

# An Adaptive Whale Optimization Algorithm Guided Smart City Big Data Feature Identification for Fair Resource Utilization

Kapil Sharma, Sandeep Tayal

**Abstract:** World improvement is the development of every single province of the world. Smart city implies changed hardware to adjusted individuals. Smart cities have the most indispensable part in altering distinctive regions of human life, touching segments like transportation, wellbeing, vitality, and instruction. Productively to make measurements to improve distinctive smart city benefits huge information frameworks are put away, prepared, and mined in smart cities. For the change and course of action of huge information applications for smart cities, different difficulties are faces. In this paper, we propose a wrapper display based ideal element recognizable proof calculation for ideal use of assets given highlight subset age. Nine component determination techniques used for compelling element extraction. At last, which includes best add to the ideal usage of assets got by means of a novel element recognizable proof calculation made by the application out of a Whale Optimization Algorithm with Adaptive Multi-Population (WOA-AMP) system as inquiry process in a wrapper display driven by the notable relapse demonstrate regression model Random Forest with Support Vector Machine (RF-SVM). Our proposed calculation gives the exact method to choose the most agreeable feature blend, which prompts ideal asset usage.

**Keywords:** Feature selection, Whale Optimization Algorithm (WOA), Adaptive Multi-Population (AMP), Random forest, Smart city.

## I. INTRODUCTION

As another sort of reasonable improvement, the thought "Smart City" knows a tremendous expansion among the current years [1]. The little and substantial regions are proposing another city display, called "the smart city," which speaks to a gathering of normal innovation estimate, alluring and secure, agreeable, interconnected and doable [2]. The innovative Internet of Things (IoT) solutions is empowering Smart City practices the overall world. It empowers to control contraptions and manage, remotely screen, and to make novel encounters and important information from huge surges of steady data [3]. The basic characteristics of a brilliant city join an irregular condition of information development compromise and an expansive usage of information resources [4]. The fundamental parts of urban change for a splendid city should fuse shrewd industry, keen development, keen organization, wise life and splendid organizations [5].

Each part of an economy of nations is changed by using smart city big data. Such change engages urban communities

to finish the learning norms and necessities of the employments of the savvy city by understanding the essential keen condition characteristics [6]. The smart city abuses preferred standpoint of rising advancements, for instance, wireless sensor network (WSN), to limit asset utilization and cost [7]. The rising advancements among one with the enormous probable to improve smart city administrations are huge information investigation [8]. At the exhibit, a great deal of information is being made from different information sources like PCs, advanced mobile phones, cameras, sensors, interpersonal interaction destinations, worldwide situating frameworks, diversions and business exchanges [9]. The dataset made in the current world of digitizing creates, powerful information stockpiling and handling offices have presented challenges on the logical stages and traditional information mining [10] [11]. The use of huge information in a smart city has numerous points of interest and difficulties, together with the openness of substantial mathematical and storerooms to practice floods of information delivered inside a brilliant city condition [11][12].

Data Computation and Processing Phase (DCPP) takes after nine element feature techniques for successful component extraction. They are DIA affiliation factor, Chi measurement, Information Gain, Document Frequency, OCFS, DPFS, Comprehensive Measurement Feature Selection, Mutual Information, and enhanced Gini record [13],[14],[15]. The huge test here is we need to distinguish which technique is appropriate for particularly recognizing the highlights.[38] To defeat this test, we have required a viable approach in light of recognized highlights for ideal usage of assets.[37]

The upcoming sections of the research paper contains, section 1 contains the introduction of the smart city feature selection, section 2 has the recent related techniques as a literature survey, section 3 contains the proposed Whale optimization with Adaptive Multi-Population (WOA-AMP), section 4 represents the results of the anticipated system and section 5 provides the conclusion of the proposed method.

## II. RELATED WORKS

Yintong Wang et al. [16] proposed a proficient Semi-administered Representatives Feature Selection calculation given data hypothesis (SRFS).

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# An Adaptive Whale Optimization Algorithm Guided Smart City Big Data Feature Identification for Fair Resource Utilization

SRFS has a place with channel approaches and has performed especially well in evacuating the unimportant highlights and bunching the excess highlights. At first, they built up importance pick up the system through which the pertinence of highlights can estimate in the unlabelled information. Promote they presented the parcel of the guided non-cyclic diagram to group the repetitive highlights. At long last, they expanded the current Markov blanket calculations to abuse the extra data entropy contained in the unlabelled information. Also, they found, pertinence picks up measure is an essential advance to investigate the data of unlabelled information, and lessening the time unpredictability.

Ahamad Tajudin Khader and Laith Mohammad Abualigah et al. [17] exhibited a mixture of PS (particle swarm) improvement calculation through administrators of genetic for the component feature issue. The adequacy of the got highlights subsets assessed by using the k-means bunching. The element choice issue is defined as an improvement issue to locate an ideal subset of useful content highlights. Besides, it dispenses with uninformative highlights. The outcomes demonstrated that the proposed technique diminishes the number of uninformative highlights as well as essentially improves the execution of the content clustering calculation; the accomplished outcomes are similarly superior to the aggressive strategies.

Kuan-Cheng Lin et al. [18] proposed a Feature choice [39] strategy in light of an enhanced particle swarm advancement calculation for enormous information arrangement. The proposed calculation is known as 'Improved CSO' (ICSO) and adjusted starting the amicable particle swarm advancement. They led investigations to decide if the two proposed techniques enhance the execution of conventional CSOs when connected exclusively. The execution of the general ICSO in include choice was assessed utilizing an SVM. They utilized different datasets to encourage correlations of ICSO and CSO and likewise led a trial to research the impacts of fluctuating SVM restrictions on CSO and ICSO yields.

Sina Tabakhi et al. [19] displayed an unsupervised component choice strategy given subterranean ant colony optimization, called UFSACO. The technique looks to locate the ideal element subset through a few emphases without utilizing any learning calculations. Additionally, the element importance will be processed in light of the comparability between highlights, which prompts the minimization of the repetition. Along these lines, it can be named a channel based multivariate strategy. The proposed technique has a low computational many-sided quality; along these lines, it can be connected for high dimensional datasets. The test comes about on a few habitually utilized datasets demonstrate the productivity and adequacy of the UFSACO technique and additionally enhancements over past related strategies.

Simon Fong et al. [20] proposed a novel lightweight component determination calculation, especially to mine gushing information on the fly, and it is utilized the APSO (accelerated particle swarm optimization). The assessment comes about demonstrated that the incremental technique acquired a higher pick up in exactness every second caused in pre-handling. Specifically, APSO is intended to utilize for information mining of information streams on the fly. A

combinatorial blast is tended to utilized swarm seek approach connected incrementally. This approach likewise fits better with genuine applications where their information land in streams.[36] What's more, an incremental information mining approach is probably going to take care of the demand for enormous information issue in benefit registering.

## III. FEATURE SELECTION BASED WHALE OPTIMIZATION USING WRAPPER BASED METHOD

The way toward disposing of the insignificant features and excess features from the database is known as features choice, which is used to improve the learning algorithm. The two criteria, named as assessment and search criteria feature collection approaches arranged. By utilizing the wrapper and channel approaches the chose feature subsets assessed. Algorithm of Learning is utilized as a part of the wrapper strategy in the determination procedure [21].

Big data smart cities [34] reasonable usage of assets is the fundamental goal of our proposed strategy. For this activity, numerous improvement strategies are utilized. In our proposed article, whale enhancement technique is used to get the reasonable used ideal list of capabilities.[35] By utilizing this ideal technique list of capabilities to be chosen and decrease the computational period; additionally, the forecast institution of metrics has the preferred qualities over the current strategies.

### 3.1 Wrapper Method

The feature selection in the basis of novel Whale Optimization Algorithm is working based on wrapper-based strategy. The usage of the classifier as in the form of the controller of the feature selection system is the foremost feature of the wrapper strategies. The subsequent three main schemes are used in the feature selection in wrapper [22]:

- Classification Scheme
- Criteria of Feature Evaluation
- Search Scheme

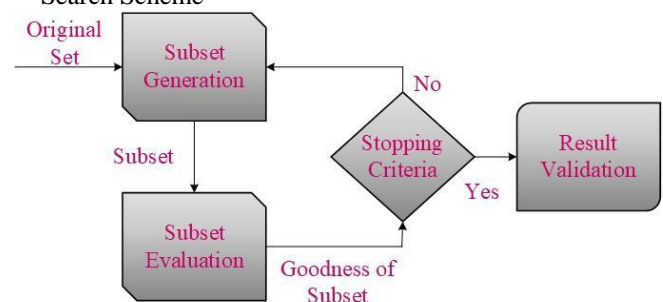


Fig 3.1 Process of Feature Subset Selection

A Subset Generation is a heuristic pursuit process where look for space contains states, each one of which demonstrates a cheerful subset for evaluation. Two things must be settled for subset age, Search starting stage, and Search framework. Hunt starting stage can be forward, backward, bi-directional, and unpredictable. An interesting framework must pick the contender subsets [6].

An Evaluation display is used to survey each as of late made candidate.

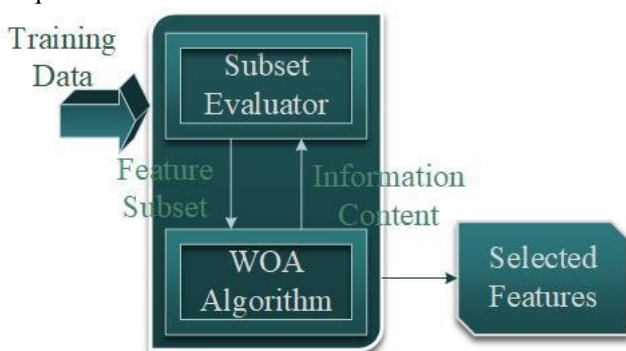
In perspective of the dependence on learning calculations that will be associated with pick feature set an evaluation demonstrate is arranged into two social affairs, one is needy criteria second one is self-ruling criteria. Wrapper demonstrate uses subordinate criteria, and for feature choice, it needs a learning computation. Fairness of feature or its subset is assessed with the help of critical features of the arrangement data without associating any learning algorithm.

In include subset decision, a stopping model speaks to when the feature decision process will stop. A bit of the routinely used halting criteria are according to the accompanying:

- Exhaustive search finishes.
- If a progressive expansion or evacuation of any element does not influence comes about component determination process could be ceased.
- If the agreeably decent subset chosen.

Toward the end, comes about are approved by utilizing grouping blunder rate of classifiers as an execution marker. Examinations are led to compare the characterization error rate on the full arrangement of the classifier learned on highlights, and that prepared on the chose include subset [8].

Wrapper based component subset assessment strategies prompt learning calculations amid assessment venture to calculate the decency of a chose include subset given the calculation's precision so are computationally costly when contrasted with channels. As far as prescient or arrangement, exactness wrapper strategies viewed as better than the channel. The utilized element order criteria or target work in the wrapper highlight determination is regularly mirroring the grouping execution and also the number of highlights. A non-specific portrayal of the wellness work speaking to for both order execution and the number of chose includes as portrayed in condition (10) In wrapper-based techniques, the single assessment of guaranteed arrangement is exorbitant as it generally applies preparing and testing of the given more tasteful. Along these lines, the proficient choice of the look technique is fundamental.



**Fig 3.2: Wrapper Approach for Feature Selection**

The wrapper is a moderate component determination strategy. As per the reliance standard embraced by the wrapper display, it requires a foreordained acceptance calculation and utilizations its execution measure to be connected on the chosen subset to figure out which highlights are chosen. It by and large gives better execution as it chooses includes more qualified to the fated acceptance calculation. However, it is computationally more costly and moderate, which may not be appropriate for other acceptance calculations once in a while. The highlights chose by the classifier are utilized to anticipate

the class marks of covered up occurrences; exactness is typically the evaluator of the produced subsets, however, cost high to figure precision for each element subset. Consequently, in the wrapper technique, it is imperative to distinguish the choice strategy most appropriate for the given dataset and characterization strategy. Besides, the subset of highlights chose is the negligible containing all the pertinent highlights for the objective class. Fig 3.2 shows the wrapper-based feature selection approach. The training set produced to subset evaluator. The dataset is too big, so the set is given to the optimization algorithm to evaluate the optimal dataset. The reduced dataset value is processed under the correlation process to get the optimal feature set. The most relevancy data considered as the optimal set and the other values are given back to the subset evaluator.

### 3.2 WOA

Here the WOA is said to be a fresh optimization algorithm. The WOP algorithm used to mimic the Humpback whales natural behavior. Hunting behavior is the main character of these whales in the path of survival. This technique is to address the optimization problems, and the hunting strategy has been introducing and to chase the prey in the search space; the capability to employ the best agent or random is the whale algorithms uniqueness. By using spirals, humpback whales bubble-net attaching mechanism is simulated [23].

The demonstrating of this calculation incorporates three administrators to mimic the scan for prey (investigation stage), the surrounding prey, and the air pocket net searching (abuse stage) conduct of humpback whales. The numerical definition is displayed and clarified as takes after:

- **Prey Encircling:** By using the best hunt operator whale calculation begins here. The present activities are the best and also whether it is the area of the prey or near this expects it. Whatever remains of the operators subsequently refresh their areas in the direction of the finest pursuit specialist.

$$\vec{P} = \left| \vec{B} \cdot \vec{x}^*(t) - \vec{x}(t) \right| \quad (1)$$

$$\vec{x}(t+1) = \vec{x}^*(t) - \vec{A} \cdot \vec{P} \quad (2)$$

Here, a recent repetition of the method represented as  $t$ ; coefficient vectors are denoted as  $\vec{A}$  and  $\vec{B}$ . The best solution in the location vector represented as  $\vec{x}^*$ , and the location vector is  $\vec{x}$ .  $\vec{x}^*$  must be updated iteratively for the actuality of better solution.  $\vec{A}$  and  $\vec{B}$  Vectors are deliberate in the following expression:

$$\vec{A} = 2 \cdot \vec{a} \cdot \vec{r} - \vec{a} \quad (3)$$

$$\vec{B} = 2 \cdot \vec{r} \quad (4)$$

where, over the number of iterations from 2 to 0,  $\vec{a}$  is linearly decreased and random vector in [0, 1] denoted as  $\vec{r}$ .

# An Adaptive Whale Optimization Algorithm Guided Smart City Big Data Feature Identification for Fair Resource Utilization

The above demonstrating gives some operator to refreshing that one area in the district of the present finest arrangement also emulates enclosing the victim. For n measurements it also encourages the look space, also the specialists encourage the hypercube development using the about the finest arrangement accomplished.

**Exploitation Phase:** It is also known as bubble-net attacking also two tactics are used to work the task:

**Mechanism of Shrinking encircling:** here, based on the eqn

3,  $a$  value is reduced and subsequently the changeability

range of  $\vec{A}$  is also reduced by  $a$ . it indicates that  $a$  is

arbitrarily positioned in  $[-a, a]$ . Here over the optimization

time from 2 to 0 the value of  $a$  is reduced. Where, The

unpredictability of  $\vec{A}$  in  $[-1, 1]$ , determine the search agents

new location next to the best current location and past agent

location.  
 ▪ **Spiral updating position:** The distance amongst the locations of whale and its prey is estimated. By using humpback whales of helix shape, the spiral equation is formed among prey locations also whale to enhance the movement. It exposed in the following equation:

$$\vec{x}(t+1) = \vec{P} \cdot e^{bl} \cdot \cos(2\Pi l) + \vec{x}^*(t) \quad (5)$$

$$\vec{P} = \left| \vec{x}^*(t) - \vec{x}(t) \right| \quad (6)$$

The  $i^{th}$  whale distance is given in eqn 6, and the logarithmic spiral shape constant is denoted as  $b$ , and in the region of  $[-1, 1]$  random number is denoted as  $l$ . It has a whale movement in the direction of its prey is simultaneously spread over the shrinking circling, and it placed in a spiral-shaped path. Consequently, the whale's next position updated by the 50% postulation of the opportunity to control between the binary modes.

```

Algorithm: 1
Input:
    D (f1, f2, ..., fn) // A dataset D with |D| features
    S0 // A initial subset of features
    l // A stopping criterion +
Output:
    S* // A (sub) - optimal set of features
Begin
    Initialize S0* = S0;
    f(S0*) // Evaluate (S0, D, l); // Evaluate goodness of fit of S0 on
    D w.r.t. learning task l
    Step 1: Start the Whale Population X1(t=1,2,3,...n).
    Step 2: Calculate the fitness of each whale.
    Step 3: Set the best whale is X*.
    Step 4: While (t < maximum number of iterations) do
        for (each search whale) do
            Update a, A, C, l and p.
            if (p < 0.5) then
                if (|A| < 1) then
                    Updating whale position is by Eq. (1).
                else
                    if (|A| >= 1) then
                        Choose the random whale Xrand.
                        Updating whale position is by Eq. (9).
                    end
                end
            else
                if (p >= 0.5) then
                    The whale position is modifying by the Eq. (5).
                end
            end
        end
        Verify if any search agent goes beyond the search space and
        amend it.
        Calculate each search agent's fitness.
        If there is a better solution update X*.
        t = t + 1
    end
    while t not reached
    
```

Fig 3.3: Algorithm of WAO with Feature Subset Selection

$$\vec{x}(t+1) = \begin{cases} \vec{x}^*(t) - \vec{A} \cdot \vec{P} & \text{if } p < 0.5 \\ \vec{P} \cdot e^{bl} \cdot \cos(2\Pi l) + \vec{x}^*(t) & \text{if } p \geq 0.5 \end{cases} \quad (7)$$

where,  $p$  is a random number in  $[0, 1]$ .

**Exploration Phase:** A global optimization is attaining in

WOA in this phase. To accommodate the search agent  $\vec{A}$  is

set casually from  $[-1, 1]$  and which is used to retreat as of the

reference whale. It means the value of  $\vec{A}$  ranges from either

less than the -1 or greater than 1. Search agent location

simplified through choosing an agent in randomly and that

permits WOA to execute the global search. The mathematical expression of the displaying of this assessment appliance given below:

$$\vec{P} = \left| \vec{C} \cdot \vec{x}_{rand} - \vec{x} \right| \quad (8)$$

$$\vec{x}(t+1) = \vec{x}_{rand} - \vec{A} \cdot \vec{P} \quad (9)$$

Where random location for the arbitrary whale denoted as

$\vec{x}_{rand}$  and that preferred since the present residents. The

WOA pseudo-code presented in Algorithm 1.

### 3.3 Feature selection of WOA

Whale optimization algorithm approach utilized for consist of optimal in a wrapper-form strategy. The significant standard for the wrapper-based technique is used to put on the order of methodology as a manual for determination strategy includes some enhanced part which chose the feature set. This article applies the WOA adaptively for the ideal element subset to discover that expanding order execution. With an underlying best pursuit operator, the whales ceaselessly modify their areas to any point in the space begins the suitable operator in the WOA. As in conditions (1) and (2) their work to refresh the situations toward the best pursuit specialist from that forward point. With a similar measurement in the dataset, the individual arrangement portrayed as a constant vector. The arrangement vector esteems limited to  $[0, 1]$  and constant. While the estimations of arrangement fitness calculation are binary signified. A connected fitness work is normally coordinating several chose features and the grouping execution. This can be spoken to the following condition.

$$f_o = \beta \cdot H + (1 - \beta) \frac{\sum_i \theta_i}{N} \quad (10)$$

Based on the above equation,  $f_o$  is represented as a function

of fitness specified a vector  $\theta$ ,  $N$  sized with  $1/0$  components,

which is elaborating the unselected or selected feature subset.

In the database, the whole amount of features described as  $N$ .



From the given selected feature subset,  $H$  is represented as a classification error.  $\beta$  is a constant. Finally, the constant handling the trade-off amongst classification errors to feature subset quantity. The organization enactment is the main objective, so  $\beta=1$  use in this work.

### 3.4 Regression Model Random Forest with Support

#### 3.4.1 Vector Machine (RF-SVM):

##### Random Forest:

This procedure comprises of an outfit of various relapse trees. Random forest regression is a tree-based strategy that includes stratifying or portioning the predictor space into various straightforward locales. To make a forecast for a given perception, the mean of the reaction estimations of the preparation perceptions in a similar area is regularly connected [24].

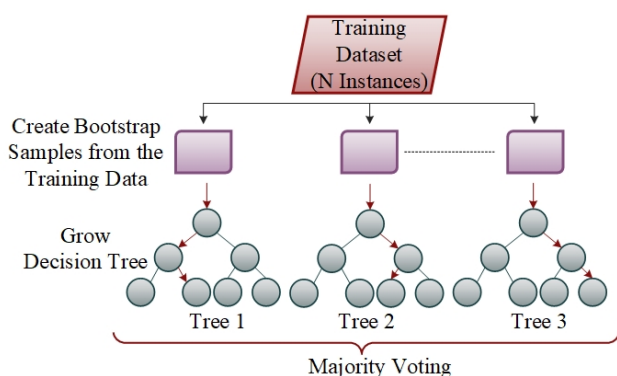


Fig 3.4: Random Forest Pictorial Representation

It is the piece of programmed learning technique. "Bagging" and irregular subspaces ideas consolidated by utilizing this calculation. The choice tree forest calculation prepares on numerous choice trees driven on somewhat unique subsets of information.

The arbitrary backwoods is a piece of the set strategies that takings the choice tree as a separable indicator, and depend on the techniques for Random Subspace pardoning boosting, Randomizing Outputs, and Bagging [25]. The calculation of random forest is truly outstanding among characterization calculations - ready to order a lot of information with precision. It is an outfit learning technique for characterization and relapse that builds various tree choice at preparing period and conveys the class that is the method of the programs yield through singular trees.

**Algorithm: 2**

##### For $b = 1$ to $B$ Make

- Draw  $Z^*$  of size  $N$ .
- Construct a random forest tree  $R_f$  to the initial condition, through the repeatedly reconstructing the associated steps for every end child of the tree, till the point that the base hub evaluates  $n_{\min}$  is makes to a minimum.
  - From the  $p$  variables, select the  $m$  variables randomly.
  - Among the  $m$  pick the finest variable/split-point.
  - Divide the node

Output the group of trees  $\{T_{b_1}^B\}$ .

Fig 3.5: Algorithm of Random Forest

The prediction making at the novel point  $x$  is denoted by:

**Regression:**

$$\hat{F}_{rf}^B(X) = \frac{1}{B} \sum_{b=1}^B T_b(X) \quad (11)$$

**Classification:**

The  $b^{\text{th}}$  random forest tree prediction is assumed by  $\hat{C}_b(x)$ .

$$\hat{C}_{rf}^B(X) = \text{majority vote} \left\{ \hat{C}_b(X) \right\}_1^B \quad (12)$$

In random forest arrangement technique, numerous classifiers are produced from littler subgroups of the information and late their distinct outcomes are collected in light of a voting mechanism to create the coveted yield of the informational info index. This outfit learning system has, as of late turned out to be exceptionally prevalent. Previously from the RF, Bagging, Boosting and were the main two group education strategies utilized. RF has been broadly connected in different zones together with sedate present-day disclosure, organize interruption identification, arrive cover examination, FICO assessment investigation, remote detecting and quality microarrays information examination and so on [26] [27].

Two approaches are used to assess the blunder proportion. They are the training and testing part. To fabricate the backwoods, the preparation part is used, and to figure the blunder rate, the test part-use. An alternative path is to utilize the Out of Bag (OOB) blunder assess. Since irregular backwoods calculation figures the OOB mistake amid the preparation stage, we don't have to part the preparation information.

#### 3.4.2 SVM:

It is an assessable grouping approach and depends on the boost of edge among the occasions also the hyper-plane partition. The technique observed as the best content arrangement of performance. It is said to be a non-probabilistic paired direct classifier, which can straightly isolate the classes by a substantial edge, it winds up a standout amongst the most intense classifier equipped for taking care of limitless dimensional component vectors.

SVM is a coordinated machine learning computation which can be used for both backslide tasks and gathering. Regardless, it is, for the most part, utilized as a few portrayal issues. In this check, we plot every datum thing in  $n$ -dimensional space point with the estimation of each segment being the estimation of a specific mastermind.

# An Adaptive Whale Optimization Algorithm Guided Smart City Big Data Feature Identification for Fair Resource Utilization

By at that point, we execute assembling through discovery the hyper-plane and that distinctive the double classes to an incredible degree well.

It has demonstrated effective in characterizing supposition archives, including style. The guideline for help vector machine calculation is to tackle arrangement and relapse issues. It has connected to numerous fields. SVMs were produced in the 1990s given the hypothetical contemplations of Vladimir Vapnik on the advancement of a measurable hypothesis learning is said to be Vapnik-Chervonenkis hypothesis. SVMs were immediately received aimed at their capacity to work through vast information, the modest hyper constraints number, their hypothetical certifications, also their great outcomes by and by.

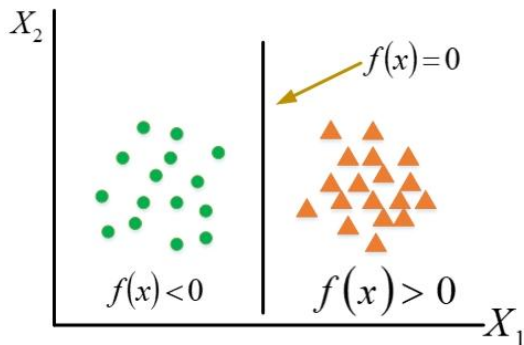
A linear classifier is measured to make the SVM is less demanding for twofold arrangement issue with highlights  $x$  and  $y$  names.  $y \in \{-1, 1\}$  is used to designate the constraints  $w, b$  and class labels:

$$f(x) = w^T x + b \quad (13)$$

where,

The normal to the line denoted as  $w$ . Bias displayed by  $b$ .

It is spoken to via an isolating the hyperplane of  $f(x)$  in the sense of geometrically separates the information space into two assorted districts subsequently bringing about the grouping of the info information space into two classifications [28]:



**Fig 3.6:** Separating the Hyperplane  $f(x)$

The capacity  $f(x)$  means that the isolation of hyperplane in two locales also encourages in a grouping of the informational index. Hyperplane creates two locales symmetrically and compares to two classifications of information underneath two class names. An information point "a" has a place with both of the area relying upon the estimation of  $f(a)$ . On the off chance that  $f(a) > 0$  it has a place with one district and if  $f(a) < 0$  it has a place with another region.

Accept that the information comprises of  $n$  information vectors where every datum vector is spoken to by  $x_i \in R^n$ , where  $i=1, 2, \dots, n$ . Class is given, and a chance to mark that should exist allocated to the information directions to execute managed order stay signified using  $y_i$ , which is  $+1$  aimed at information vectors of one classification and  $-1$  aimed at the further classification of information vectors. By using hyperplane, the informational collection can be geometrically isolated. Subsequently, the hyperplane is spoken to by a line it can likewise be scientifically spoken to the following eqn[29]:

$$w^T x_i + b \geq +1 \quad (14)$$

$$w^T x_i + b \leq -1 \quad (15)$$

The hyperplane mathematical formation indicated below:

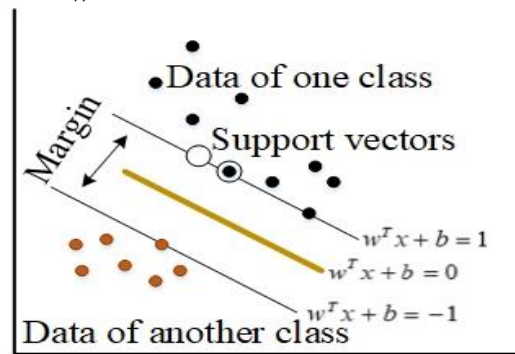
$$f(x) = \text{sgn}(w^T x + b) \quad (16)$$

Where, sign function is indicated as  $\text{sgn}()$ , which is scientifically characterized through the equivalence, as shown below [31]:

$$\text{sgn}(X) = \begin{cases} 1 & \text{if } X > 0 \\ 0 & \text{if } X = 0 \\ -1 & \text{if } X < 0 \end{cases} \quad (17)$$

The following condition gives the separation  $D$ . It is from the hyperplane to the point is spoken to scientifically:

$$D = \frac{|w^T x + b|}{w} \quad (18)$$



**Fig 3.7:** Support Vector Machines Hyperplane

The margin is displayed by:

$$\frac{W}{\|W\|} \cdot (X_+ - X_-) = \frac{W^T (X_+ - X_-)}{\|W\|} \quad (19)$$

$$= \frac{W^T \left( \left( \frac{+1-b}{W^T} \right) - \left( \frac{-1-b}{W^T} \right) \right)}{\|W\|} = \frac{2}{\|W\|} \quad (20)$$

Many hyperplanes use in this optimization, and these hyperplanes have split the data into two regions. But the hyperplane is selected via the SVM, in the two regions the hyperplane is the extreme distance from the nearby data points. But few hyperplanes are there, and that should fulfill this condition. Finally, the accurate classification results are provided the SVM by ensuring that criterion [32].

The means took after while utilizing SVM in arranging information are specified in the beneath algorithm:

### Algorithm: 3

**I/P: I: Given data**  
**O/P: V: Maintenance vectors set**  
**Start**  
 Separate the given data set into two sets of data items  
 To support the vector set, V then add them  
 The divided n data items are then loop  
 If a data element is not allocated to any of the class labels means then add that to set V.  
 If inadequate data substances are created then  
**break**  
**end the loop**  
 Train and test using the SVM classifier  
**End**

**Fig 3.8: SVM Algorithm**

**IV. EXPERIMENTS RESULTS**

**A. Dataset:**

City Pulse of EU FP7 Assignment [33] includes a few SC applications in light of IoT. Inside the extent of the pollution, task, road traffic, climate, social, parking and library information was gathered starting the urban areas of Brasov and Aarhus in Denmark and also Romania individually in the vicinity of 2015 and 2013. In this investigation, CityPulse EU FP7 pollution dataset Task is utilized to understand the novel framework. The dataset has eight features such as particulate issue, ozone, sulfur dioxide, carbon monoxide, nitrogen dioxide, timestamp, longitude, and latitude utilized for exploring. Seventeen thousand five hundred sixty-eight examples are presented in the dataset and that are assembled at five-minute intervals. Each test esteem set as standard of EPA's AQI. In this examination, nitrogen dioxide and ozone toxins are chosen as expectation of air quality.

**B. Thresholds:**


In this part, by considering the AQI (Air Quality Index) critical level (100), its levels are separated into three. Based on the alarm color, the threshold values are defined, and it is described in the below table.









**Table 4.1: Threshold value for AQI**

Index value	Level	Alarm Colour
0 - 50	Healthy	Green
51 - 100	Medium Healthy	Yellow
101 - 500	Unhealthy	Red

According to these threshold values, the test datasets of nitrogen dioxide and ozone are independently labeled as Healthy, Medium Healthy, and Unhealthy. And it is enumerated in table 4.2.

**Table 4.2: The Alarm based Decision Table**

Ozone	Nitrogen Dioxide	Alarm based Colour
Healthy	Healthy	

Healthy	Medium Healthy	
Healthy	Unhealthy	
Medium Healthy	Healthy	
Medium Healthy	Medium Healthy	
Medium Healthy	Unhealthy	
Unhealthy	Healthy	
Unhealthy	Medium Healthy	
Unhealthy	Unhealthy	

As shown in table 4.3, evaluating the predicted values and observed values of pollutant attentions together, the final alarm colors are labeled.

**C. Performance Metrics:**

The following well-known methods such as Precision, Confusion Matrix (CM), False Negative Rate (FNR), Accuracy metrics, F1-Score, Specificity, False Positive Rate (FPR) and G-mean are used to estimate the alarm color matching performance of the novel prediction strategy. Precision and Recall then showed as;

$$Precision = \frac{TP}{(TP + FP)} \tag{21}$$

$$Recall = \frac{TP}{TP + FN} \tag{22}$$

$$Specificity = \frac{TN}{(FP + TN)} \tag{23}$$

$$FPR = \frac{FP}{FP + TN} \tag{24}$$

$$FNR = \frac{FN}{FN + TP} \tag{25}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{26}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{27}$$

$$G - mean = \sqrt{Sensitivity \times precision} \tag{28}$$

The precision and recall harmonic mean is said to be a combine measure between recall and precision, the balanced F-score or traditional F-measure:

# An Adaptive Whale Optimization Algorithm Guided Smart City Big Data Feature Identification for Fair Resource Utilization

$$F - Score = 2 \times \frac{Precision \times recall}{Precision + recall} \quad (29)$$

Where, True Negative is indicated by *TN*, True Positive is indicated by *TP*, False Negative is represented by *FN* and False Positive is denoted as *FP*.

### D. Results Analysis:

Here the outcomes of double air pollutant concentrations and assessment of air quality prediction model are introduced. To appraise that prediction performance from several perspectives, we used Precision, False Negative Rate, G-Mean, False Positive Rate, F1-Score, Recall, Accuracy metrics, and Specificity.

In terms of error criteria, the proposed strategy gives a significant development. Precision, Confusion Matrix (CM), F1-Score, and Recall values are obtained according to the results from the arrangement and which is prepared by using

**Table 4.3: Evaluation of Performance Metrics**

Methods	Precision	Recall	Specificity	FPR	FNR	F1-measure	G-mean	Accuracy
Proposed	0.94	0.95	0.92	0.57	0.15	0.941	0.943	0.978
HMM-SVM	0.92	0.9	0.9	0.5	0.23	0.92	0.91	0.96
ANN	0.84	0.81	0.86	0.45	0.65	0.55	0.82	0.85
KNN	0.74	0.79	0.79	0.49	0.61	0.81	0.76	0.81

**Table 4.4: Pollution Level Ranking of Cities**

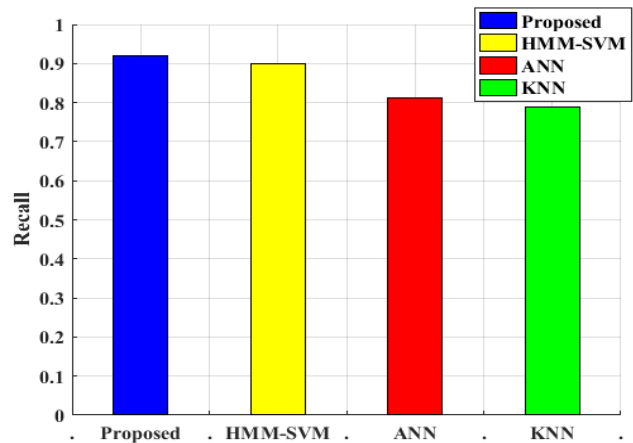
CITIES	POLLUTION LEVEL RANKING
1	9
2	3
3	10
4	2
5	1
6	4
7	8
8	7
9	5
10	6

Table 4.4 gives the pollution level ranking of cities. Here, the ranking of the cities is evaluated by computing the pollution rates between the pollutants ozone and nitrogen dioxide. According to the air quality index, the health concern level calculated, and the alarm is predicted the color. The cities ranked by using this alarm. Based on the unhealthy cities are ranked. Let us consider ten cities, among that we find out the hazard level of each city. According to the hazardous level of the city, the lowest level is said to be rank 1, further levels are mentioned as rank 2, rank 3...etc. The graphical representing the ranking of cities is shown in fig 4.9. The following figures are the performance analysis of the special matrices.

The performance analysis of graphical representation is shown in Fig 4.1. It represented the proposed method has good specificity performance compared to other existing methods HMM-SVM, ANN, KNN.

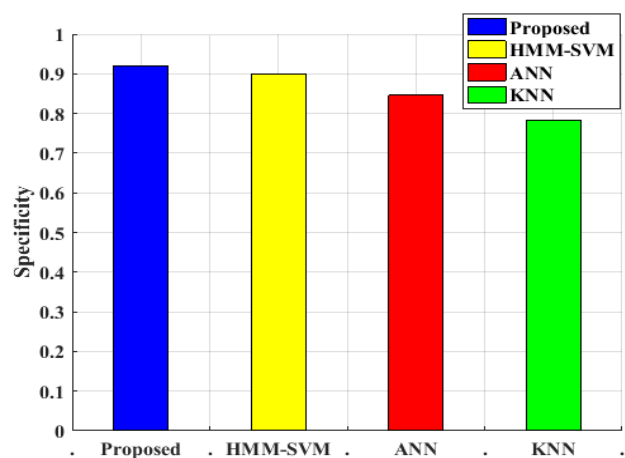
threshold values. Table 4.1 gives the threshold values, and table 4.2 gives the decision values.

Next, Table 4.3 represents the performance metrics values of the Precision, False Negative Rate, G-Mean, False Positive Rate, Recall, F1-Score, specificity and Accuracy metrics based on the existing methods HMM-SVM, ANN, and KNN.



**Fig 4.1: Performance of Specificity**

Fig 4.2 and Fig 4.3 gives the graphical representation of the recall and precision performance. It has high values rather than the HMM-SVM, ANN and KNN



**Fig 4.2: Recall Performance**



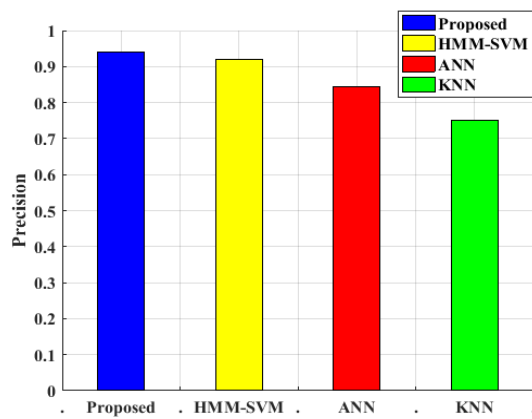


Fig 4.3: Precision Performance

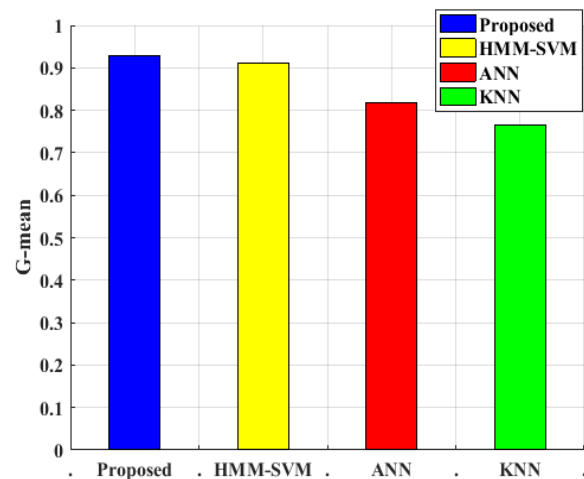


Fig 4.6: G-mean Performance

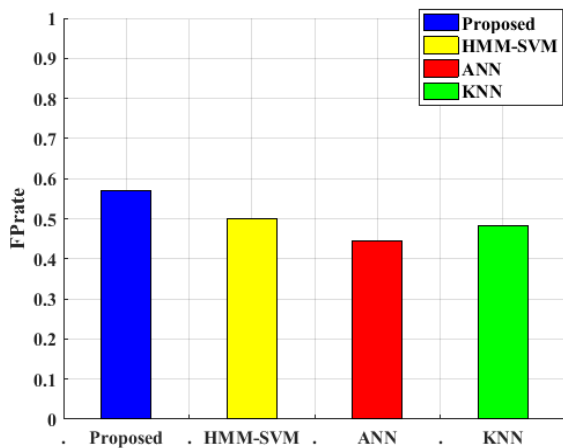


Fig 4.4: FPR Performance

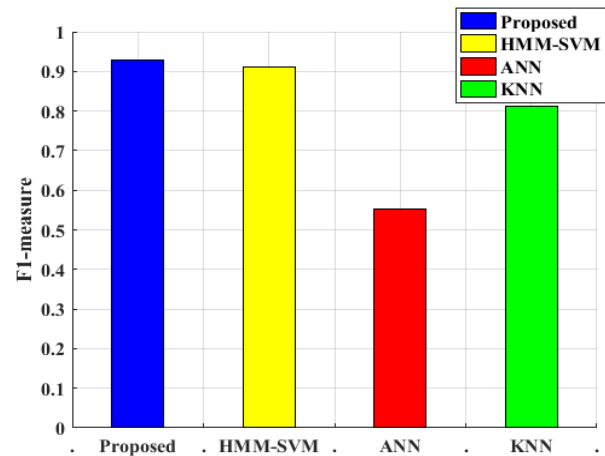


Fig 4.7: F1-measure Performance

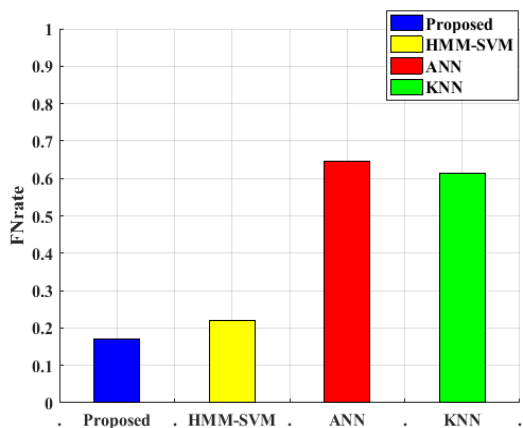


Fig 4.5: FNR Performance

Fig 4.4 and fig 4.5 represents the false positive and negative rate performance. When compared to the existing approaches such as HMM-SVM, ANN, and KNN, our proposed method has good performance rate.

Fig 4.6 and 4.7 shows the graphical representation of the performance of G-mean and F1-measure. By seeing this representation, our proposed method has a high-performance value.

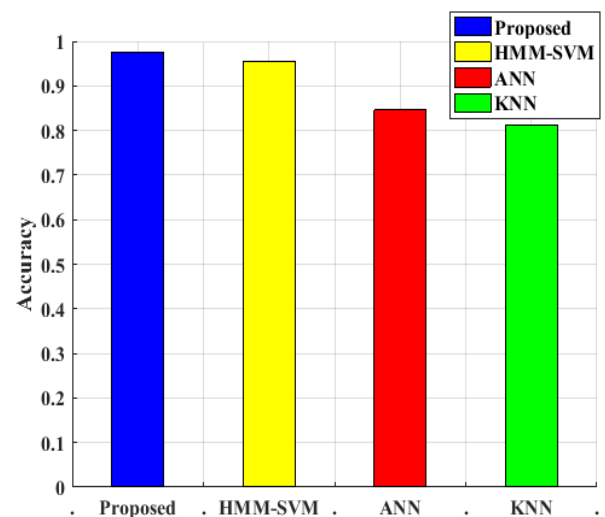
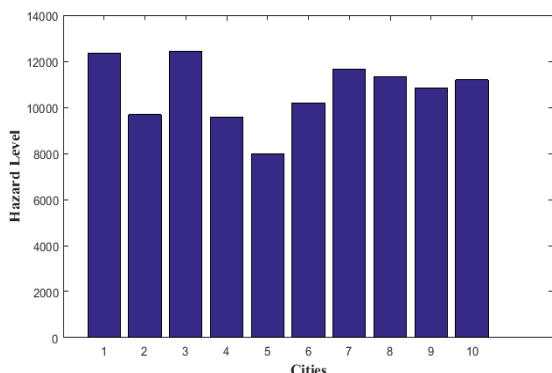


Fig 4.8: Performance of Accuracy

# An Adaptive Whale Optimization Algorithm Guided Smart City Big Data Feature Identification for Fair Resource Utilization

Fig 4.8 represents the performance accuracy graphical representation. Accuracy of the proposed method is high compared to existing methods such as HMM-SVM, ANN, and KNN.



**Fig 4.9: Ranking Level of Different Cities**

Fig 4.9 gives the graphical representation of different cities. In which, the city having the lowest hazardous level marked as rank 1. City 5 having rank one position that is hazardous level is low.

## V. CONCLUSION

Smart cities have the most indispensable part in altering distinctive regions of human life, touching segments like transportation, wellbeing, vitality, and instruction. Big data smart cities fair resource utilization is the main goal of this method. In this method, Whale optimization is used to get the optimal resource set, and the whale optimization method is performed based on the wrapper method. From the City pulse dataset, air pollution datasets are utilized for the performance analysis. Finally, the regression model Random Forest with Support Vector Machine (RF-SVM) classifier is developed to get the performance analysis. The novel approach is implemented in the MATLAB platform the enactment is evaluated based on the identified subset of features leads to optimal resource utilization and obtained results compared to earlier wrapper model-based algorithm. Our proposed method has a good performance compared to the other existing methods, and the cities are ranked based on the hazardous level of pollution.

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