A Smart Vehicle Charging Station Identification Based On IOT with Hybrid Grey Wolf-Bat Optimization Enriched On Artificial Neural Networks Recognition Methods

Vijayaprabhu Arumugam

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Abstract

The tendency towards the green energy resolution, in the recent days there is a substantial increase in electric vehicles. Hence, identification of available charging station towards the travel is a major issue. For this purpose, this research work intends to develop a smart vehicle charging station with proper route mapping and monitoring units. The aim of this work is to identify the nearby available charging point by developing an advanced charging station with Internet of things (IOT) enabled. The availability of charging slot for the particular time is also identified by the image processing. In particular, Anisotropic Filtering (AF) will be suitable for this work for improving the image quality by reducing the noise. Along with that co-occurrence matrix is deployed for texture analysis of the image processing. Hybrid Grey Wolf Bat optimizer (GWBO) is utilized for efficient tracking of fastest route. At last, Artificial Neural network (ANN) technique implementation perfectly identifies whether the empty space is available or not in the charging station for our vehicle. Various scales are analyzed for the validation of results with the conventional methods.

Vijayaprabhu A
Department of ECE
Siddharth Institue of Engineering and Technology (Autonomous), Puttur, India
Vijayaprabhu85@gmail.com

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I. Introduction

Over the past few years, Electric Vehicles (EV) have gained importance because of their appeal as a credible alternative to gas-powered vehicles. With electric vehicles (EVs) projected to become a major mode of transportation in the future, there has been much debate about their adoption, notably among legislators [1]. EVs, on the other hand, require a charging station that allows them to "recharge" their batteries in the same way that gasoline-powered vehicles do. While EVs are pollution free, the electricity used to charge their batteries may be drawn from traditional power plants, decreasing their appeal as an environment-friendly mode of transport. Many countries currently use coal, oil and natural gas for its energy [2].

Fossil fuels are nonrenewable; they bring on finite resources that will become too expensive or too environmentally damaging to retrieve. Solar energy is never exhausted since it is constantly replenished. Solar energy is renewable energy and it is mostly called "clean energy" or "green power" because it doesn't pollute the air does not result in carbon emission [3]. There has recently been a push to create solar-powered EV charging stations that generate clean electricity. Our paper is all about the charging station design, working and uses with the disadvantages of the system. Every station is composed of a plug that becomes attached to a vehicle, supplying it with electric power to charge the vehicles [4].

As the number of EVs on the road's increases, charging stations in both parking structures and private garages are likely to become more prevalent [5]. The distribution grid, EV owners, and parking structure operators will all have standards that these stations must meet. User authorization, authentication, and payment are just a few of the many activities these charging stations will do for security and financial reasons. The SOC of a battery may be determined in a variety of methods. These methods may be classified into three groups: The three categories are electrochemical, adaptive, and electrical. Electrochemical techniques are exceedingly exact, but they require electrical power [6]. As a result of the battery's chemical composition, software implementation is difficult. A comparable circuit model and a solution approach are required for adaptive battery processes. The accuracy of adaptive techniques is determined by the efficiency of the corresponding model. Observable factors like charge/discharge current, terminal voltage, and internal resistance, on the other hand, are all required for electrical techniques. Due to its simplicity and ease of implementation, the coulomb counting (electric) approach is one of the most often used approaches to estimate SOC [7]. The battery state of charge is an important BMS evaluation indicator (SOC). The SOC refers to the amount of charge left in the battery cells about its capacity. There is currently no direct technique to determine the SOC of a Li-ion battery. As a result, it can only guess at the SOC by looking at battery metrics like current, voltage, temperature [8].

The smart electric vehicle charging station identification in the real time journey is an inevitable, due to the discharging of battery is unavoidable at the travelling time. The main aim of developing the smart electric vehicle charging station identification is to properly identifying the vacant slot in the particular time slot to avoid delay in the ongoing travel, In today modern world, IOT gains an attention in almost all the engineering relevant areas where some of the application includes security, healthcare, transportation, smart agriculture, energy and aerospace [9], IOT is very popular due to its benefits of minimum human effort, saves time, enhancing security and efficient resource utilization. Wireless sensor networks and communication grasp a maximum advantage of IOT for information sharing at the real times [10], this system gains the advantages of

- IOT enabled with image processing properly identifies the vacant slots in the nearby charging stations.
- Neural networks benefits in taking the smart decision in case of colloidal situation

- Anisotropic filtering optimization is used for enhancing the image quality of textures on surfaces at the vacant position in the charging slot.
- Grey wolf Bat optimizer is used to find the best optimal solution at the shortest time.

II. Related Works

Modernization process evolves growth in industries and rapid increase in vehicles causes emission of toxic gases, to reduce the carbon emission it is evident that world is shifting towards electric vehicles (EVs) proposes the idea of smart charging station in smart cities [11][12]. The system involves designing small communication devices that transmit data over the internet by making use of the Internet of things (IOT). The optimization algorithm from the current location is identified by the optimization algorithm from the targeted vacant closest nearby charging location by the use of Global Positioning System (GPS) data [13]. NP-hard optimization issues are solved via metaheuristic algorithms. These algorithms, which have two primary parts exploration and exploitation strive to balance these two in order to find the best feasible near-optimal solution. One metaheuristic algorithm with poor exploration and exploitation is the bat algorithm. In this study, some of the solutions generated by the bat algorithm are subjected to the exploration and exploitation operations of the Gray Wolf Optimizer (GWO) algorithm [14][15]. driving characteristic parameters analysis of the characteristic parameters and the correlation between power consumption and the characteristics of the correlation between the strong and weak, using principal component analysis on the characteristics of dimension reduction, based on information entropy fuzzy clustering method for driving modes are classified, can accurately reflect the actual characteristics of running condition of road users in the driving characteristic parameters [16], A dynamic road network model is built to decrease the trip time on the road network when drivers go to charging stations. A driving mode identification model is created based on the personalized driving circumstances [17]. A unique energy consumption model is created by identifying and analyzing various driving modes. the effects of solar power plant electricity output on the load curve, commonly referred to as the duck curve, and offer a substitute by charging electric vehicles in the IOT integrated multi-level charging stations [18]. By generating alternate loading on the power grid, an effort is made to innovate the load curve by neutralizing the dip and abrupt rise in the duck curve. By enhancing charging technologies with the use of an IOT interface and offering incentives to consumers to use EVCS at work, it also helps the promotion of EV usage. In order to promote green mobility, it also discusses the notion of switching from a fossil fuel-based revenue structure to one that is centralised and taxes EV charging. Both the quantity of electric vehicles (EVs) and the size of the smart grid are rapidly growing in both the spatial and temporal axes. This necessitates a dynamic spatiotemporal allocation technique for charging stations that is effective (CSs). Such an allocation method should adhere to technological and financial limitations while offering appropriate pricing services at various deployment stages [19]. Distributed generation (DG) units must also be dynamically assigned in both space and time as additional CSs are granted in order to make up for the increase in loads brought on by the demands for EV charging. Therefore, new models must be established because present power grid models are inadequate to reflect such spatio-temporal change. In this study, we offer a stochastic geometry-based spatiotemporal expanding power grid model [20].

Nowadays, bio-inspired algorithms are excellent tools for resolving a variety of practical optimization issues. For issues involving global function optimization, we provide a hybrid strategy in this study that combines the Grey Wolf Optimizer (GWO) and the Bat Swarm Optimizer (BA) [21]. While BA is renowned for being more exploitative due to its limited exploration capability in specific circumstances, GWO is well known for its balanced exploration/exploitation behavior [22]. We successfully explore the search space using GWO exploration techniques, and we hone the solution using BA local search capabilities. In our hybrid method, known as (GWOBA), GWO is utilized to independently explore the issue space and then passes the top two answers to BA to direct its local search, which is then conducted in-depth until the best solution is discovered [23] [24].

A memory-based ant colony optimization (MACO) method is created for the suggested multi-source data associated DEVD model [25]. In order to update the pheromone that directs the search and to aid in the reactions to environmental changes, MACO keeps a memory library of historically effective solutions [26]. A partial reassignment technique is also suggested to re-optimize some of the allocated customer-EV pairs in the historically best solution in response to dynamic changes. Also, a local search swap or replacement method is intended to improve performance [27].

Table 1. Comparative analysis between existing and proposed classification techniques

Methodology	Pros	Cons
Region based convolution neural network	Increased Accuracy, High scalability	More Noise, Higher error rate
Ensemble based classification	Reduced Complexity Better performance results	Computation problem, Non-parametric approach
Contrastive Feature Extraction Network	Distortion problem can be solved easily, Accurate Recognition Rate	Increased over fitting, Higher complexity
Deep convolution neural networks	Speed processing, Accurate Recognition	Need more time for training
Wavelet Neural Network (WNN)	Higher Efficiency, Detection is faster	High Computational complexity

III. Proposed Work

This section provides a thorough explanation of the suggested methodology, along with an overview of its design and examples of its algorithms. The primary contribution of this research is the locate the nearby charging location system that integrates IoT technologies for efficiently assigning charging space. In this framework, an IoT-based monitoring and controlling unit is also used to decrease waiting times, process delays, and reaction times. In the charging station, a number of users must invest their time in charge the cars where they are wanted. The proposed concept opposes using a car charging management programme to shorten wait times. The suggested model's general architecture is depicted in Fig. 1, where an IoT cloud server is set up to notify users of information about nearby charging station. The request was automatically created and sent to the IoT server unit when the user need to charge the automobile. The controlling device then gives the camera the go-ahead to record a picture of the associated vacant slot in order to monitor the user's preferred charging area. With less waiting in line and waiting time, this form of monitoring system enables the user to quickly locate their vehicle in the charging space.

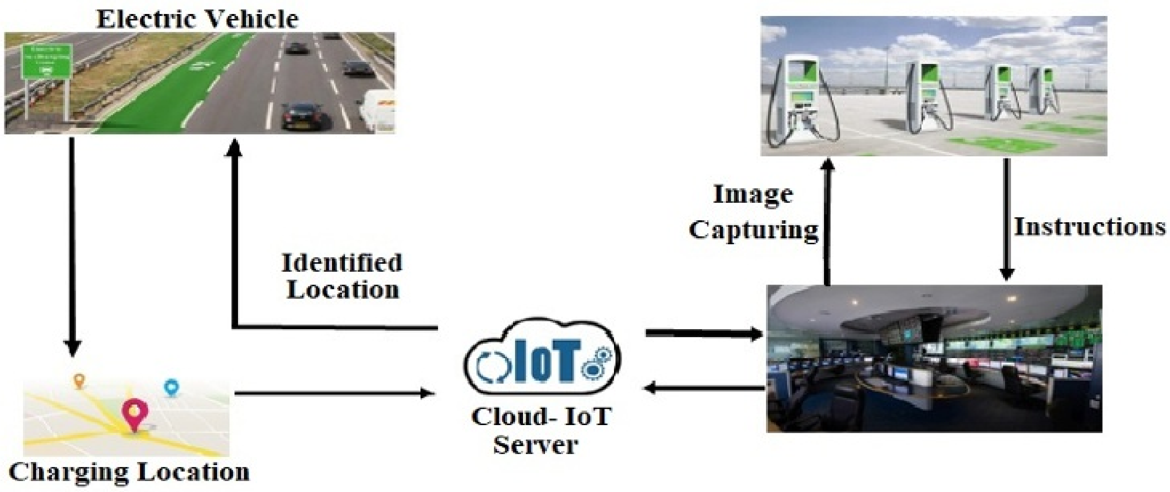

Fig. 1. Block Diagram of the Proposed Model

The hybrid GWOBA algorithm combines the strong exploration capabilities of the GWO algorithm with the strong exploitation capabilities of the BA algorithm. the GWO algorithm, first is iterated to find a better set of solutions after being initiated with a random set. Only the top two solutions (X, X) are supplied to the bat algorithm (BA) as an initial guess after MaxIter/2 iterations in order to help the algorithm concentrate on them.

The hybrid algorithm's best solution is then returned by BA after running for a total of MaxIter/2 iterations.

A. GWOBA Optimization Algorithm

Input: n Number of agents
MaxIter Maximum iterations
$r0i$ Initial pulse emission rate
Ai Loudness
Result: The optimal solution ($X*$)

- Step 1 *Initialize the grey wolf population Xi ($i = 1, 2, \ldots, n$) randomly*
- Step 2 *Initialize a, A, and C*
- Step 3 *Evaluate the positions of wolves*
- Step 4 $X\alpha =$ *The best search agent*
- Step 5 $X\beta =$ *The second best search agent*
- Step 6 $t = 0$
- Step 7 while ($t < MaxIter/2$) do
- Step 8 for *each Xi* do
- Step 9 Update Xi position.
- Step 10 end
- Step 11 Update a, A and C
- Step 12 Evaluate the positions of wolves.
- Step 13 Update $X\alpha$ and $X\beta$
- Step 14 $t = t + 1$
- Step 15 end
- Step 16 *Initialize the first two bats* $X1 = X\alpha$, $X2 = X\beta$ *and initialize the rest* $(n - 2)$ *bats* Xi ($i = 3, 4, \ldots, n$) *randomly*
- Step 17 *Initialize frequencies fi, pulse rates ri and the loudness Ai*
- Step 18 *Find the best solution based on fitness* $X*$
- Step 19 while ($t < MaxIter$) do
- Step 20 for *each Xi* do
- Step 21 Generate new solution (*Xnew i*) by adjusting frequency
- Step 22 if $rand > ri$ then
- Step 23 Generate a local solution (*Xnew i*) around the best solution $X*$ Xnew
- Step 24 end
- Step 25 if $rand < Ai$ *and fitness* (*Xnew i*) $<$ *fitness* (Xi) then
- Step 26 Update the position of Xi to *Xnew i*
- Step 27 Reduce Ai
- Step 28 Increase ri
- Step 29 end
- Step 30 Update $X*$
- Step 31 end
- Step 32 $t = t + 1$
- Step 33 end
- Step 34 return $X*$

IV. Probability Correlated Neural Network (PCNN) based Identification

Following optimization, the most appropriate features are taken into account as the input for classification, one of the crucial steps in recognition systems. compared against KNN, DT, NB, C4.5, SVM, RVM, DNN, DBN, and LSTM, among other classification methods. Here, the major goal of applying the classification technique is to quickly and reliably forecast the location of the requested car. It is a type of machine learning technique that uses features as the input and produces a predicted or recognized label. This algorithm generates the output function as follows: bi=b1, b2...bN. The input layers in this algorithm consist of samples with the formula ai=a1, a2,...aN, where ai denotes the input vector. The following are the algorithmic steps used in this

Step 1: The center value is computed by estimating the distance value as shown in below:

$$D_{is} = \sum_{y=1}^{n} \exp\left(-\frac{|a_i - p_i|}{(Nei_{r/2})^2}\right)^2 \qquad (1)$$

Step 2:

$$D_{is} = Di_{tp} \exp\left(\frac{(S_s - S_p)}{(Nei_{r/2})^2}\right)^2 \qquad (2)$$

Step 3: For all input samples, the distance value is computed as follows:

$$Fxy = \|aj - pi\| \qquad (3)$$

Step 4: Correspondingly, the minimum distance value is estimated as follows:

$$p_i' = \frac{1}{h_i} \sum_{a \in c_i} a (1 \le b \le m) \qquad (4)$$

Step 5: Then, the cluster center is estimated and position updation are performed, and the output associates with the hidden layer could produce the recognized results.

Step 6: Finally, the weight value can be updated according to the learning parameter

V. Results and Discussion

The performance study of both traditional and novel strategies used to identify the vacant slot in the charging station. Moreover, photographs of vacant slot and without them are used to validate the performance of the car charging system. The user database that was developed contains information on 100 photographs of cars in occupied lots and 100 images without cars. Precision, recall, accuracy, f1-score, similarity coefficients, and time consumption are some of the numerous types of measurements used to validate the outcomes of the available place. Figure 3 displays the Mean Absolute Error (MAE) of both current and new methodologies, including the k-means, deep LSTM, and recurrent neural network categories. By using this evaluation method, which produces a decreased MAE value, as compared to the other techniques, it is found that the proposed GWBOPCNN technique offers the reduced MAE value.

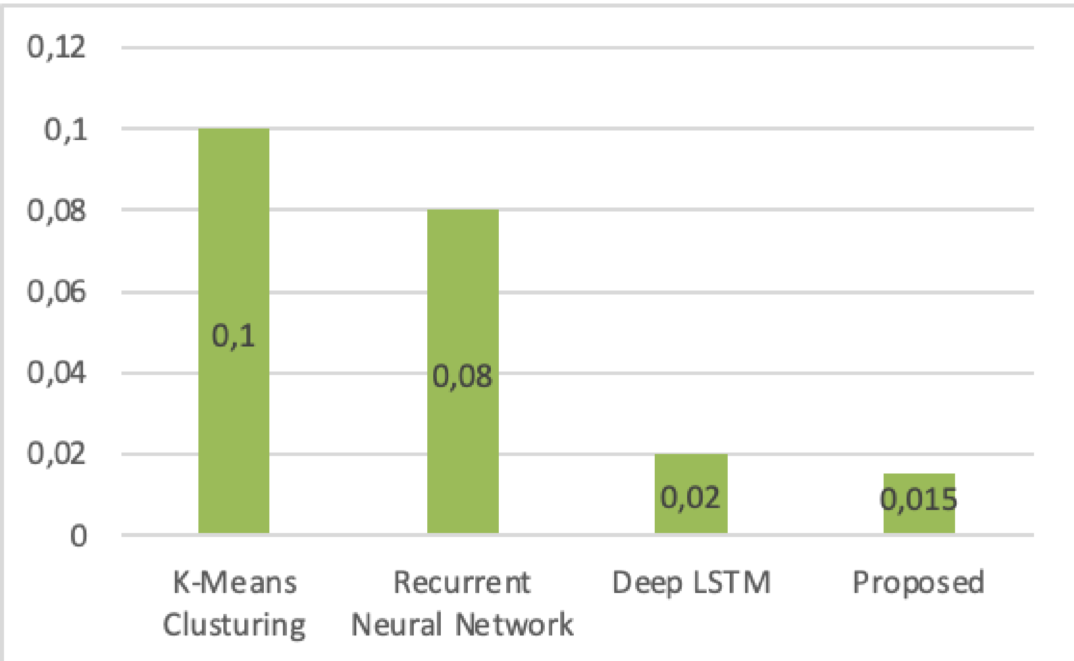

Fig. 2. MAE analysis

Table 2. Comparative analysis between existing and proposed Schemes

Parameters	MLP	KNN	RF	DT	EL	PCNN
Precision	63.62	73.04	87.80	91.01	92.77	97.2
Recall	51.09	67.44	80.31	90.18	89.54	96.9
F1-score	56.68	70.33	83.45	90.30	90.08	95.7
Accuracy	60.46	75.31	86.56	92.32	92.44	98.5

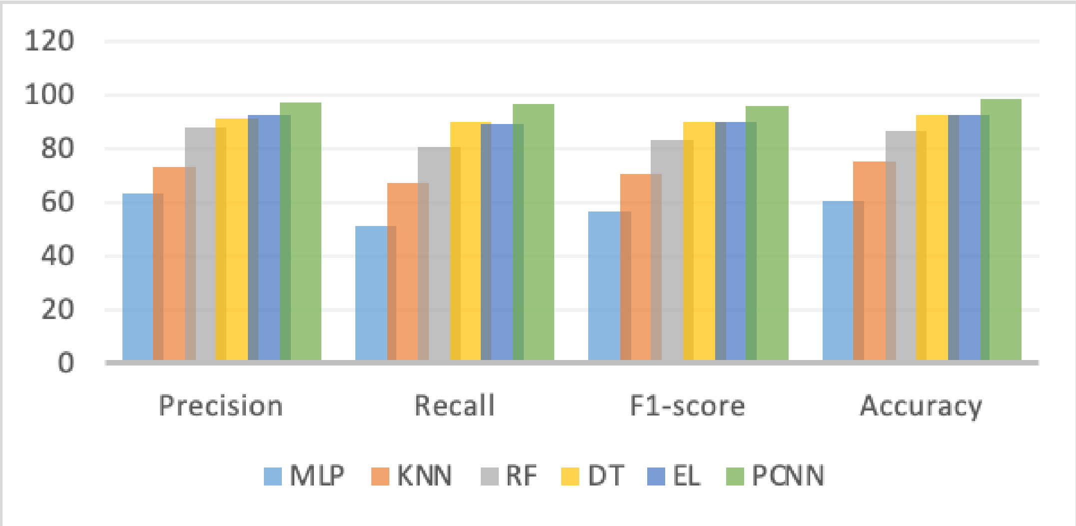

Fig. 3. Comparative analysis between existing and proposed schemes

Table 3. Detection accuracy of proposed slot

Memory size	Mask RCNN	Proposed
5	88.2	91.6
25	89.2	93.3
50	92.6	96.4
100	94.5	96.8
150	92.3	98.2

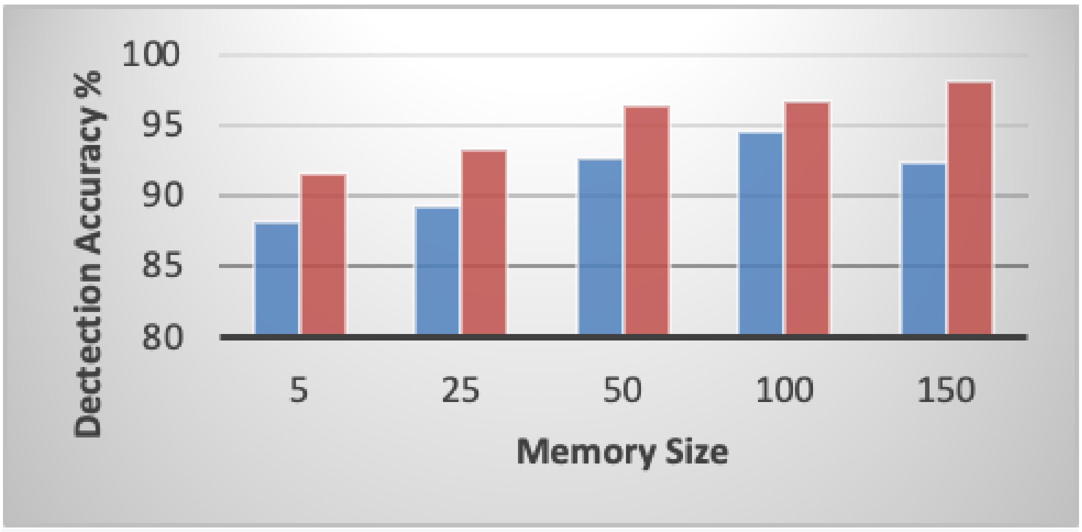

Fig. 4. Detection accuracy Vs Memory size

Table 4. Time accuracy and spatial accuracy

	Mask RCNN		GWBO-PCNN	
Memory size	Time accuracy (%)	Spatial accuracy (%)	Time accuracy (%)	Spatial accuracy (%)
5	91.3	71.2	92.6	73.7
25	90.9	79.9	93.4	84.6
50	88.7	84.2	91.6	94.2
100	88.8	86.5	90.7	93.4
150	86.3	87.8	89.8	92.8

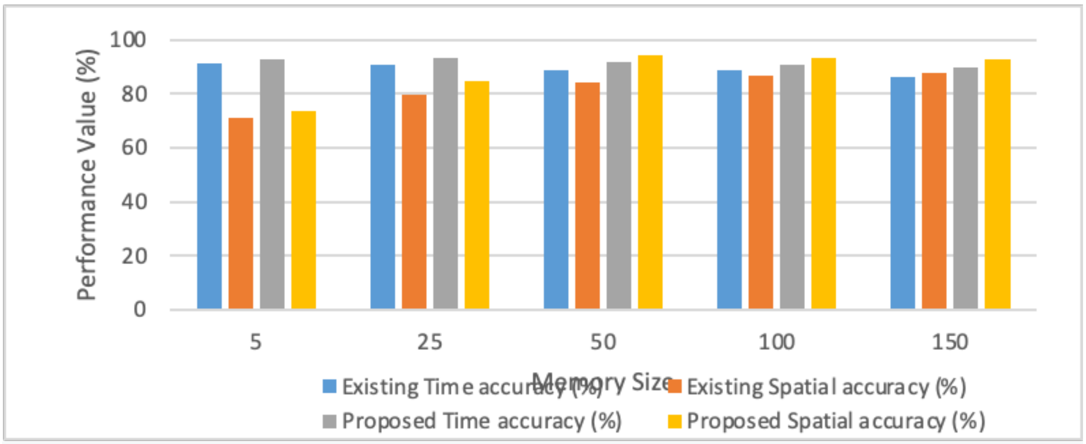

Fig. 6. Spatial and time accuracy analysis of conventional and proposed techniques

VI. Conclusion

This work is to identify the nearby available charging point by developing an advanced charging station with Internet of things (IOT) enabled. The aim of the paper is being to develop an IOT based monitoring system and controlling for reducing the waiting time, delay of the process and increased response time. Controlling unit instructs camera to capture the vacant slots, this improves the user to identify the vacant spot with reduced queuing and delay time. Anisotropic Filtering (AF) will be suitable for this work for improving the image quality by reducing the noise. Along with that co-occurrence matrix is deployed for texture analysis of the image processing. Hybrid Grey Wolf Bat optimizer (GWBO) is utilized for efficient tracking of fastest route. At last, Artificial Neural network (ANN) technique implementation perfectly identifies whether the empty space is available or not in the charging station for our vehicle. Various scales are analyzed for the validation of results with the conventional method. During evaluation, the performance of the proposed technique is validated and compared by using various measures. From the obtained results, it is concluded that the proposed GWBO based ANN technique outperforms the other techniques by accurately recognizing the car image with reduced error rate.

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