RESEARCH PAPER

Employment of Artificial Intelligence in Parking Systems: A novel approach

Nirmal Kumar Agarwal
Assistant Professor, Department of Electrical Engineering, JSS University, Noida (UP), India
nirmalnitham@gmail.com*
Vimal Gupta
Assistant Professor, Department of Computer Science Engineering-AIML, JSS University, Noida (UP), India
vimalgupta09@gmail.com
Tarun Kumar Chartterjee
Presidio, USA
reachtarunchatterjee@gmail.com*
Nitima Malsa
Associate Professor, Department of Computer Science Engineering, JSS University, Noida (UP), India
nitima.malsa@gmail.com
Corresponding Author * [nirmalnitham@gmail.com, reachtarunchatterjee@gmail.com]

Received:1st August,2026; **Revised:**5thAugust,2026; **Accepted:**8thAugust,2026; **Available Online:**20thAugust, 2026

Abstract—Significant issues in parking management, such as traffic congestion, excessive fuel consumption, wasteful use of parking spots, and environmental pollution, have been brought about by the rapid development of urban populations and the number of automobiles. Conventional parking systems typically rely on rudimentary sensors with limited decision-making capabilities, manual monitoring, or predetermined allocation algorithms. Opportunities to create intelligent parking systems with real-time car identification, parking-space occupancy prediction, automatic allocation, and adaptive parking guidance are presented by artificial intelligence (AI),.In this work, a deep learning categorization model, an occupancy prediction algorithm, an adaptive parking allocation system, and camera-based car identification are all integrated into an AI-enabled smart parking framework. A sensor layer, an edge computing layer, an AI processing layer, a communication layer, and a user interface layer make up the suggested architecture. While historical occupancy rates, time of day, and demand for parking are utilized to forecast future space availability, image data is used to estimate parking availability. To reduce parking search time, needless driving distance, and allocation conflicts, a multi-objective allocation system is developed. Scalability, real-time operation, and interaction with smart city infrastructure are all supported by the framework's design. Precision, recall, F1-score, occupancy-prediction error, reaction time, parking-search length, and energy usage can all be used to assess performance. The suggested architecture offers a workable basis for creating intelligent parking solutions, but its efficacy needs to be proven by comparative analysis and experimental application. the parameters, such as precision. SVM, NLP, ANN, have been used to accuracy, precision, recall, F1-Score. Compared to other approaches, SVM has been found to achieve the best performance parameters.

Index Terms—AI, SVM, NLP, accuracy, precision

How to cite this article: Agarwal NK, Gupta V, Chartterjee TK, Malsa N., Employment of Artificial Intelligence in Parking Systems: A Novel Approach. Int J Drug Deliv Technol. 2026;16(87s): 771-775; DOI: 10.25258/ijddt.16.87s.77

I. INTRODUCTION

Urbanization, population growth, and an increase in private automobiles are putting more strain on urban transportation networks. As a result, parking management is now a crucial part of intelligent transportation systems (ITS). Drivers sometimes look for open spots in traditional parking facilities without having accurate information regarding their availability. This procedure decreases operating efficiency, lengthens travel times within parking lots, and causes needless vehicle movements.

Conventional parking systems frequently use individual proximity sensors, entrance and exit counters, or manual supervision. These methods may have limits in terms of scalability, maintenance, adaptability, and predictive capability, even though they can offer valuable occupancy information. In general, a simple sensor-based system can detect whether a certain space is occupied, but it is not always able to forecast future demand or identify the best parking allocation.By collecting valuable information from camera photos, sensor measurements, previous parking records, and contextual data, artificial intelligence presents the possibility of overcoming these constraints. Vehicles may be recognized using computer vision, and parking spots can be categorized as either occupied or empty. While optimization algorithms can suggest suitable spots based on distance, availability, vehicle type, and user requirements, machine-learning models can estimate parking demand. Create an AI-based system that uses sensor data or camera images to identify occupied and unoccupied parking spots. Examine parking-space classification and car detection using deep learning. Utilize time-dependent demand data and historical records to forecast parking occupancy. Create a clever allocation system that takes user needs, distance, availability, and space compatibility into account. Establish a technique for evaluating environmental performance, accuracy, response time, and resource usage. Determine the implementation issues related to security, computing requirements, privacy, and communication dependability.

The suggested framework combines AI, IoT, edge computing, and a parking-management server with real-time parking recognition and short-term occupancy prediction. It also develops a multi-objective allocation approach and establishes a repeatable evaluation plan. Implementation and comparison with current techniques should be used to determine its uniqueness. IoT-enabled parking systems track the occupancy of parking spaces using sensors, wireless connection, and distributed or centralized software. The platform receives sensor measurements, updates availability data, and notifies drivers. Reviews of smart parking systems address security issues, enhanced parking use, and real-time availability [1], [2]. Despite this, large installations might need a lot of infrastructure, upkeep, and communication.

An alternative to placing separate sensors in each parking spot is computer vision. To ascertain if cars are parked in designated areas, images from stationary cameras can be examined. Previous reviews address parking-space identification applications, datasets, and computer vision techniques [3]. Poor lighting, shadows, rain, occlusion, camera movement, and shifts in viewing angle can all have an impact on performance.

Images of labelled cars and parking spaces are used by deep learning algorithms to acquire visual representations. While object-detection algorithms may directly spot automobiles, convolutional neural networks (CNNs) are frequently employed for image categorization and feature extraction. In their investigation of a vision-transformer-based intelligent parking system, Sadek and Khalifa [5] found that their evaluated model had 95% test accuracy, whereas a CNN baseline had 90%. These values are unique to that particular study and should not be regarded as performance guaranties for other facilities.

Combining occupancy identification with demand estimate, enhancing robustness under varying environmental conditions, taking user needs into account during allocation, striking a balance between accuracy and computational expense, measuring operational advantages rather than just accuracy in classification, and safeguarding personal data are all significant research challenges. The suggested framework links system-level evaluation, allocation optimization, short-term prediction, and visual detection.

II. AI-BASED SMART PARKINGSTRUCTURE

There are five functional layers in the suggested architecture. The sensing layer gathers data from contextual sources, entry and exit counters, fixed cameras, and optional magnetic or ultrasonic sensors. The trained model, timestamped occupancy records, and image preprocessing are all done by the edge-computing layer. Parking space allocation, demand forecasting, and occupancy categorization are all carried out by the AI processing layer. Space IDs, reservations, timestamps, and operational limitations are all maintained and updated via the communication and management layer. Current availability, suggestions, reservations, and navigation are all displayed on the user interface layer.

Camera and sensors → image preprocessing → AI occupancy detection → demand prediction → intelligent allocation → parking guidance → occupancy feedback is the conceptual workflow. The system state is updated by feedback from vehicle entry, exit, and space observations. Instead of continuing to report observations as current, the system should designate them as stale when an edge device or communication channel breaks.

A.Edge Computing and Sensing

The main input for a vision-based implementation is camera images. By processing images locally and sending occupancy data rather than raw video, an edge device can save connection traffic. When cameras are blocked or there is inadequate lighting, sensor fusion can be added.

B.User Interface and AI Processing

The allocation module suggests appropriate space, a prediction model projects future availability, and the vision model projects current occupancy. Recommendations and availability can be displayed by a digital display, mobile application, or web application. Updates should be verified by the management system, and concurrent reservations of the same space should be prohibited.

III. MATHEMATICAL MODELING

A. Parking Occupancy Classification

Let N places be available in the parking facility. Space i's occupancy state at time t is represented by $x_i(t) \in \{0,1\}$, where 0 indicates vacant and 1 indicates occupied. $N_o cc(t) = \Sigma_i\ x_i(t)$ and $N\text{ר}_a c(t) = N - N_o cc(t)$ are the total occupied and unoccupied spaces. $R_o cc(t) = 100\ N_o cc(t)/N$ is the occupancy ratio.

B. AI-Based Occupancy Estimation

Let $f\theta$ be a trained AI model with parameters θ and I_t be a camera picture. The expected likelihood that space i is occupied is $p_i(t)$. The binary estimate, where τ is a classification threshold, is $x\rho_i(t) = 1$ when $p_i(t) \geq \tau$ and 0 otherwise. Binary cross-entropy can be minimized through model training: $L = -(1/M)\ \Sigma_j\ [y_j \log(p_j) + (1-y_j) \log(1-p_j)]$, where y_j is the ground-truth label and M is the number of training samples.

C. Parking Occupancy Prediction

Let z_t include historical and contextual information like the day of the week, time of day, entry and exit counts, and recent occupancy. Future occupancy is estimated via a prediction model using the formula $\hat{N}_o cc(t+h) = g\varphi(z_t)$, where φ stands for model parameters and h is the prediction horizon. Gradient-boosted trees, random forests, recurrent neural networks, and temporal transformers are examples of potential models. With outputs limited to the facility capacity, future vacancy is projected as $\hat{N}_{va} c(t+h) = N - \hat{N}_o cc(t+h)$.

D. Intelligent Parking Allocation

Let a_{ij} $\{0,1\}$ represent the assignment of vehicle j to space i. Duplicate assignments are avoided via the requirements $\Sigma_j\ a_{ij} \leq 1$ for each space and $\text{₹}_i\ a_{ij} \leq 1$ for each vehicle. Let d be the driving distance, w be the walking distance, and r be the penalty for breaking a user requirement. Minimizing $\Sigma_{i2j}\ a_{ij}\ (\alpha d_{ij} + \beta w_{ij} + \gamma r_{ij})$, where α, β, and γ are non-negative weights, is a simplified goal. Additionally, reservations, safety limitations, vehicle-size compatibility, accessible-space standards, and verified occupancy must all be enforced by the allocation.

IV.PERFORMANCE PARAMETERS EVALUATION

A. Dataset Preparation

Lower and high occupancy, daylight and darkness situations, shadows, partial occlusion, and, if relevant, changing weather should all be included in the dataset. Every parking-space area should be marked as either occupied or unoccupied, and a representative subset should be examined separately. In training and testing, near-duplicate images can be avoided by partitioning by time, camera, or recording session. Initial development can be supported by public datasets, but before deployment, site-specific validation is required. 70% of data has been trained and 30% of data has been tested.

B. Evaluation Metrics

$$accuracy = \frac{(T_P + T_N)}{(T_P + T_N + F_P + F_N)} \quad (1)$$

$$\Pr ecision = \frac{T_P}{(T_P + F_P)} \quad (2)$$

$$\mathrm{Re}call = \frac{T_P}{(T_P + FN)} \quad (3)$$

$$F1 - score = 2 \times \frac{\Pr ecision \times \mathrm{Re}call}{(\Pr ecision + \mathrm{Re}call)} \quad (4)$$

The positive class must be defined explicitly, for example, occupied space. For occupancy prediction, mean absolute error is MAE = (1/K) Σ_k $|N_k - \hat{N}_k|$, where N_k and $\hat{N}_k$ are observed and predicted occupancy counts. Operational metrics should include average and 95th-percentile processing latency, average parking-search time, distance travelled, utilization rate, reservation-conflict rate, and energy consumption.

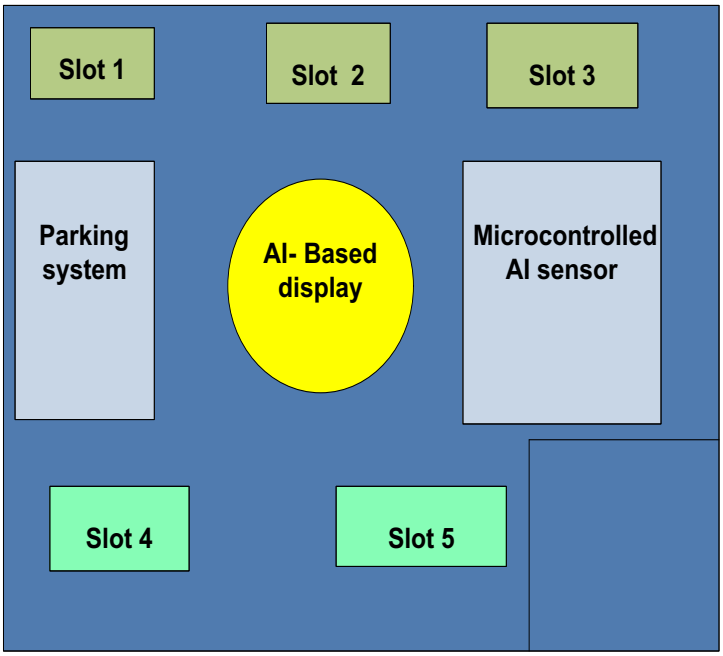


Fig.1 Structure of the proposed parking system

C. Artificial Intelligence Methods

The date and hourly occupancy data were included in the dataset's 13,100 items. A retrospective analytic approach was used to evaluate prior occupancy levels, using a variety of inputs that gave the model data on occupancy rates from an hour before to forecasts. The first step in the research technique was doing a review of the literature to find keywords associated with machine learning and parking forecasts. After that, relevant databases were searched for academic articles, paying particular attention to publication quality and peer-reviewed status.The second stage involved gathering information and choosing the variables needed to create the machine learning models. After the data was prepared through data processing, two different kinds of models—classifiers and regressors—were created. The models' performance was evaluated using evaluation metrics, and the outcomes and conclusions from the model development stage were addressed. 70% of data has been trained and 30% of data has been tested.

D. Experimental Results

No measured results are claimed in this paper. The following values must be filled in after implementation and testing. The structure of the proposed system has been shown in Fig.1 in which five slots have been located for the placing of various cars can be parked. The position of various parking places have been determined by using microcontroller controlled with AI based sensor. After sensing the various positions, exact location will be identified by using the display which is assessed with AI. The various parameters like accuracy, precision, recall, F1-Score have been estimated with AI methods like SVM, NLP, and ANN. Such estimation has been assessed with Table.1.

Table.1 Estimation of various parameters with various AI methods

Metric	SVM	ANN	NLP
Accuracy (%)	98.8	91.2	93.6
Precision (%)	89.6	88.6	86.5
Recall (%)	75.6	69.2	62.3
F1-score (%)	69.8	64.6	63.8

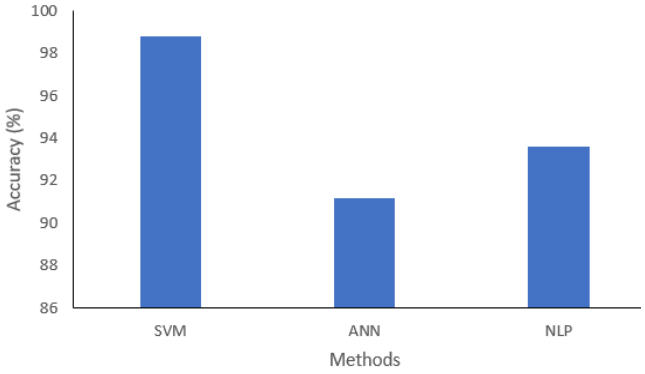


Fig.2 Comparison of accuracy with SVM,ANN, NLP

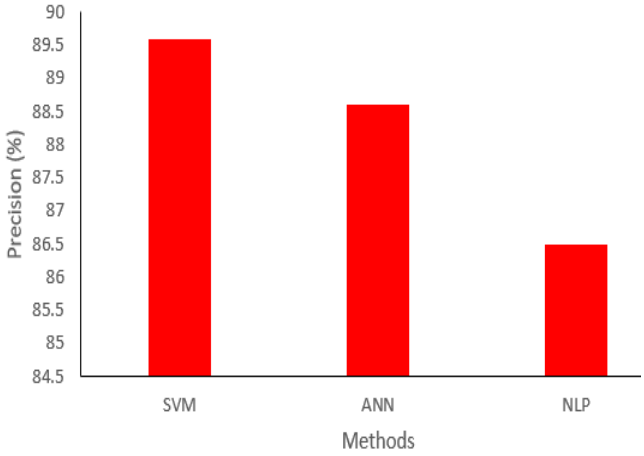


Fig.3 Comparison of precision with SVM,ANN,NLP

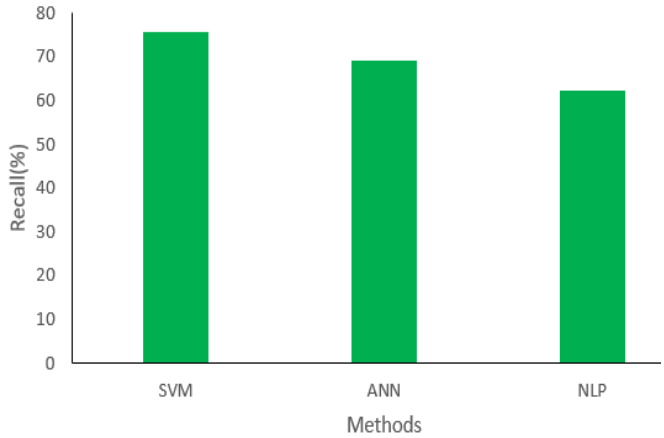


Fig.4 Comparison of recall with SVM,ANN, NLP

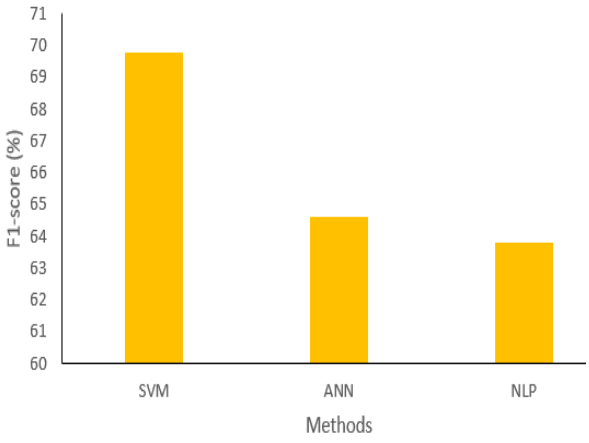


Fig.5 Comparison of F1-score with SVM,ANN, NLP

The graphical comparison of accuracy, precision, recall, F1-Score have been estimated with AI methods like SVM, NLP,ANN has been displayed in Fig.2, Fig.3, Fig.4, Fig.5 respectively. It is observed that most improved parameters like accuracy, precision, recall, F1-Score has been attained with SVM in contrast to other methods.

V. RESULTS & DISCUSSION

* In a single parking-management workflow, the system integrates perception, prediction, and decision-making. Demand prediction may assist drivers and operators in anticipating periods of high utilization, automated visual monitoring may eliminate the requirement for a single sensor in each area, and allocation optimization may take reservations, accessibility, vehicle compatibility, and distance into account.

* The suggested system's structure is depicted in Fig. 1, where five parking spaces are available for different types of vehicles. A microcontroller operated by an AI-based sensor has been used to calculate the positions of different parking spaces. The display, which is evaluated by AI, will determine the precise location after sensing the various positions.

*Reduced traffic, fuel use, or emissions are not always the result of high classification accuracy. These results need to be quantified in controlled experiments or calculated using an explicit traffic and energy model. Additionally, recommendations ought to be explicable, such as by stating that a certain location was chosen due to its availability, proximity to the destination, and suitability for the vehicle.

* Figures 2, 3, 4, and 5 show the graphical comparison of accuracy, precision, recall, and F1-Score that have been estimated using AI techniques including SVM, NLP, and ANN.When compared to other approaches, SVM has been found to achieve the most improved parameters, including accuracy, precision, recall, and F1-Score.

VI. CONCLUSION

The fast growth of metropolitan populations and the number of cars has resulted in significant parking management difficulties, including traffic congestion, excessive fuel use, wasteful use of parking spaces, and environmental pollution. Conventional parking systems usually rely on manual monitoring, predefined allocation algorithms, or simple sensors with limited decision-making capabilities. Artificial intelligence (AI) offers opportunities to develop intelligent parking systems with real-time automobile identification, parking-space occupancy prediction, automatic allocation, and adaptive parking advice.

This work integrates an AI-enabled smart parking framework with a deep learning categorization model, an occupancy prediction algorithm, an adaptive parking allocation system, and camera-based automobile identification. The proposed architecture consists of a sensor layer, an edge computing layer, an AI processing layer, a communication layer, and a user interface layer. Image data is used to estimate parking availability, while past occupancy rates, time of day, and parking demand are used to predict future space availability.

The design of the framework supports real-time operation, scalability, and integration with smart city infrastructure. Performance can be evaluated using precision, recall, F1-score, occupancy-prediction error, response time, parking-search duration, and energy consumption. Although the proposed architecture provides a practical foundation for developing intelligent parking solutions, comparative analysis and experimental implementation are required to demonstrate its effectiveness. the metrics, such accuracy. Accuracy, precision, recall, and F1-Score have all been measured using SVM, NLP, and ANN. It has been discovered that SVM achieves the best performance parameters when compared to alternative methods.

REFERENCES

[1] “A review of smart parking systems,” Transportation Research Procedia, vol. 73, pp. 289–296, 2023. doi: 10.1016/j.trpro.2023.11.920.

[2] “A Survey on IoT Driven Smart Parking Management System: Approaches, Limitations and Future Research Agenda,” IEEE Access, vol. 11, pp. 119523–119543, Oct. 2023. doi: 10.1109/ACCESS.2023.3327306.

[3] R. A. Hadi, L. E. George, and Z. J. Ahmed, “Computer Vision-based Approaches, Datasets, and Applications of Smart Parking Systems: A Review,” Iraqi Journal of Science, vol. 65, no. 2, pp. 979–1000, Feb. 2024. doi: 10.24996/ijs.2024.65.2.32.

[4] A. Raj and S. D. Shetty, “Smart parking systems technologies, tools, and challenges for implementing in a smart city environment: A survey based on IoT & ML perspective,” International Journal of Machine Learning and Cybernetics, vol. 15, no. 7, 2024. doi: 10.1007/s13042-023-02056-5.

[5] R. A. Sadek and A. A. Khalifa, “Vision Transformer Based Intelligent Parking System for Smart Cities,” in Proc. 20th ACS/IEEE International Conference on Computer Systems and Applications (AICCSA), 2023. doi: 10.1109/AICCSA59173.2023.10479293.

[6] H. Lee, I. Chatterjee, and G. Cho, “A Systematic Review of Computer Vision and AI in Parking Space Allocation in a Seaport,” Applied Sciences, vol. 13, no. 18, Art. no. 10254, 2023. doi: 10.3390/app131810254.

[7] F. del Rosario Reyes Salazar, J. J. Valdivia Ríos, H. T. Ráez Martínez, and G. H. Pachas Quispe, “IoT and new technologies to improve Smart Parking efficiency: Systematic Review,” in Proc. LACCEI International Multi-Conference for Engineering, Education, and Technology, 2024. doi: 10.18687/LACCEI2024.1.1.999.

[8] Sumana de, Paromita Goswami, Neetu Faujdar, Ghanshyam Singh, Gynaecological Disease Diagnosis Expert System (GDDES) Based on Machine Learning Algorithm and Natural Language Processing,IEEE Access,, vol.12,2024

[9]Yajing Fan, Shuyang Yu, Bin Gu, Ziran Xiong, Zhou Zhai, Heng Huang,Yi Chang, Global Model Selection for Semi-Supervised Support Vector Machine via Solution Paths, IEEE Transactions on Neural Networks and Learning Systems, vol.36, no.2, pp.2154 – 2168, 2025