective optimization approach was designed in [9] to minimize reconstruction error and coverage while enhancing target detection and reducing running time. However, this approach fails to be effective in densely populated areas.

FTSS method was designed in [10] to enhance target tracking. But, it did not address multi-target tracking or energy harvesting in the network. The Glowworm Swarm Optimization algorithm was developed in [11] based on the clustering concept to improve coverage as well as connectivity within network, thereby improving seamless broadcast. However, it did not improve the performance of target tracking. A barrier coverage-based forest fire detection method was designed in [12] to improve model's accuracy. But, time complexity of fire recognition process remained unaddressed. A particle swarm optimization (PSO) algorithm was designed in [13] based on RSSI. But, the achievement rate of target tracking decreased.

Energy-efficient node deployment was developed in [14] with the aim of object detection with higher accuracy. However, it did not address other artificial intelligence techniques to further enhance detection accuracy by improving the coverage ratio. DL method was developed [15] for accurately detecting target movement through offline similarity function ranking learning. But, the error minimization was not effectively addressed in the target detection process.

### 1.1 Contributions of the paper

To overcome problems of conventional techniques, new GDFBSCA model is developed through below contributions.

- To enhance accuracy of target tracking in WSNs, GDFBSCA model utilizes the Float Boost ensemble classifier along with the Serial Correlated Autoregressive model.
- The Float Boost ensemble classifier employs ToA technique to calculate distance measurements and implements a triangulation process. This approach significantly improves the accuracy of target location detection.
- To minimize the error, censored regression is employed to identify the weak learner with the least error. Gradient descent is then utilized to achieve accurate target location detection.
- To improve target tracking accuracy, a serial correlated autoregressive model is utilized.
- Finally, an experimental evaluation is conducted to compare result of GDFBSCA model against conventional methods using various parameters.

### 1.2 Structure of the manuscript:

Subsequent sections of this paper are structured as follows: Section 2 introduces the related works. Section 3 outlines GDFBSCA, with a clear diagram. Section 4, investigates simulation settings through database explanation. Section 5 conducts a result comparison of different metrics for proposed algorithm, comparing it with conventional techniques. Lastly, Section 6 summarizes the manuscript.

## 2. Literature review

Novel positioning algorithm was developed in [16] based on RSS measurement and maximum likelihood estimation, aiming to accurately position the target object. But, the algorithm did not minimize the target object detection error. A novel deep learning algorithm was designed in [17]. However, it did not improve state estimation accuracy. Multi-sensor combined localization

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of moving targets was presented in [18] with the aim of minimizing error covariance and improving tracking accuracy. But, the cooperative positioning of multiple moving target detection remained unaddressed. An adaptive Kalman Filter was introduced in [19] to enhance the efficiency of target object detection. However, it did not minimize the error rate. A two-step least squares algorithm was designed in [20] to position multiple non-coincident dynamic targets with reduced computational complexity. However, it did not effectively minimize the error rate.

A fast time-frequency difference positioning method was designed [21] to improve accuracy of target detection within a short timeframe. But, machine learning techniques were not applied to further improve this accuracy. A Particle Swarm Optimization algorithm was designed in [22] for network optimization to predict target trajectories by minimizing network energy consumption and increasing network lifetime. However, reducing detection time posed a significant challenge. An artificial fish swarm algorithm (AFSA) was developed in [23]. But, time complexity of the target positioning and tracking process was not reduced. A model-free reinforcement learning model was designed in [24] to achieve satisfactory tracking actions and reduce tracking delay and overall energy consumption. But, it did not minimize time complexity.

A measurement compensation-basis of mixture population Monte Carlo method was developed in [25] to facilitate target tracking under limited energy conditions. But, numerous target tracking was not addressed. Multi-target tracking method was developed [26] based on temporal uncertainty with minimal computation time. But, the error rate remained unaddressed. The average consistency method was presented [27] for target movement forecast as well as effectively improved positioning accuracy. But, it did not significantly enhance the overall positioning accuracy. A self-localization algorithm was developed in [28] for mobile targets based on a wake-up media access control (MAC) protocol utilizing received signal strength indication (RSSI). But, it failed to consider both large and small areas for enhancing the accuracy and energy efficiency of target node detection. A DNN was designed [29] using Lion Assisted Firefly Algorithm (LAFA) for target object detection with minimal error. But, the complexity of target object detection remained unaddressed. POMDP approach was designed in [30] for target tracking, effectively balancing network energy utilization.

## 3. Proposal methodology

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WSN is network of spatially allocated, wirelessly connected SN designed to observe and gather information on physical or environmental conditions. WSNs are widely used forest fire detection application due to their ability to continuously monitor large, remote areas in real time and detect early indicators of fires, such as sudden temperature rises, smoke, or gas changes. WSNs provide rapid alerts, enabling early firefighting interventions that significantly limit fire spread and reduce damage. Target detection and localization in WSNs for forest fire detection involves identifying the specific indicators of fire (targets) and determining their precise locations within the monitored area. This capability is essential for indicating the origin of a fire and tracking its spread, enabling a timely response. New ensemble learning method called GDFBSCA model developed for accurate Target detection and localization in WSNs.

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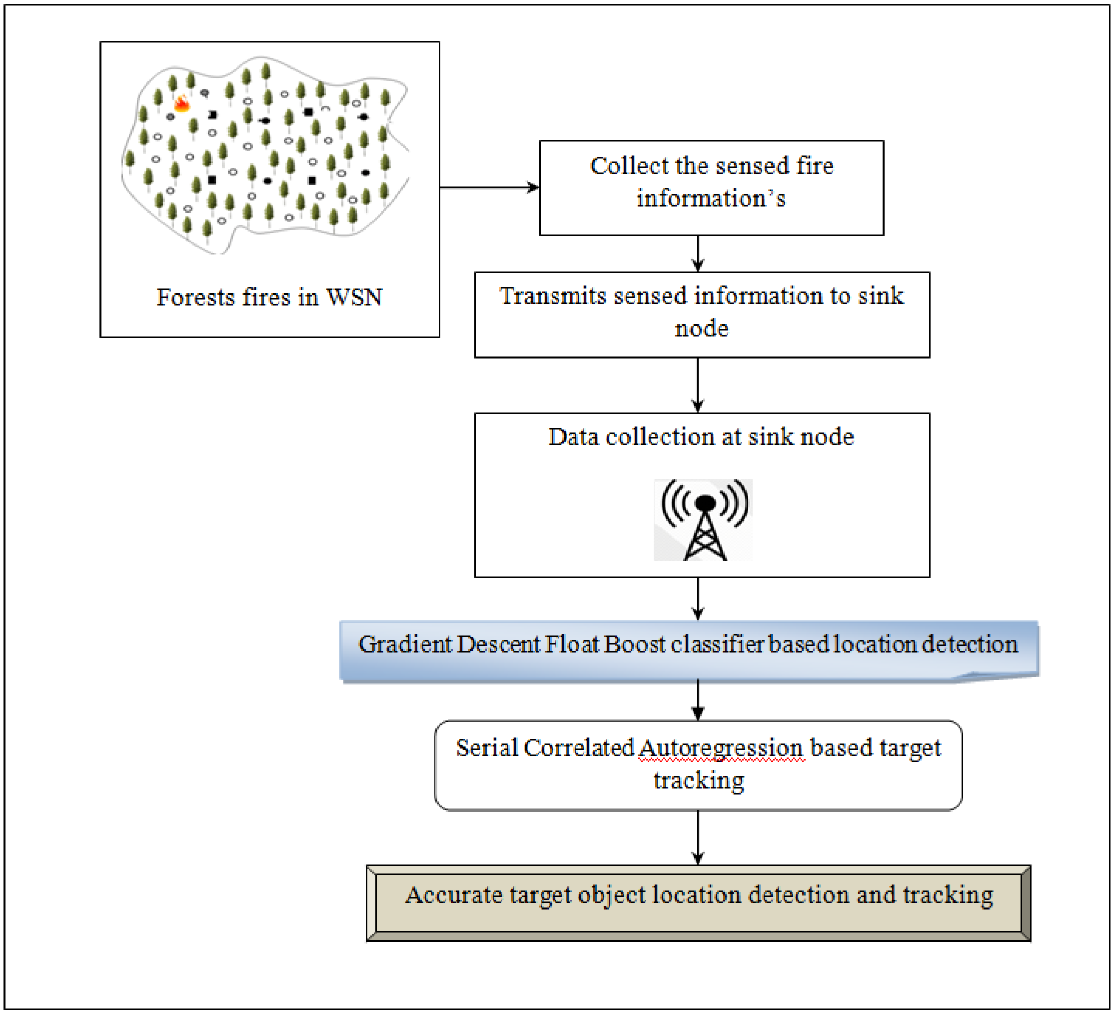


**Figure 1 architecture diagram of proposed GDFBSCA model**

Figure 1 depicts structural design diagram of GDFBSCA model to recognize target object and location detection at WSN. Initially, sensor nodes are distributed randomly in sensing region. WSN is organized in undirected graph '$G = (V, E)$', where '$V$' indicates a sensor nodes $Sn_i \in Sn_1, Sn_2, Sn_3, \dots. Sn_n$ deployed in a forest area, and '$E$' specifies the edges i.e. connection among SN. $Sn$ in forest region gathers the fire related information's i.e. data packet $Dp_1, Dp_2, Dp_3, \dots Dp_n$. The sensed information's are transmitted into the remote base station for localizing the target and tracking the trajectory.

### 3.1 Gradient Descent Float Boost classifier based target location recognition

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The WSN designed for forest fire detection, the network setup typically involves two kinds of nodes $Sn_i \in Sn_1, Sn_2, Sn_3, \dots .Sn_n$ strategically distributed across the forest area to maximize coverage and communication efficiency. These nodes are responsible for detecting environmental changes, such as temperature, smoke, and humidity. They cover designated areas to sense specific conditions indicating potential fires. Once a target object (fires) penetrate network, the SN switch to high-alert mode as well as sense information's related to fire i.e. data packet $Dp_1, Dp_2, Dp_3, \dots Dp_n$ and send to sink node or base station for identifying target object location in WSN. The sink node utilizes the Float Boost classifier for identifying the target object location.

Float Boost is ensemble method designed to improve result of any given learning method through transforming weak learners to sturdy ones. A weak learner is base classifier which not have capability to provide accurate target detection results. In contrast, boosting combines multiple weak learners to form a strong ensemble, significantly improving accuracy by minimizing error. The proposed technique utilizes the Float Boost ensemble algorithm to improve performance of target object detection through superior accuracy. The Float Boost ensemble algorithm employs a Multiplicative Upper Bound Winnow as a weak learner to identify target objects. The ensemble structure of Float Boost is illustrated in Figure 2.

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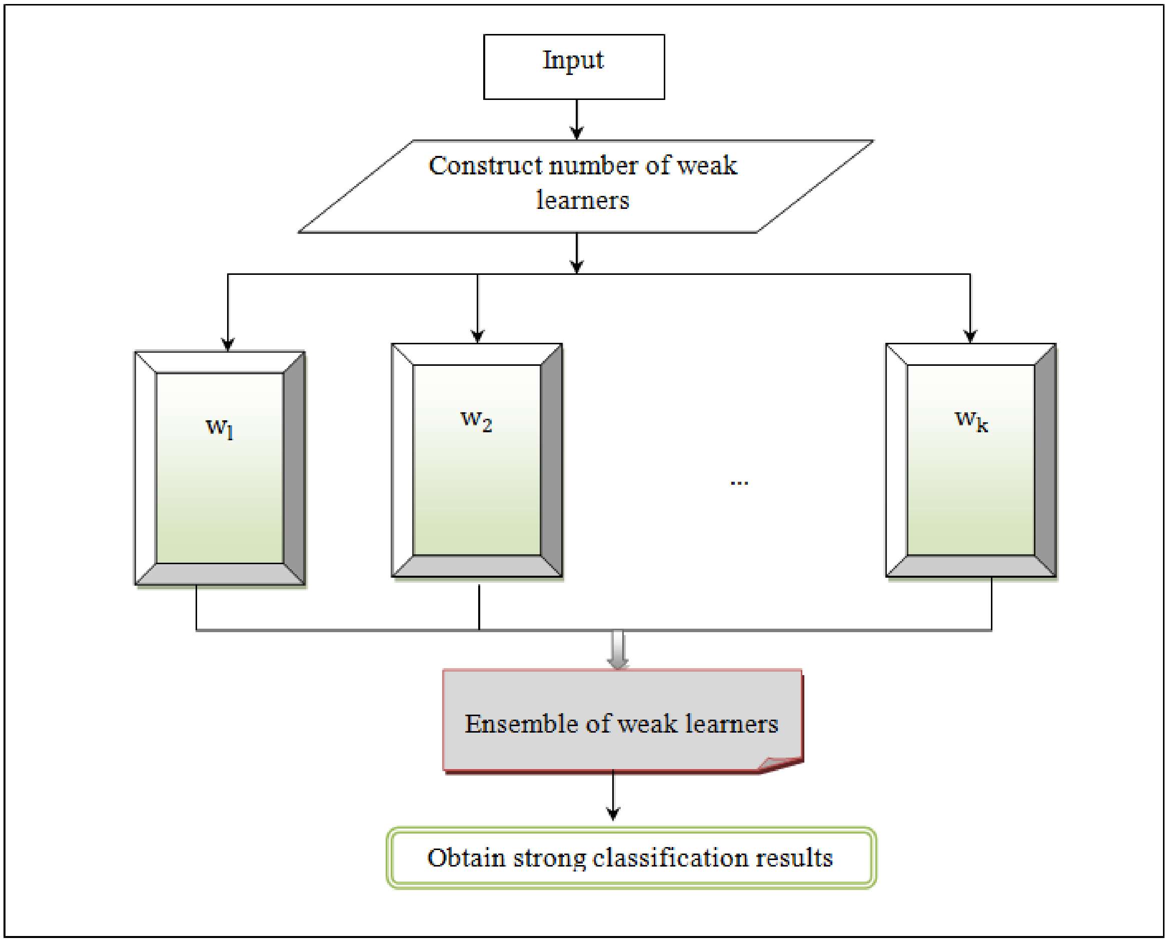


**Figure 2 flow process of ensemble structure of Float Boost method**

Figure 2 depicts flow procedure of ensemble structure of Float Boost to improve the target detection performance. The proposed ensemble technique considers set of training samples i.e. $Dp_1, Dp_2, Dp_3, \dots Dp_n$. Float Boosting consists of four main processes namely initialization, forward inclusion, conditional exclusion, and output. A key innovation of this Boosting lies in the conditional exclusion stage, where the least significant weak classifier is removed from the ensemble. This removal occurs only if it results in an error rate that remains above a specified threshold.

- **Initialization stage**

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Method sets up the initial parameters and conditions for the boosting process. This includes defining the initial weights for the training samples, where typically, all samples are assigned equal weights.

- **forward inclusion phase**

After the initialization, forward inclusion phase is executed. During the forward inclusion phase, the algorithm iteratively adds weak classifiers to the ensemble. In each iteration, it identifies the weak learner as a Multiplicative Upper Bound Winnow linear classifier that best reduces the error based on the weighted training samples. The selected weak classifier is then incorporated into the ensemble to classify the instances.

Multiplicative Upper Bound Winnow is a machine learning classifier that more suitable to high-dimensional data. The Multiplicative Upper Bound Winnow algorithm utilizes ToA technique to find out distance among SN and target. Through computing time it takes for signal to travel as of target node to each sensor node, algorithm accurately estimate distances. This information is essential for effectively localizing the target within a WSN and enhancing the performance of the classification and detection processes.

ToA refers to specific time at which a signal, transmitted as of nearby sensor nodes, reaches a target. The ToA is determined by measuring the time difference between when a signal is transmitted and when it is received

$$D = |t_{tr} - t_{rcd}| \quad (1)$$

Where, $D$ denotes a distance from the sensor nodes, $t_{tr}$ denotes transmitted signal and $t_{rcd}$ indicates a received signal. When multiple sensor nodes detect a fire indicator (e.g., smoke or temperature increase), the data is used to calculate the fire's location by triangulating based on the distance and sensor position. Base station receives information's sent by the source node and finds the exact location using triangulation.

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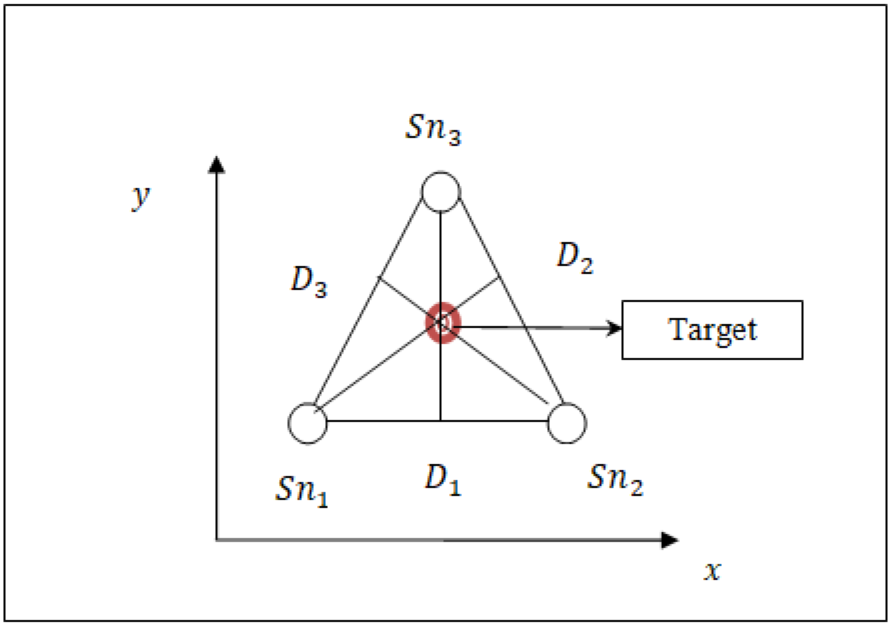


**Figure 3 triangulation based target object location detection**

Figure 3 illustrates the triangulation-based target object location detection. In figure 5, distance among three sensors nodes $Sn_1$, $Sn_2$ and $Sn_3$ are represented by '$D_1$' , $D_2$ and $D_3$ respectively. The intersection point of a triangle, often referred to as the centroid is identified as target point. Centroid separate every median to two section.

If a triangle has three vertices (i.e. sensor nodes) at $Sn_1(x_1, y_1), Sn_2(x_2, y_{12})$, $Sn_3(x_3, y_3)$, the coordinates of the centroid is calculated as follows,

$$P = \left(\frac{x_1+x_2+x_3}{3}, \frac{y_1+y_2+y_3}{3}\right) \quad (2)$$

Where, $P$ indicates a center point i.e. target location. Three sensor nodes serve as an approximate location for the target if these nodes detect the target's presence within their coverage area.

The Multiplicative Upper Bound Winnow algorithm maintains a weight '$\beta$' for each target location detection results, initialized to a value (typically 1). For a given output, the prediction is made by multiplying the weight and the detected output.

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$$Z = \sum \beta * P \quad (3)$$

If the estimated multiplied sum output exceeds a certain threshold, classify the instance as belonging to the correctly classified. Otherwise, it is incorrectly classified. After making a prediction, the weights are updated based on the correctness of the prediction. If the target prediction is correct, the weights remain unchanged. If the prediction is incorrect, the weights are updated based on the multiplicative weights update method that decrease the weights for the next round by multiplying it by a factor of $(1 - \eta)$. The updating process is given below,

$$\beta_{new} = (1 - \eta) * \beta \quad (4)$$

Where, $\beta_{new}$ denotes a new weight, $\eta$ denotes the learning rate or decay factor, typically a value between 0 and 1. This process is repeated until find the accurate classification results.

- **conditional exclusion phase**

After that, conditional exclusion phase is processed in ensemble learning helps to refine the model by selectively removing weak classifiers based on their performance. First, weak learners are summed to one solitary learner

$$Y = \sum_{j=1}^{k} w_j \quad (5)$$

Where, $Y$ denotes a predicted output of strong learner and $w_j$ indicates weak learners output. Training error is calculated for every outcomes which referred as square difference among actual and forecasted output.

$$RT = (Y_{act} - Y)^2 \quad (6)$$

Where, $RT$ indicates training error, $Y_{act}$ represent actual output and $Y$ symbolize observed output as of weak learner. Every weak learner is reweighted depend on their error rate. In this phase, censored regression is applied for selecting the best location detection output by removing the weak learner results. Censored regression is ML method in which dependent variables (i.e. weak learners) are categorized based on above or below a certain threshold. The term censoring point refers to a specific threshold or that acts as a boundary, beyond which certain weak learners are excluded or censored.

The proposed regression process involves two kinds of censoring namely left-censoring and right-censoring. In case of left-censoring, the error value of the weak learners is recognized to

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be below a defined limit. Conversely, right-censoring happens when the observed error value of the weak learners exceeds a particular threshold. This threshold acts as a boundary, distinguishing lower error value from higher ones.

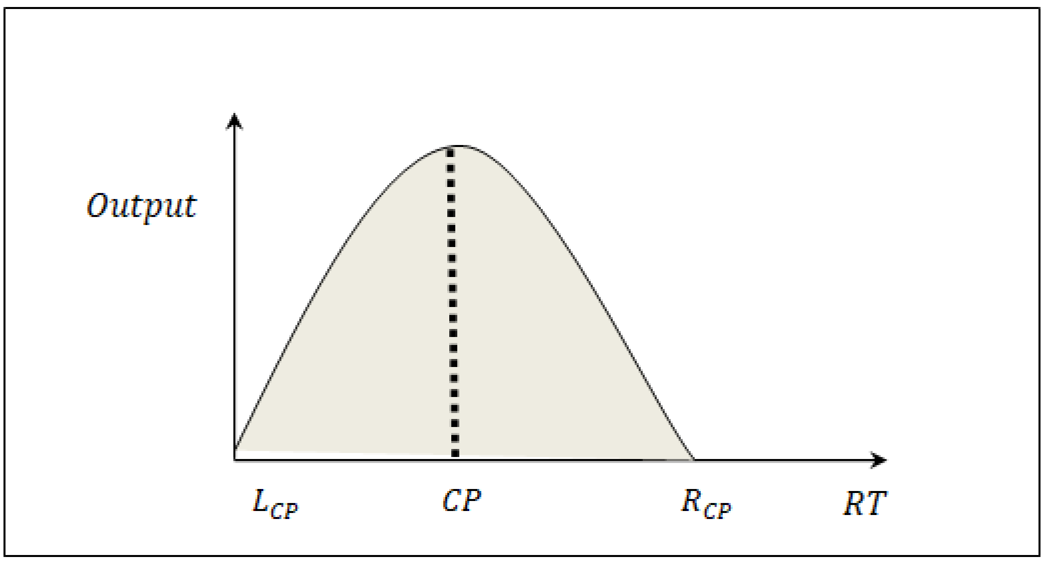


**Figure 4 censored regression outcome**

Figure 4 shows the censored regression outcome in graphical structure. From the graph, the error values are provided as input at horizontal axis whereas censoring output observed at vertical axis. From the figure 3, $CP$ indicates a censoring point or threshold. The Left Censoring ‘ $L_{CP}$’ occurs when the error value of weak learners is minimum than ‘$CP$’. The Right-Censoring point ‘ $L_{CP}$’ happen when error value of weak learner’s exceeds a certain threshold ‘$CP$’. It s mathematically expressed as follows,

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$$\boldsymbol{z} = \begin{cases} RT > CP \ ; \ Select\ weak\ learners \\ RT < CP \ ; \ Remove\ weak\ learners \end{cases} \quad (7)$$

Where, $z$ denotes censored regression output, $CP$ indicates threshold or censoring point. If error value is superior than threshold, the weak learners are selected for accurate target location detection. If the error value is minimum than threshold, weak learners are not selected and it censored. Then apply gradient descent to discover weak learner through minimal error.

$$Y = \arg\min\ RT(w_j) \quad (8)$$

From (),arg $min$ denotes a argument of minimum function, $RT(w_j)$ indicates error rate of weak learners. Like this, weak learners with lesser error are selected as final output for final location detection process.

**3.2 Serial Correlated Autoregressive (AR) Analysis based target tracking**

Target tracking is process of tracking movement of a target object within the monitored area based on previous observations. In WSNs, Serial Correlated Autoregressive (AR) Analysis is employed in proposed technique to model and analyze sensed data for identifying and tracking a moving target. This analysis captures the correlation between locations of target in a time series, allowing predictions of future values based on past observations. Auto regression analysis is a statistical modeling technique used for analyzing and predicting time series data. This model used to predict the next position of the target based on past location observations, allowing for smoother and more accurate tracking.

For a target tracking system, the Serial Correlated Autoregressive model for serial correlated analysis is expressed as follows,

$$P_t = \beta + \sum_{r=1}^{b} \vartheta_r\, P_{t-r} + \varepsilon_t \quad (9)$$

Where, current sensed data (e.g., target's position) at time 't', '$\beta$' denotes a constant term representing the baseline level of the series, $\vartheta_r$ indicates an autoregressive coefficients capture the influence of past location values in the series, allowing the model to adjust predictions based on historical patterns, $P_{t-r}$ denotes a past observed values, such as the target's detected position from previous time steps**,** $b$ denotes a order of the autoregressive model, which indicates number of past

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observations that are employed to forecast current value '$P_t$', $\varepsilon_t$ denotes a error term, which captures random variations in the target's behavior that are not explained by past values. It is typically supposed to normally allocated through mean zero. In the case of target tracking, indicates that the current position estimate is based largely on the previous position for consistent movement while filtering out noise. This autoregressive approach enhances the reliability of tracking in WSNs by adapting to temporal serial correlations in target movements, allowing for more precise predictions.

**// Algorithm 1: Gradient Descent Float Boost Serial Correlated Autoregressive model**

**Input**: Number of sensor nodes $Sn_i \in Sn_1, Sn_2, Sn_3, \dots . Sn_n$, data packets $Dp_1, Dp_2, Dp_3, \dots Dp_m$
**Output**: improve target location detection and tracking accuracy

**Begin**
Initialize the sensor nodes $Sn_i \in Sn_1, Sn_2, Sn_3, \dots . Sn_n$
**for each** node
Construct the number of weak learners '$w_k$'
Measure the distance between the nodes using (1)
Compute the center of triangle using (2)
Multiply the weight and the detected output using (3)
$\boldsymbol{if}$ ( $correctly\ detected\ target$ ) **then**
Obtain the target location detection
**else**
Update the weight using (4)
**End if**
Combine the weak learners $Y = \sum_{j=1}^{k} w_j$ (5)
For ach weak learners ''
**Measure** square difference between the actual and predicted output using (6)
**End for**
**if** ( $\boldsymbol{RT} > CP$) **then**
Select the weak learners for location detection
**else**
Remove the weak learners for location detection
**End if**
**End for**
**Apply** gradient descent to find arg min $RT(w_j)$
Obtain the target location
Apply Serial Correlated Autoregressive model
Predict the movement of target using (9)
Track the target object
**End**

Algorithm 1 illustrates process of target object location detection and tracking at WSN. Number

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of SN is provided as input to the Float Boost ensemble classifier. When the target node enters the network, the nodes monitor it by measuring distance. The weak learner then locates the target object using the triangulation process. Censored regression is applied to analyze the weak learner's error rate against a threshold value. If computed error surpass threshold, weak learner is selected. Otherwise, it is discarded. The gradient descent function is then employed to refine the target location detection. Next, the serial correlated autoregressive model is applied to track moving objects within the network. This process enhances target tracking accuracy while minimizing time requirements.

## 4. Simulation Settings

Simulations of GDFBSCA model and conventional PF-SVM [1], adaptive dynamic programming model [2] are executed by NS3 network simulator. To perform simulation, forest fire database is collected from https://archive.ics.uci.edu/dataset/162/forest+fires. A total of 500 SN are employed in forest region for target detection. DSR routing protocol is employed to enable target detection in WSN, while Random Waypoint model is employed as mobility method. SN collect data and system detects burned areas within the forest.

**Table 1 Simulation Parameters**

| Simulation Parameters | Values |
|---|---|
| **Network Simulator** | NS3 |
| **Simulation area** | 1100 m * 1100 m |
| **Number of sensor nodes** | 50,100,150,200,250,300,350,400,450,500 |
| **Number of data packets** | 50,100,150,200,250,300,350,400,450,500 |
| **Mobility models communication** | Random Waypoint model |
| **Mobility time** | 0 – 30m/s |
| **Routing Protocol** | DSR |

## 5. Performance Comparison Analysis

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Performance study of GDFBSCA model and conventional PF-SVM [1], adaptive dynamic programming model [2] are explained through the various parameters.

### 5.1 Target tracking accuracy

It is measure of detecting and tracking the position of a target object over time within a given area. It is often referred as ratio of properly tracked positions to total number of positions tracked. A higher target tracking accuracy indicates better performance of the tracking system.

$$TTA = \left(\frac{TP+TN}{TP+TN+FP+FN}\right) * 100 \quad (10)$$

Where, $TTA$ denotes Target tracking accuracy, $TP$ denotes a true positive where the target was present, and the system correctly detected it, $TN$ indicates a true negatives where no target was present, and the system correctly identified its absence, FP denotes a False Positive where method wrongly detects target when none is there, FN indicates a false negative where method fails to detect the target when it is present. It is computed in percentage (%).

**Table 2 comparison of $TTA$**

| Number of sensor nodes | Target tracking accuracy (%) | | |
|---|---|---|---|
| | GDFBSCA | PF-SVM | Adaptive dynamic programming model |
| **50** | 98 | 90 | 86 |
| **100** | 97.35 | 92.36 | 88.05 |
| **150** | 96.45 | 92.89 | 87.56 |
| **200** | 97.33 | 93.4 | 89.56 |
| **250** | 96.89 | 92.56 | 88.05 |
| **300** | 98.05 | 93.15 | 90.06 |
| **350** | 98.48 | 92.56 | 88.45 |
| **400** | 97.56 | 94.05 | 90.23 |
| **450** | 98.24 | 93.45 | 89.05 |
| **500** | 97.37 | 92.22 | 88.47 |

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**Figure 5 graphical analyses of $TTA$**

Figure 5 depicts $TTA$ through varying numbers of sensor nodes ranging from 50 to 500. The comparison involves three different algorithms namely GDFBSCA model and existing PF-SVM [1], adaptive dynamic programming model [2]. The graph clearly demonstrates that the GDFBSCA model achieved better accuracy than the other conventional techniques. This observation is attained during statistical evaluation. In an experiment conducted with 50 sensor nodes, the GDFBSCA model attained accuracy of 98%. In contrast accuracy of [1] and [2] were observed to be 90% and 86%, respectively. Similar a variety of accuracy results were attained for every technique. Overall performance outcomes of proposed GDFBSCA model are compared to existing methods. Comparison outcomes illustrates that GDFBSCA model improves accuracy by 9% compared to [1] and 17% compared to [2]. The GDFBSCA model enhances accuracy by performing target object location detection and tracking. Initially, SN are distributed throughout forest area. They begin sensing fire-related information and transmit it to the base station. BS detects target object's location using a float boost classifier based on Time of Arrival (ToA). The triangulation method is then employed to determine the target node's precise location. Following this, a Serial Correlated Autoregressive model is applied to track the target object's location and detect its trajectory in the forest fire, enhancing the accuracy of the process.

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### 5.2 Target tracking error

Target tracking error is measure of detecting and tracking the position of a target object over time within a given area. It is often defined as the ratio of incorrectly tracked positions of the target.

$$TTE = \left(\frac{FP+FN}{TP+TN+FP+FN}\right) * 100 \quad (11)$$

Where, $TTE$ denotes Target tracking error, $TP$ denotes a true positive where the target was present, and the system correctly detected it, $TN$ indicates a true negatives where no target was present, and the system correctly identified its absence, FP represent False Positive where method wrongly detects target when none is there, FN indicates a false negative where method fails to detect the target when it is present. It is calculated in percentage (%).

**Table 3 comparison of $TTE$**

| Number of sensor nodes | $TTE$ %) | | |
|---|---|---|---|
| | GDFBSCA | PF-SVM | Adaptive dynamic programming model |
| 50 | 2 | 10 | 14 |
| 100 | 2.65 | 7.64 | 11.95 |
| 150 | 3.55 | 7.11 | 12.44 |
| 200 | 2.67 | 6.6 | 10.44 |
| 250 | 3.11 | 7.44 | 11.95 |
| 300 | 1.95 | 6.85 | 9.94 |
| 350 | 1.52 | 7.44 | 11.55 |
| 400 | 2.44 | 5.95 | 9.77 |
| 450 | 1.76 | 6.55 | 10.95 |
| 500 | 2.63 | 7.78 | 11.53 |

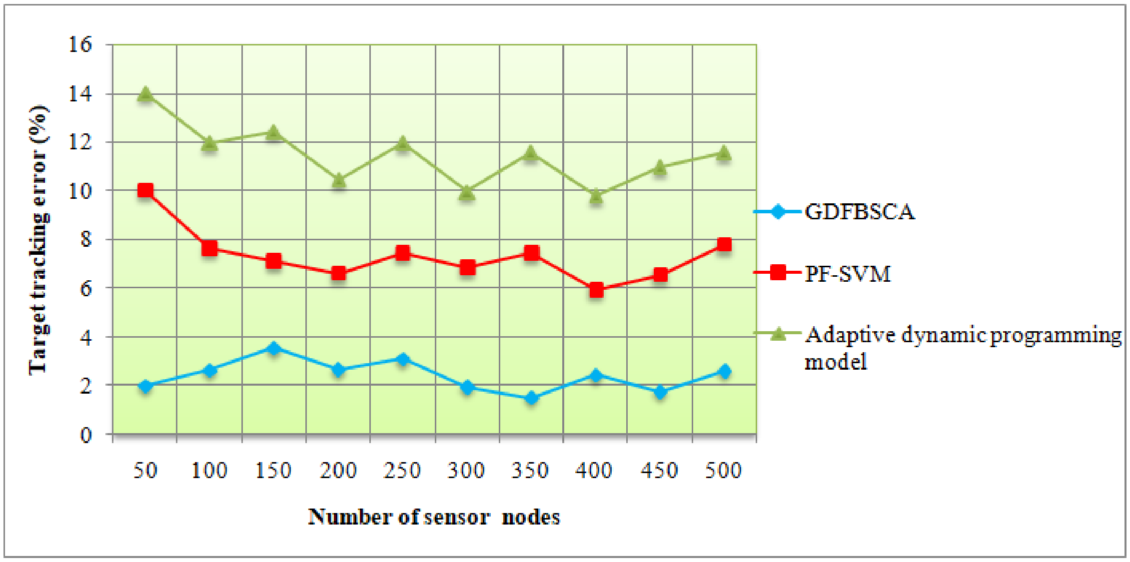


**Figure 6 graphical analyses of target tracking error**

In Figure 6, the performance outcomes of $TTE$ are illustrated versus number of sensor nodes. GDFBSCA model and existing PF-SVM [1], adaptive dynamic programming model [2] are employed to evaluate error rate in target tracking. The results demonstrate that the GDFBSCA model achieved minimal target tracking error compared to the other two conventional techniques. Let us consider number of data samples to be 50 in the first run. By applying the GDFBSCA model, the error rate was found to be 2%, 10% for [1] and 14 for the [2] respectively. Similar various performance outcomes are obtained for each method with varying SN. Entire comparison reveals which target tracking error result is minimized by 66% compared to [1] and by 78% compared to the [2] The improved performance is achieved by applying a censored regression model to the float boost classifier, which selects weak learner results based on a censoring point. Finally, a gradient descent function is used to accurately detect location information with minimal errors, thereby enhancing prediction accuracy and reducing incorrect target detection within the forest area.

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### 5.3 Target tracking time

It measured as amount of time taken through method for target tracking with the number of SN. It is calculated as below,

$$TTT = \sum_{i=1}^{n} Sn_i * Tme \ [TT] \qquad (12)$$

Where, $TTT$indicates the target tracking time, $Tme$ $[TT]$ indicates a time for target tracking and '$Sn_i$' denotes a sensor nodes. It is measured in milliseconds (ms).

**Table 4 comparison of Target tracking time**

| Number of sensor nodes | Target tracking time (ms) | | |
|---|---|---|---|
| | GDFBSCA | PF-SVM | Adaptive dynamic programming model |
| **50** | 15.5 | 17.5 | 20 |
| **100** | 17.3 | 20.6 | 22.5 |
| **150** | 19.6 | 21.7 | 23.6 |
| **200** | 21.5 | 23.5 | 25.5 |
| **250** | 23.6 | 25.8 | 28.6 |
| **300** | 25.8 | 27.2 | 30.3 |
| **350** | 27.8 | 30.5 | 32.5 |
| **400** | 30.3 | 33.7 | 35.6 |
| **450** | 32.6 | 35.4 | 37.8 |
| **500** | 34.4 | 37.2 | 40.2 |

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**Figure 7 graphical analyses of** $TTT$

Figure 7 portrays performance results of $TTT$ using GDFBSCA model and conventional PF-SVM [1], adaptive dynamic programming model [2]. Result of $TTT$ for all three methods enhances with number of SN. Particularly, target tracking time for the GDFBSCA model is significantly reduced compared to conventional [1] ,[2]. The overall results of the GDFBSCA model are compared to outcomes of conventional methods. Comparison shows performance of $TTT$ with GDFBSCA model is significantly minimized by 9% and 17% than the [1] and [2]. The diminution is because of GDFBSCA model, which utilizes the float boost ensemble classifier. In this model, a number of weak learners are constructed to detect the target location within a specific area. Cen sored regression is employed to eliminate weak learners with higher error rates. Consequently, location detection is performed with a minimal number of results, reducing the overall time required for target object detection.

## 6. **Conclusion**

In this paper, an improved GDFBSCA model has been developed to significantly enhance effectiveness as well as accuracy of target object recognition at wireless sensor networks.By applying the float boost ensemble classifier, the model efficiently constructs weak learners to identify target locations within specified areas. Using censored regression, weak learners with higher error rates are filtered out, improving the detection process and reducing the computational time required to locate fires. This GDFBSCA model not only optimizes detection but also enables tracking of moving objects for timely and effective forest fire management. A comprehensive experimental assessment is conducted with various performance parameters with number of sensor nodes. Overall performance results demonstrate GDFBSCA model achieves improved accuracy with minimal error and reduced time consumption compared to conventional methods.

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