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A Novel Approach to Detect Parking Space Occupancy for Efficient Urban Management

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Abstract

Objectives: This study aims to develop A Novel Approach to Detect Parking Space Occupancy for Efficient Urban Management utilization and enhance user experience with real-time, accurate data. *Methods/Analysis*: The proposed system detects the parking space occupancy for efficient urban management by using a Multi-Component Attention Graph Convolutional Neural Network (DPSO-MCAGCNN) and processes data from the PKLot dataset. Pre-processing is performed using the Maximum Correntropy Quaternion Kalman Filter (MCQKF) for normalization. Key features like area, perimeter, and aspect ratio are extracted using the Second-Order Time-Reassigned Multi synchro squeezing Transform (SOTRMT) and analyzed through MCAGCNN. The Leaf-in-Wind Optimization (LWO) technique is incorporated to optimize the MCAGCNN for higher accuracy. *Findings*: The proposed system achieves significant improvements over existing methods, including 27.84%-29.27% higher accuracy, 25.87%-29.84% improved R^2, and 16.27%-19.84% reduced Mean Squared Error (MSE). Evaluation metrics such as RMSE, MAE, and MAPE confirm its robust performance. *Novelty/Improvement*: The integration of LWO into MCAGCNN enhances optimization and precision, surpassing the performance of state-of-the-art methods like EUPE-SVM, RTPM-YOLOv5, and MASP-LSTM, making it an innovative solution for intelligent parking management.

Keywords: PKLot Dataset; Leaf In Wind Optimization; Maximum Correntropy Quaternion Kalman Filter; Multi Component Attention Graph Convolutional Neural Network; Second-Order Time-Reassigned Multisynchrosqueezing Transform.

1. Introduction

In recent years, the rapid urbanization and surge in vehicular usage have highlighted the critical need for efficient parking management systems [1]. With cities becoming more densely populated, the availability of parking spaces has emerged as a major concern, directly impacting traffic congestion, fuel consumption, and environmental pollution. Highly developed technologies, including computer vision, machine learning, and IoT, have begun to transform urban infrastructure, enabling smarter and more adaptive solutions [2, 3]. Among these, detecting parking space occupancy has become a focal point for improving urban mobility and reducing inefficiencies [4, 5]. This innovation not only alleviates the frustration of searching for parking but also contributes to sustainable city planning. Despite these advancements, existing systems often face several limitations [6]. Many solutions rely on hardware-intensive setups such as sensors embedded in the ground, which can be costly to install and maintain [7, 8]. Alternatively, some systems use outdated methods, like manual monitoring, which lack scalability and accuracy [9]. Furthermore, the integration of data from disparate sources often poses challenges, leading to errors in real-time occupancy detection [10]. These drawbacks undermine the efficiency of parking systems and limit their widespread adoption in resource-constrained urban areas.

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1.1. Literature Survey

Among the frequent research work that depends on Parking Space Occupancy Detection Systems with the help of deep learning, some of the recent investigations were presented as follows:

Channamallu et al. [11] have introduced a solution to address these problems that worsen traffic and pollution while reducing urban productivity by applying machine learning algorithms to categorize occupancy levels and accurately predict parking spot availability. It makes use of a dataset that was gathered from January 2022 to June 2023 from a college campus garage. Rafique et al. [12] have presented a sophisticated parking management system that uses the quick inference speed and high YOLO v5 performance for vehicle recognition instead of parking slot categorization, overcoming the limitations of data-driven systems. The parking lot's condition was assessed using the plot dataset as a baseline, and the model's 99.5% accuracy reflected state-of-the-art performance.

Canli & Toklu [13] have developed a new smartphone app called "smart parking" to reduce the issue of parking, which was developed using deep learning and cloud computing. The program developed a deep learning-based parking space prediction service that uses long short-term memory (LSTM). Harish Padmanaban & Sharma [14] have introduced road mapping and traffic flow management; open parking spots were identified and used. The suggested method uses data from sensors, cameras, and other sources to identify available parking spots and accurately predict their availability. A machine learning technique was used to optimize the use of open parking spaces in road mapping and traffic flow management.

Elomiya et al. [15] have presented a novel fusion of deep learning (DL) methods with the ANFIS to overcome these drawbacks. DL models outperformed non-linear modeling, automated feature learning, and long-term connection identification in parking data over time. In the suggested regard, ANFIS was selected specifically because it was effective at representing uncertainty using fuzzy set theory. The fusion models ANFIS-RNN, ANFIS-GRU, and ANFIS-LSTM were developed by combining ANFIS with long short-term memory (LSTM), recurrent neural networks (RNN), and gated recurrent units (GRU). Neupane et al. [16] have developed a brand-new technology called "Shine" that recognizes license plate, car, and handicap badges (also known as cards, badges, or access badges) using an object identification algorithm based on deep learning. The system verifies the driver's eligibility to use accessible parking spaces by interacting with the central server. The mean absolute error was high, as was the mean square error. Deep learning-based object detection method that recognizes the car, disability badges, and license plate (henceforth referred to as badges, cards, or access badges) and, through communication with a central server, confirms the driver's eligibility to use accessible parking spots.

Balamutas et al. [17] have presented a system that was then used for the identification of cars. The system was developed on the theory that every vehicle leaves behind distinct magnetic traces that may be compared and matched. It makes use of anisotropic magnetoresistive sensors. Signal-to-noise ratio computation for module derivatives between signal and ambient noise provides crucial information for neural network input.

1.2. Research Gap

Recent research on Parking Space Occupancy Detection Systems using deep learning has made significant strides, but several gaps and drawbacks remain. One approach uses a machine learning method to forecast parking spot availability and classify occupancy levels based on data gathered from a college campus garage, though it may not generalize well to urban or high-traffic areas, and fails to account for factors such as weather or traffic changes. Another method employs a high-performance vehicle recognition system, achieving high accuracy, but focuses only on vehicle detection rather than comprehensive parking space categorization, which can be affected by varying lighting or weather conditions. A smartphone app for smart parking integrates deep learning and cloud computing with Long Short-Term Memory (LSTM) to forecast available spaces, but its reliance on cloud services introduces delays and requires stable internet, while its ability to handle unpredictable parking environments remains uncertain.

A system combining cameras, sensors, and machine learning to identify open parking spots for traffic management faces scalability challenges in large urban areas with dense traffic. A fusion of deep learning and Adaptive Neuro-Fuzzy Inference System (ANFIS) overcomes some modeling limitations but introduces computational complexity and longer training times, and its performance could be hindered by a lack of historical data or sudden shifts in parking demand. A deep learning-based object identification system to verify eligibility for accessible parking struggles with accuracy, as indicated by high mean absolute and square errors, likely due to poor image quality or insufficient training data for detecting smaller objects. Lastly, a system using anisotropic magneto-resistive sensors to detect vehicles through magnetic traces faces issues with electromagnetic interference, reducing reliability, and doesn't account for dynamic parking behaviors like overlapping magnetic traces in busy areas. Overall, while these methods show promise, they face challenges related to scalability, processing efficiency, adaptability, and data reliability, highlighting the need for more robust, generalized, and efficient solutions capable of addressing complex parking conditions.

1.3. Contribution

- This research Paper discusses to Detect Parking Space Occupancy for Efficient Urban Management using Multi Component Attention Graph Convolutional Neural Network (DPSO-MCAGCNN).
- The PKLot dataset of the information gathered.
- During the pre-processing stage, normalize the data by Maximum Correntropy Quaternion Kalman Filter (MCQKF).
- The Feature extraction Using Second-Order Time-Reassigned Multisynchrosqueezing Transform (SOTRMT).
- The Intelligent Parking Space Occupancy Detection System Leveraging Computer Vision is added using the Multi Component Attention Graph Convolutional Neural Network (MCAGCNN).
- The Leaf in wind optimization (LWO) which increases the performance of the MCAGCNN.

1.4. Organization

The remaining portion of this work is structured as follows: sector 2 describes the proposed methodology, sector 3: illustrates the results and discussion, and Sector 4: the conclusion.

2. Proposed Methodology

In this section, Detect Parking Space Occupancy for Efficient Urban Management using MCAGCNN (DPSO-MCAGCNN) is proposed. The proposed technique makes clever use of computer vision to determine parking spot occupancy. To differentiate between occupied and vacant parking spots, live video streams are analyzed using machine learning and image processing techniques. The input data is first obtained from the PKLot dataset. The acquired data is then passed into the MCQKF for pre-processing. The data is normalized using the MCQKF. The pre-processed data is then passed through a transform procedure to feature extraction using Second-Order Time-Reassigned Multisynchrosqueezing Transform (SOTRMT). Then the extracted data is fed to the network for detection using a Multi-Component Attention Graph Convolutional Neural Network (MCAGCNN). This technique is used to detect the Parking Space Occupancy. Consequently, in order to optimize the MCAGCNN weight parameters, the Leaf in Wind Optimization (LWO) is proposed in this research. The block diagram of the proposed DPSO-MCAGCNN approach is represented in Figure 1. Accordingly, detailed descriptions are given below.

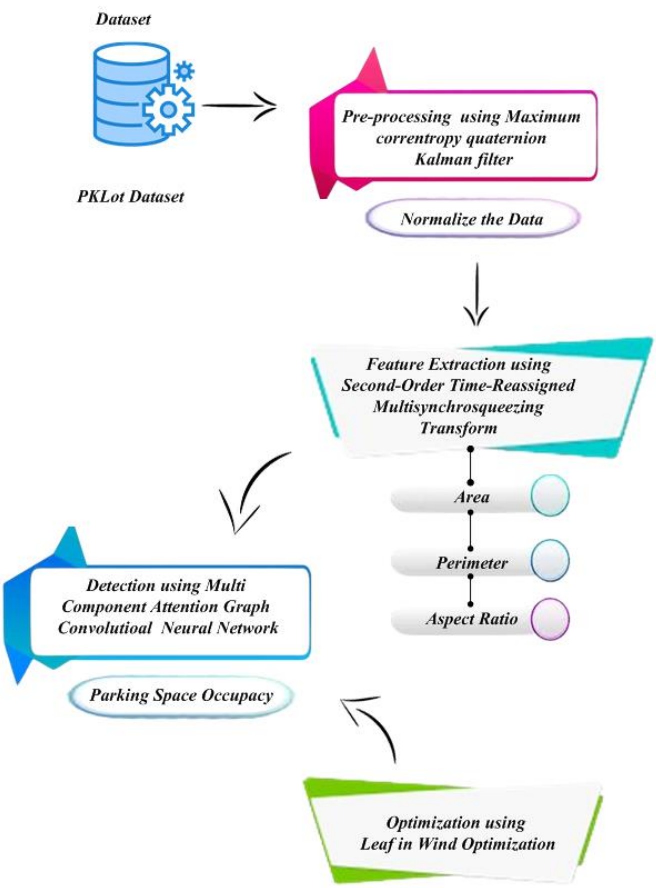
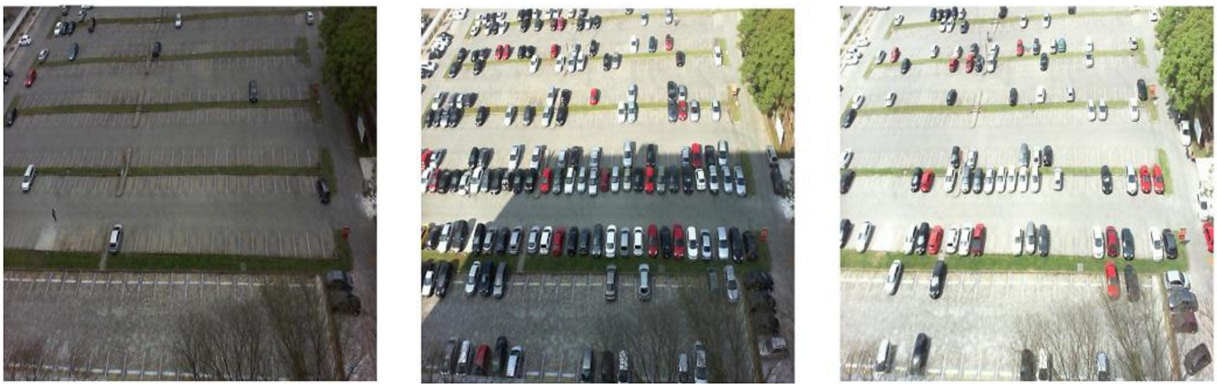


Figure 1. Block diagram of DPSO-MCAGCNN.0

2.1. Data Acquisition

The 12,416 parking lot images in the PKLot dataset were taken from security camera frames. Images of sunny, overcast, and rainy days are included, and the parking spots are marked as either occupied or vacant. The original dataset's rotated rectangle annotations were surrounded by a bounding box, which allowed us to convert the annotations to several common object detection formats [18].

Figure 2 shows the input data image. The input data consists of images extracted from the PKLot dataset, which includes 12,416 images of parking lots captured under varying weather conditions such as cloudy, sunny, and rainy days. Figure 2 shows examples of the input images where each parking space is labeled as either occupied or empty. The images are taken from surveillance cameras, providing a top-down view of the parking area. To prepare the dataset for object detection tasks, the original rotated rectangle annotations were converted into standard bounding boxes, enabling compatibility with popular object detection frameworks. This ensures precise detection of vehicles within individual parking spaces while maintaining consistency across various lighting and weather scenarios.



(a) **(b)** **(c)**

Figure 2. Input data images

2.2. Pre-Processing Using Maximum Correntropy Quaternion Kalman Filter (MCQKF)

In this section, the Maximum Correntropy Quaternion Kalman Filter (MCQKF) [19] is discussed. MCQKF offers significant advantages for data normalization, particularly in dynamic, noisy environments such as urban parking systems. Unlike conventional normalization strategies like z-score normalization or min-max scaling, which assume Gaussian distributions and may struggle with outliers or irregularities, MCQKF leverages the maximum correntropy criterion (MCC) to enhance robustness by capturing non-linear dependencies and focusing on higher-order moments. This reduces sensitivity to noise and outliers, ensuring more accurate normalization of complex, multi-dimensional data. The recursive nature of MCQKF allows for real-time processing, continuously adapting to changing conditions like varying parking space occupancy. Its quaternion-based filtering preserves the interdependencies among data features, making it well-suited for sensor data normalization in challenging environments. By normalizing the data, MCQKF improves the performance of the Intelligent Parking Space Occupancy Detection System, which utilizes computer vision to track car movements. The filter's ability to withstand non-Gaussian noise and outliers increases the accuracy of occupancy status updates, ensuring reliable performance and optimizing the effectiveness of parking management systems.

$$y_l = B_l y_{l-1} + x_{l-1} \tag{1}$$

where, y_l represents the state vector at length l,B_l represents the state transition matrix, x_{l-1}represents the process objective function$l$.

$$z_l = I_l z_l + w_l \tag{2}$$

where, Z_l represents the output vector at length l, I_l represents the output matrix at time step l, z_l represents the state vector at time l andw_k represents the measurement noise at time step.

$$\hat{Y}_{l|l} = \hat{Y}_{l|l-1} + L_l\left(z_l - I_l \hat{y}_{l|l-1}\right) \tag{3}$$

where, $\hat{Y}_{l|l}$ represents the prior state of y_k, $\hat{Y}_{l|l-1}$ represents the posterior state estimates of y_k, L_l represents the estimator gain matrix, $\left(z_l - I_l \hat{y}_{l|l-1}\right)$ represents the correction term.

$$\hat{Y}_{l|l-1} = B_l \hat{Y}_{l-1|l-1} \tag{4}$$

where, $\hat{Y}_{l|l-1}$ represents the prior state estimate at the time$l$, B_l represents the state transition matrix, $\hat{Y}_{l-1|l-1}$ represents the previous state estimate at time $l-1$.

$$K_l = F\left[\left(y_l - \hat{y}_{l|l}\right)^I \left(y_l - \hat{y}_{l|l}\right)\right] \quad (5)$$

where, K_l represents the variation between the posterior estimate $\hat{y}_{l|l}$ and the statey_l,F denotes the process objective function$I$. Finally, the MCQKF is successfully normalized the data. Then, the pre-processed output is fed to Second-Order Time-Reassigned Multisynchrosqueezing Transform (SOTRMT) for feature extraction.

2.3. Feature Extraction Using Second-Order Time-Reassigned Multisynchrosqueezing Transform (SOTRMT)

In this section, the Second-Order Time-Reassigned Multisynchrosqueezing Transform (SOTRMT) [20] is used for feature extraction. SOTRMT offers significant advantages for feature extraction in dynamic environments, such as parking space occupancy. Unlike traditional methods like Short-Time Fourier Transform (STFT) or Fourier Transform (FT), which struggle with non-stationary signals, SOTRMT excels in handling rapid, transient changes by providing superior time-frequency resolution. Its second-order reassignment mechanism enhances the detection of short-term fluctuations, making it more effective than techniques like Empirical Mode Decomposition (EMD) or Wavelet Transform (WT), which may suffer from resolution trade-offs or noise interference. This fine-grained localization of signal components allows for more accurate and robust feature extraction, which is crucial for dynamic sensor data analysis. The extracted features, including area, perimeter, and aspect ratio; provide improved time-frequency localization, resulting in more accurate and reliable recognition of vehicle presence in parking slots. By reducing noise and interference, this technique enhances detection accuracy, ultimately optimizing resource allocation and improving the overall efficiency of parking management systems. Extraction of Area, is shown in Equation 6.

$$St(s,\eta) = \int_{-\infty}^{+\infty} U_w^h\,(s,x)\delta(\eta - \hat{x}(s,x))cx \quad (6)$$

where, $St(s,\eta)$ represents the Extraction of Area, $U_w^h(s,x)$ represents the Short-Time Fourier Transform n time-domain, $\delta()$represents the Dirac delta function, $\hat{x}(s,x)$ represents the instantaneous frequency. Extraction of Perimeter, is shown in Equation 7:

$$St(s,\eta)^{[M]} = \int_{-\infty}^{+\infty} St(s,\eta)^{[M-1]}\,\delta(\eta - \hat{x}(s,x))cx \quad (7)$$

where, $St(s,\eta)^{[M]}$indicates the Extraction of perimeter,M indicates the iteration number, $\delta()$ represents the Dirac delta function, $\hat{x}(s,x)$ and represents the instantaneous frequency.

$$W(x) = Bf^{-(x-x_0)^2/2t^2} f^{-i(b+ax+dx^2/2)} \quad (8)$$

where, $W(x)$ represents the frequency domain signal model, B represents the constant part of the signal frequency amplitude, t represents the single frequency amplitude's frequency spread parameter, x_0 represents the single frequency amplitude's center frequency, b, a and d represents the coefficients of a quadratic polynomial. Extraction of aspect ratio, is shown in Equation 9:

$$\hat{\tau}(s_0,x_0) = -\zeta(r_w(s_0,x_0)x + O_w(s_0,x_0)) \quad (9)$$

where, $\hat{\tau}(s_0,x_0)$ represents the aspect ratio, $\zeta(.)$represents the imaginary part of the complex number, x_0 represents the centre frequency of the single frequency amplitude.

$$w_q(s) = \frac{1}{2\pi H^*(0)} \int\int_{Q^2} Sw^{[M]}\,(s,x)f^{ixs}c\tau cx \quad (10)$$

where, $w_q(s)$ represents the reconstruction formula for Second-Order Time-Reassigned Multisynchrosqueezing Transform, $H^*()$ represents the complex conjugate, M represents the iteration number. Finally, the features like Area, Perimeter and Aspect Ratio are extracted. Then, the extracted features are fed to the MCAGCNN for prediction $w_q(s)$.

2.4. Prediction using Multi-Component Attention Graph Convolutional Neural Network (MCAGCNN)

In this section, MCAGCNN [21] is discussed. MCAGCNN is used to detect the parking space Occupancy. Through the integration of multi-component attention methods, MCAGCN improves the resilience and accuracy of occupied space detection while extracting features from parking image. This method makes it easier to manage parking availability, maximize resource consumption and improve user comfort in metropolitan settings.

$$O(Y) = \prod_{m-1}^{y_0=0} O\left(Y_{y0+1}\middle|Y_{y0-V_{c+1}},\ldots,Y_{y0}\right) \quad (11)$$

where, $O(Y)$ represents the multi-component history information,V_c denotes the sequence length, m denotes the feature dimension of each data point, Y_{y0} represents the number of time slices included per hour.

$$L_f = L + (L-1)(f-1) \tag{12}$$

here, L_f indicates the kernel of the dilated convolution, Lindicates the convolutional kernel's size, f and indicates the dilation factors.

$$Y * g_v(\cdot) = \sum_{d=0}^{L-1} g_y(d)Y(y - f \times d) \tag{13}$$

where, $*$ represents the convolution operation, $g_V$represents the time series and convolutional filter, Y represents the joint probability distribution of time series, L signifies the quantity of nodes inside the graph. d Signifies the quantity of time slices that are incorporated in an hour, g_y represents missing a certain number.

$$X = \sum_{L=0}^{L} O^l C E_l^h \tag{14}$$

where, Lrepresents the convolutional kernel's size, O^l represents the series of diffusion matrices, Xrepresents the generalized the diffusion convolution layer, C represents the details of the day of the week and time of day at the specified moment, E^h represents the step of the recognition information.

$$\tilde{X}_{sfo} = Soft\,max\big(Re\,L\,U(R_1 R_2^Y)\big) \tag{15}$$

here, $\tilde{X}_{sfo}$represents the create a normalized adaptive adjacency matrix, $Softmax$represents the $Soft\max$ function's inherent characteristics, $Re\,L\,U$represents the activation function is omitted, R_1represents the parameter matrix of the source node, R_2represents the parameter matrix of the target node. Finally, MCAGCNN detected the Parking Space Occupancy. In this work, Leaf in wind optimization (LWO)is assigned to enhance MCAGCNN. Here, LWO is assigned for turning weight parameter of MCAGCNN.

2.5. Optimization using Leaf in Wind Optimization (LWO)

The proposed Leaf in Wind Optimization (LWO) [22] is utilized to enhance the weight parameters of the proposed MCAGCNN. When it comes to an intelligent parking space occupancy detection system that uses computer vision, Leaf in Wind Optimization provides a number of benefits. By dynamically adapting to changes in the environment, it improves accuracy and ensures reliable identification even under difficult circumstances. Additionally, LWO offers the advantage of reduced processing time through its efficient resource usage, maximizing computational power without overloading the system. This methodology not only enhances system dependability but also facilitates scalability, making it ideal for various parking situations. Furthermore, LWO contributes to the robustness of the system, allowing it to perform consistently in diverse environmental conditions, and it improves the overall adaptability of the system for a wide range of applications.

Step 1: Initialization

Randomness is used to create the initial population of LWO. Equation 16 is then used to derive the initialisation.

$$D = \begin{bmatrix} d_1^1 & d_1^2 & \cdots & d_1^P \\ d_2^1 & d_2^2 & \cdots & d_2^P \\ \vdots & \vdots & \vdots & \vdots \\ d_M^1 & d_M^2 & \cdots & d_M^P \end{bmatrix} \tag{16}$$

where, D represents the set of all leaves, M indicates the total count of leaves, P indicates the dimensionality of the leaf motion space.

Step 2: Random Generation

The input weight factor $L_f andX$ developed randomness through LWO technique.

Step 3: Fitness Function

A randomly generated solution is produced from initialized data. It is computed through parameter optimisation. Then the formula is derived in Equation 17

$$FitnessFunction = optimizing[L_f andX] \tag{17}$$

The parameter L_f represents the increasing the accuracy and X represents the decreasing in Mean Absolute Error.

Step 4: Breeze Driven Leaf Strategy for Optimizing L_f

OptimizingL_f in the Breeze Driven Leaf strategy involves fine-tuning the adaptive amplitude of movement and the impact of breeze factors to improve the responsiveness and accuracy of the parking space detection system.

$$L_f = d_{new}^{1,k} + F_1 \cdot p_{wind}^t \cdot sin(\delta) \cdot \delta \cdot j \tag{18}$$

where, δ represents the uniformly distributed random number, p_{wind}^t represents the magnitude of the impact of the breeze on the spiral motion, F_1 represents the factor that determines the adaptive amplitude of movement.

Step 5: Strong Wind Driven Leaf Strategy for Optimizing $\boldsymbol{X}$

Optimizing $\boldsymbol{X}$ in the Strong Wind Driven Leaf strategy involves calibrating the wind-driven algorithms and environmental signal inputs to enhance the system's capacity to precisely identify parking space occupancy under varying conditions.

$$X = \begin{cases} FP^k + a_3 \cdot (GP^k - FP^k) if a_4 < b2 \\ d_{new}^{2,k} \qquad otherwise \end{cases} \tag{19}$$

where, $b2$ represents the reset probability, a_3 and a_4 represents two uniformly distributed random numbers.

Step 6: Termination Criteria

In this stage, the weight factor value of generator $L_f andX$ Multi Component Attention Graph Convolutional Neural Network were improved with the use of LWO; continue step 3 iteratively until the stopping is met $L_f andX$.Then DPSO-MCAGCNN assesses the detection by increasing the Accuracy.

3. Result with Discussion

The result of the proposed DPSO-MCAGCNN was discussed. The proposed DPSO-MCAGCNN is implemented on a Python platform on a PC with an Intel ®core (7M) i3-6100CPU @3[U1] and 12 GB of RAM.70 GHz CPU According to certain performance metrics, the number of iterations is similar to the number of batches needed to finish an epoch. Metrics such as accuracy, mean absolute percentage error (MAPE), mean square error (MSE), coefficient of determination (R2), mean absolute error (MAE), and root mean square error (RMSE) are used to assess the DPSO-MCAGCNN method. The acquired outcomes of the proposed technique are evaluated to existing EUPE-SVM, RTPM-YOLOv5, and LSTM-MASP methods.

3.1. Performance Measures

This is a vital stage in determining the optimisation algorithm's exploration. Performance measures to evaluate to access performance like RMSE, MAE, MSE, Accuracy, Coefficient of Determination (R^2) and MAPE.

3.1.1. Accuracy

The proportion of samples (both positive and negative) relative to the total samples is measured by accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{20}$$

here, the True positive is specifies by TP, the True Negative is specifies by TN, the false positive is specifies by FP, and the false negative is specifies by FN.

3.1.2. Coefficient of Determination (R^2)

The coefficient of determination, or R^2, is the proportion of variance in the dependent variable that can be predicted from the independent variable.

$$R^2 = 1 - \frac{RSS}{TSS} \tag{21}$$

3.1.3. Mean Square Error (MSE)

The error in statistical models is computed using mean squared error, or MSE, which is the average squared difference between the observed and predicted values.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \tag{22}$$

where, n represents amount of data points, y_i real value for i^{th} data point, $\hat{y}_i$ signifies anticipated value for i^{th} data point.

3.1.4. Root Mean Square Error (RMSE)

RMSE, calculates the residual mean, takes the square root of that mean, and finds the residual norm (difference between the actual and predicted value) for each image point. Because it employs accurate measurement at each anticipated image point, root mean square error (RMSE) is frequently utilized in supervised learning applications.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \tag{23}$$

here**,** $RMSE$ represents the Root Mean Squared Error, l represents the numeral of observations, k_j represents the predicted values, $\hat{k}_j$ represents the observed values.

3.1.5. Mean Absolute Error (MAE)

The regression model's performance is assessed using a statistic called MAE. It computes the average number of errors between the actual and expected values.

$$MAE = \frac{1}{l}\sum_{j=1}^{l}\left|k_j - \hat{k}_j\right| \tag{24}$$

where, MAE indicates the Mean Absolute Error, l indicates the amount of data points, k_j denotes the observed value, $\hat{k}_j$ represents the predicted values.

3.1.6. Mean Absolute Percentage Error (MAPE)

By computing the average % difference between the actual and predicted values, a forecasting method's accuracy may be assessed using the Mean Absolute % Error measure.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_F - Y}{Y}\right| \tag{25}$$

3.2. Performance Analysis

Figures 2 to 7 depicts the simulation of proposed DPSO-MCAGCNN method. Then the proposed DPSO-MCAGCNN method is likened with existing EUPE-SVM, RTPM-YOLOv5, and LSTM-MASP methods respectively.

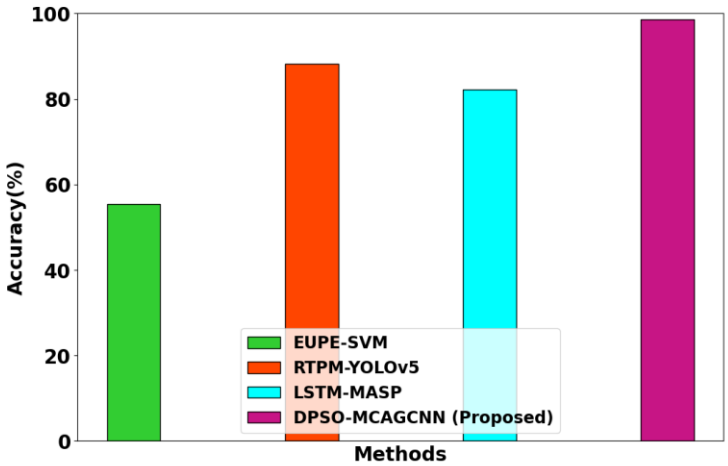


Figure 3. Performance Analysis of Accuracy

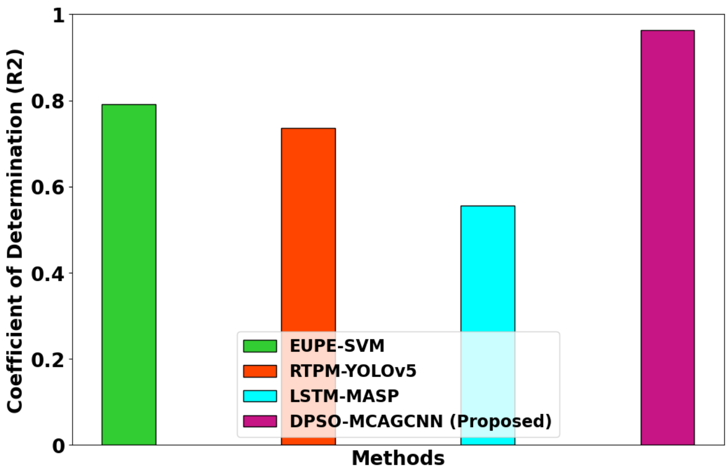


Figure 4. Performance Analysis of R^2

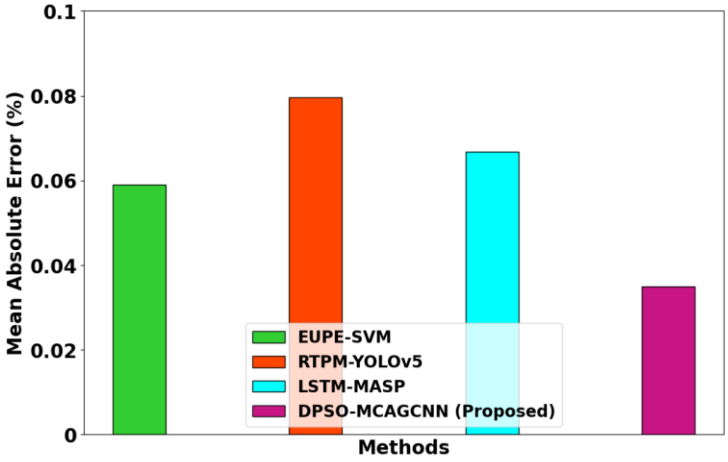


Figure 5. Performance Analysis of Mean Square Error

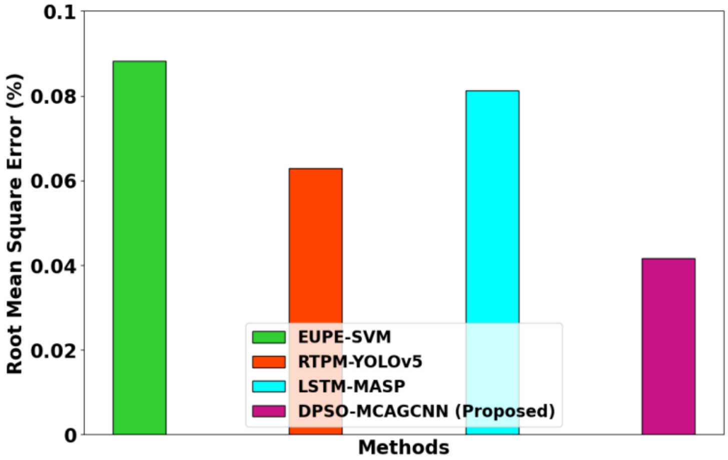


Figure 6. Performance Analysis of Root Mean Square Error

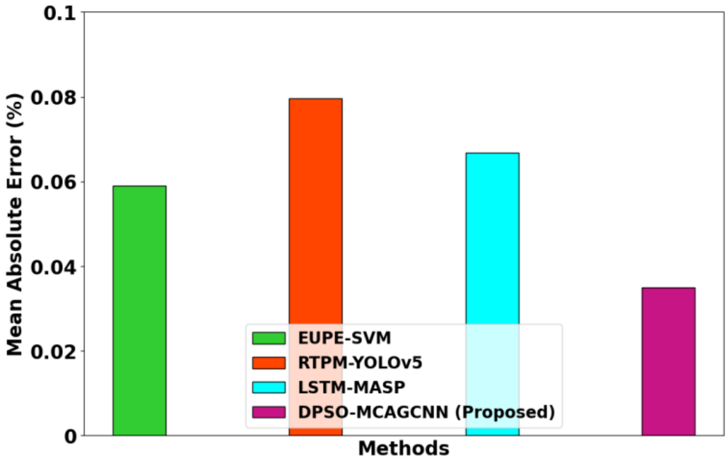


Figure 7. Performance Analyses of Mean Absolute Error

Accuracy is a critical metric in systems like Intelligent Parking Space Occupancy Detection, as it ensures reliable identification of occupied and vacant parking spaces, directly enhancing user experience and system efficiency. Figure 3 demonstrates the significant improvement of the DPSO-MCAGCNN method, achieving 27.84%, 28.42%, and 29.27% higher accuracy over EUPE-SVM, RTPM-YOLOv5, and LSTM-MASP, respectively, showcasing its superior real-time performance and reliability in diverse conditions. High accuracy minimizes errors, such as false positives or negatives, reducing driver frustration and operational inefficiencies while saving time and costs by avoiding manual interventions. Furthermore, accurate systems build user trust, enabling scalability and seamless integration with other smart city solutions like traffic management.

The Coefficient of Determination (R^2) is a critical metric for evaluating how well a model predicts parking space occupancy, indicating the percentage of variance in the data explained by the model. The graph in Figure 4 demonstrates the DPSO-MCAGCNN method's superiority, with R^2 increases of 29.84%, 25.87%, and 25.97% over EUPE-SVM, RTPM-YOLOv5, and LSTM-MASP, respectively, highlighting its enhanced predictive accuracy for parking space occupancy. A better-fitting model is indicated by a higher R2 value in systems such as DPSO-MCAGCNN. This ensures that the system makes more accurate and dependable predictions, which is crucial for effective parking management. R^2 helps assess the model's predictive power and how well it generalizes across different scenarios, giving stakeholders confidence in the system's performance.

A crucial metric in systems such as Intelligent Parking Space Occupancy Detection is MSE, which computes the average squared difference between expected and actual values. Higher prediction accuracy, which guarantees that the system more closely reflects real conditions, is indicated by a lower MSE. The graph in Figure 5 highlights the proposed DPSO-MCAGCNN method's superiority, with MSE reductions of 19.84%, 17.42%, and 16.27% compared to EUPE-SVM, RTPM-YOLOv5, and LSTM-MASP, respectively, showcasing its precision in real-time applications. A lower MSE indicates higher prediction accuracy, ensuring the system closely aligns with real-world conditions. This minimizes significant errors, which is critical in dynamic environments, enhancing reliability and efficiency. By penalizing larger discrepancies more heavily, MSE helps optimize the system's performance, ensuring consistent results and reducing the need for manual corrections.

RMSE is a critical metric for systems like Intelligence Parking Space Occupancy Detection as it measures the standard deviation of prediction errors, providing an intuitive way to assess accuracy. The graph in Figure 6 showcases the DPSO-MCAGCNN method's effectiveness, with RMSE reductions of 12.22%, 13.34%, and 18.87% compared to EUPE-SVM, RTPM-YOLOv5, and LSTM-MASP, respectively, underscoring its superior performance for real-time applications. A lower RMSE indicates that predictions are closer to actual values, ensuring higher reliability and precision in dynamic scenarios such as detecting parking space availability. By heavily penalizing significant errors, RMSE helps the system prioritize minimizing impactful discrepancies and enhancing consistency and trustworthiness.

The average magnitude of prediction errors is measured by Mean Absolute Error (MAE), which is a crucial metric in systems like Intelligent Parking Space Occupancy Detection because it offers a clear and understandable evaluation of accuracy. The graph in Figure 7 shows the DPSO-MCAGCNN method's effectiveness, achieving MAE reductions of 12.77%, 13.78%, and 14.67% compared to EUPE-SVM, RTPM-YOLOv5, and LSTM-MASP, respectively, highlighting its superior precision for real-time parking management. A lower MAE indicates more reliable and consistent predictions, essential for real-time decision-making, such as accurately identifying parking space availability.

Mean Absolute Percentage Error (MAPE) is a crucial metric in systems like Intelligent Parking Space Occupancy Detection because it expresses prediction accuracy as a percentage, making it easily interpretable and comparable across different scenarios. The graph in Figure 8 shows the DPSO-MCAGCNN method's superiority, with MAPE reductions of 17.84%, 18.42%, and 19.27% compared to EUPE-SVM, RTPM-YOLOv5, and LSTM-MASP, respectively, highlighting its effectiveness in delivering precise, percentage-based predictions for real-time parking management. By determining the average percentage error between expected and actual values, MAPE aids in assessing the system's relative performance and offers a clear image of its performance. Minimizing MAPE ensures more accurate predictions, which is essential for decision-making and user experience, especially in dynamic environments like parking space detection.

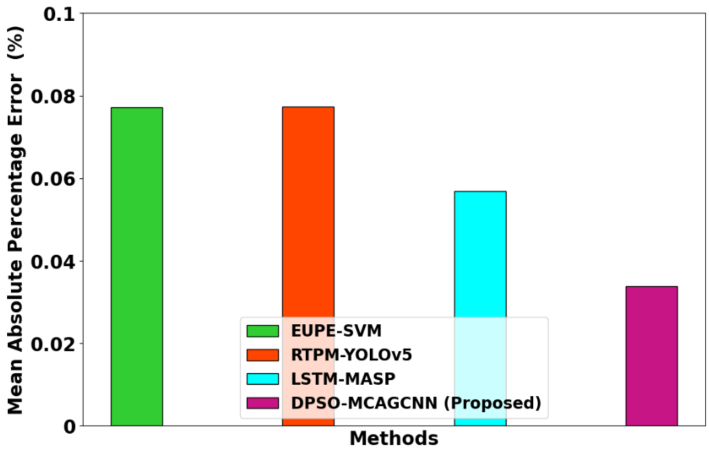


Figure 8. Performance Analysis of Mean Absolute Percentage Error

Table 1 illustrates a comparative performance analysis of the proposed DPSO-MCAGCNN method and three existing methods EUPE-SVM, RTPM-YOLOv5, and LSTM-MASP—based on recall and precision metrics. The proposed DPSO-MCAGCNN method outperforms all others, achieving the highest recall (97.8%) and precision (98.4%), indicating its superior capability in identifying and classifying relevant instances. EUPE-SVM demonstrates relatively low recall (85.7%) and precision (69.2%), reflecting its limitations in both sensitivity and accuracy. RTPM-YOLOv5 performs moderately, with recall and precision values of 90.2% and 72.6%, respectively. LSTM-MASP shows a high precision (92.27%) but has the lowest recall (82.7%) among the methods, highlighting its trade-off between accuracy and sensitivity. These findings emphasize the effectiveness of the proposed DPSO-MCAGCNN technique.

Table 1. Performance Analysis of Proposed and Existing Method

Methods	Recall	Precision
DPSO-MCAGCNN (proposed)	97.8%	98.4%
EUPE-SVM [11]	85.7%	69.2%
RTPM-YOLOv5 [12]	90.2%	72.6%
LSTM-MASP [13]	82.7%	92.27%

4. Conclusion

In conclusion, the DPSO-MCAGCNN system represents an important advancement in the management of urban parking spaces, offering substantial improvements in both detection accuracy and efficiency. The system has proven its ability to provide accurate and dependable parking space occupancy detection by using the PKLot dataset and improving data processing with the MCQKF. The performance of DPSO-MCAGCNN surpasses that of existing methods such as EUPE-SVM, RTPM-YOLOv5, and LSTM-MASP, with accuracy improvements of 27.84%, 28.42%, and 29.27%, respectively. Furthermore, the system effectively reduces the MAPE by 17.84%, 18.42%, and 19.27%, highlighting its robustness and potential to improve urban parking management. The system's superior performance underscores its potential as an essential tool in the development of smarter urban infrastructure. As cities around the world continue to grow, efficient space utilization becomes increasingly important. The DPSO-MCAGCNN system not only optimizes parking management but also provides valuable data that can contribute to the broader goal of creating more sustainable and efficient urban environments. Its ability to detect parking space occupancy with high accuracy makes it a promising solution for reducing congestion, minimizing the environmental impact of searching for parking, and improving the overall urban experience. However, the quality of the input data determines the system's success, and integrating it with the older infrastructure still presents difficulties. To address these challenges, future work will focus on enhancing the system's robustness in adverse conditions, optimizing real-time processing for larger urban areas, and conducting extensive real-world testing. Additionally, improving integration with other smart city components and refining the system's usability will be critical in furthering the development of a comprehensive, efficient urban management solution.

5. Declarations

5.1. Author Contributions

A.A.P. and P.D.N. contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available in the article.

5.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5.4. Conflicts of Interest

The authors declare no conflict of interest.

6. References

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