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DISTRIBUTED INTELLIGENCE FOR CAMPUS PARKING ALLOCATION AND TRAFFIC OPTIMIZATION

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Abstract
Efficient campus parking management is needed to minimise congestion, wastage of resources, and delays caused to students, staff, and visitors. The study focused on applying machine learning techniques to improve parking management systems using real-time data analysis. Such ML techniques comprise decision trees, SVMs, and neural networks developed through cameras and sensors for predicting parking availability, optimising resource allocation for multiple locations, and directing vehicles to them. The system dynamically adapts to varying traffic conditions, load levels, and periods of the day to allow further optimisation of space usage and improved mobility. Besides other advantages, predictive analytics endorses strategic infrastructure planning and improves operational efficiency. In essence, the findings of the study prove that the ML solutions for parking will enhance both campus mobility and traffic congestion during peak hours, thus encouraging sustainability.

Keywords: Campus parking, Machine learning, Real-time data, Sensors, Cameras, Parking management, Decision trees, SVMs, Neural networks, Traffic congestion, Smart mobility.

1. Introduction

The contemporary parking impediments faced by urban campuses—from educational institutions to business hubs to healthcare facilities—remain a major concern. Insufficient parking spots, erratic availability, and the lack of competent parking management cause serious traffic congestion on campus due to the excessive search time extended by motorists, eventually leading to the irritation of both drivers and pedestrians. With the increased growth in vehicles, the current policies towards parking and their related infrastructure will not meet the demands; hence the new approaches for the same. Machine learning is fast becoming an invaluable tool owing to its futuristic way of exploring real-time data to predict the availability and optimal use of parking spaces. Some of the ML algorithms adopted are regression analysis, classification, and reinforcement learning, facilitating intelligent parking systems that forecast peak occupancy, transport drivers to available. space, and boost resource allocation. The state of IoT coupled with ML has markedly revolutionised vehicular parking by placing intelligent architecture into sensors and smart devices through the development of a smart park system whereby these motion sensors effectively assess space occupancies to be able to create a live analysis of flow per area. The smart park system, therefore, helps in the alleviation of congestion, fuel risk response time, and users' satisfaction experience. IoT-enabled sensors, including but not limited to ultrasonic sensors and infrared detectors installed in parking spaces, communicate whether a vehicle is parked, sending the status data to a central system via LoRaWAN or Wi-Fi networks. The cloud processes that information so that the parking systems update their availability, informing other users if someone parks illegally or if other forms of anomaly arrive on the space. The work field provides the users with a mobile application that makes it easier for them to know their status in real-time, permit reservations, and help them locate free parking lots using GPS directions. Integrated payment systems provide even more ease in payments. Automated access control systems check entry and exit using RFID, QR codes, or license plate recognition systems, ensuring access to reserved spaces for authorised users only. Real-time parking availability is displayed, while alerts notify the user when their parking reservation is due to expire.

A typical smart parking system integrates advanced functions to support sustainability and security through dynamic pricing by changing rates based on demand and proximity to important campus sites. It also features special parking zones dedicated towards electric vehicle use and built-in charging stations furthering these green initiatives. Intelligent video surveillance cameras and alarm systems aided security in monitoring activities, providing reports on breaches linked to unauthorized use. Additionally, predictive analytics applied via AI models can calculate the chances of demand during peak hours lending to improved anticipatory management and parking usage. With the introduction of ML and IoT-based options for parking, these improvement options form efficiency, sustainability, and user satisfaction. They provide predictive modeling leading to wiser resource allocation, reduced congestion, and smoothening of access control. Further, real-time data analytics permit adaptive responsiveness, hence optimizing operational effectiveness with the least environmental cost.. The integration of smart parking systems will thus facilitate the smooth and intelligent as well as environmentally-friendly parking experience towards decongesting rush hour traffic bottlenecks on campuses.

2. Related Work

[1] Pavement markings are of significant importance in transportation systems in that they direct not only human drivers, but also automated vehicles. Correct identification however depends on proper feature extraction. Historically, approaches have relied on the use of straight images and thus ignored the potential of omnidirectional images. This paper explores and presents three new feature extractors that have been developed for the purpose of this study for panoramic image datasets. Concerning the integration of edge and intensity distribution characteristics, the proposed technique is more successful than others techniques, especially in road markings detection classification and localization, where the improvements are very remarkable. These results demonstrate the necessity of creating special purpose systems for Omni-directional images in intelligent transportation systems to improve safety and efficiency of road travel.

[2] This study presents robust lane marking detection method based on Random Finite Set prior. It does so by classifying lane markings to random composition distributions, which permits to work with poor data such as occlusions, varying light conditions and noise artefacts. The accuracy and reliability of the extraction is enhanced by the combination of extractive and probabilistic models. The evaluation results on different datasets show its good results, which is a remarkable progress with respect to autonomous and intelligent navigation vehicle systems.

[3] This research introduces a unique method for detecting parking slots using the Equivalence Sphere method in conjunction with Progressive Probabilistic Hough Transform (PPHT). The Equivalence Sphere approach converts the parking space into a spherical representation, which provides a detailed understanding of the slant and boundaries of the slots. The integration of PPHT to the approach enables the identification of lines and their boundaries efficiently and effectively without incurring high costs regarding computation. The approach resolves some of the issues inherent in the perspective such as distortions and occlusions making it possible to detect the parking slots correctly in any situation. Tests on actual datasets exhibit the high accuracy and reliability of the system, hence its viability for use in intelligent parking systems as well as autonomous vehicles. This method marks a significant improvement in the area of research that deals with the navigation and guidance of the parked vehicles.

[4] This paper proposes a novel approach to multiple lane detection using an omnidirectional camera and anisotropic steerable filters (ASF). An omnidirectional camera provides a panoramic view and rich contextual information about the road, while ASF enhances features along the lane marking graphs in different angles and scales. The method overcomes problems of lane curvilinearity, and non-uniformities of the road surface with high precision and tolerance to multiple lanes being detected. Experiments showed that the method is more efficient in lane detection than classical methods, achieving even better results in real life driving scenarios. In this case, this presents an advantage for self-driving cars by enhancing lane detection mechanisms making it safer to maneuver between lanes.

[5] This research paper shows a lane detection algorithm that employs the Randomized Hough Transform (RHT) to analyse road images in a more effective way. According to the traditional Hough Transform, RHT addresses the issue of computational load by using random edges from an image and only searching for the appropriate segments. The System addresses such issues as noise, cutting, road conditions, and others which other systems fail to resolve in their ability to detect lanes with high precision. Results of the experiments show its superiority in both robustness and speed over the conventional ones, which makes it applicable in practice for mobile robots and Object-oriented systems - ADAS.

[6] In this paper, a solution to the problem of accurate positioning of autonomous vehicles is presented in the form of noise models of features of road surface markings acquired using multiple cameras. Road stripe features are modeled as stochastic shapes in order to capture possible degradation due to external effects such as blemishes, light conditions and obstructions. In addition, it facilitates the detection of features as well as improves the spatial accuracy owing mainly to the fact that multiple cameras provide a fuller view of the roads. When these advanced features are combined with advanced probability-based algorithms, the system provides a high level of accuracy for vehicle positioning. The experimental results verified the effectiveness of the proposed method, making it an important enhancement in self-driving systems in demanding driving situations.

[7] This article presents a solution for recognizing parking spots for self-parking vehicles based on height and salient-line probability maps as used in the existing research. Such maps help in the identification of the potential regions in three-dimensional space while the focus-line maps helps in identifying focus-lines and their corresponding features such as curbs or parking lines. The integrated strategy allows for proper recognition in aggressive conditions such as low light, blockage and messiness. Testing conducted on actual datasets proves the method to be accurate and speedy which is likely to improve autonomous valeting systems and the parking navigation system's overall efficiency.

[8] This research focuses on the development of a parking space detection system for a parking assistance system without relying on cameras. A simple parking assist system employs ultrasonic sensors, which measure distance by emitting sound waves and determining the distance of an object based on the time taken for the echo to return. It is inexpensive and effective with a good range of performance across different conditions such as low light or obstructed views. Experimental results demonstrate that the accuracy of the proposed approach in detecting the parking lots is sufficiently high for it to be considered as a realistic solution for contemporary vehicles. This method improves the convenience of parking lots for drivers.

[9] This study presents a low-cost driver assistance system based on the use of ultrasonic sensors for congested traffic navigation. Ultrasonic sensors use sound waves to detect the presence of obstacles or cars and give updated information about the distance to the objects to the driver. The system makes it possible to maneuver safely even in small distance and within dense traffic without the risks of collision. Its low-cost and flexible design encourage most people to use it. Experimental evaluations ascertain its dependability and resolve issues making this equipment useful for improving safety of drivers and stress levels in built up areas.

[10] The current research aims at incorporating ultrasonic sensors for parking space management in contemporary parking assist systems. Typically, Ultrasonic Sensors sends out sound waves and studies the echoes so as to determine the obstacles and free parking spaces respectively. The approach is acceptable and efficient, operating well under different levels of illumination and environmental settings. The results obtained from the experiments show a high level of precision in the detection of the spaces, providing a viable solution for the integration of sophisticated parking assisting technology into vehicles to improve safety and ease of the driver.

3. Proposed System

This study elaborates on an advanced, machine learning-driven smart parking system, which shall enhance campus mobility, optimise space utilisation, and minimise congestion. By integrating IoT-enabled sensors, high-resolution cameras, and real-time data analytics, the monitoring of parking occupancy and traffic is done to continuously assess their conditions. Such machine learning models, which include regression, deep learning, and reinforcement learning, could be adapted to predict parking availability based on historical trends, time of day, and dynamic traffic conditions. The result of such a prediction enables a great reduction in search time, brings congestion under control, and improves user experience. Also, AI-driven clustering will carry out optimisation for space allocation and eliminate inefficient parking patterns, allowing for maximal space utilisation. Complementary to an advance in effectiveness is the addition of smart meters, automated ticketing, and dynamic pricing to allow for an adjustment to the input of vehicles into controlled access to parking through a demand-based fee adjustment proposal. Slot detection in the proposed solution is done using computer vision with the help of the advanced object recognition models called YOLO and Mobile Net, punchy, angled at real-time monitoring and precise detection of occupied slots. The availability for this system is automated navigation assistance through mobile applications. A driver will be routed by AI to the nearest spot available. Occupancy data continuously updated with cloud-based analytics gives foresight for better space planning as well as congestion control. Access control, based on blockchain, raises security to a greater extent in that it blocks unauthorised parking, while IoT surveillance monitoring keeps an eye on the situation to apply policy. With ongoing learning comes adaptation and automated refinement of predictions, granting sustained stability into the reliable long term. By merging AI, IoT, and predictive analytics, this solution transforms campus parking into a self-configuring intelligent ecosystem with increasing efficiency, reduced emissions, and parking as a seamless experience for the users.

4. Methodology

Methodology for Car-Free Space and Parking Slot Detection Using YOLOv11, the methodology used to optimize space management of campus parking and congestion mitigation using Machine Learning (ML) has various stages and each of which is aimed at ensuring the efficient collection, examination, and application of data concerning prediction of parking availability and directing vehicles.

Data Collection: Image/Video Acquisition: Capture images or videos of the parking lot with highquality cameras installed at appropriate angles.

Dataset Preparation: Collect images of parking lots with different conditions (day/night, rainy/sunny). Annotate images with parking slot boundaries and statuses (occupied/free) in YOLO format (class_id x_center y_center width height).

Data Pre-Processing: Resize the images to the input size that the YOLOv11 would have, for example 640x640 pixels, for faster processing. Augmentation: Rotation, flipping and varying brightness transformations are applied on inputs to make the model stronger. To enhance the generalization ability of the YOLOv11 model and ensure its effectiveness across various real-world scenarios, we employed several data augmentation techniques during the training phase. These augmentations simulate diverse environmental conditions, lighting variations, and object orientations, thereby enabling the model to learn more robust features that improve its performance in unpredictable, real-world situations. The following augmentations were utilized :
Image augmentation: We applied these augmentations to simulate a wide range of real-world scenarios, including changes in lighting, weather, object orientation, and partial occlusions. This greatly improved the generalization of the YOLOv11 model, enabling it to better detect parking spaces and vehicles in various environmental conditions, thereby enhancing its robustness and accuracy in live applications

To develop a mathematical model **for the** Campus Parking System using YOLO**, we** can formulate it in terms of vehicle detection, parking spot availability, and decision-making based on real-time data. Here's how we can approach it: YOLO is applied to detect vehicles in real-time video frames. The system continuously evaluates whether a vehicle is present in each parking spot using the following steps

Frame Capture: At each time t, the system receives a video feed from the camera. The video frame contains NNN parking spots

Frame Capture: At each time t the system receives a video feed F(t) from the camera. The video frame contains NNN parking spots. Object Detection: YOLO processes the frame (t)F(t) and identifies vehicles by predicting bounding boxes around detected objects. The system then maps each bounding box $Bi\ (t)$B(i) (t) to a specific parking spot

$$D_i(t) = 1 \text{ (vehicle detected in spot i)} \tag{1}$$

The system can also optimize the parking process by helping drivers find available spots based on real-time data. Let's model the parking guidance algorithm that directs users to the nearest available spot. d(i,j) be the Euclidean distance between the user's current position iii and parking spot j Available={Pj|Sj=0} be the set of available parking spots The nearest available spot Pnearest can be found by minimizing the distance function (1), (2), (3)

$$P_{nearest} = arg_{P_j \,\epsilon\, P_{available}} \min d(i,j)$$

Where $$A = \frac{True\ Positives}{True\ Positives + False\ Positive + False\ Negative} \tag{2}$$

True Positives are parking spots correctly identified as occupied.

False Positives are parking spots incorrectly identified as occupied

False Negatives are parking spots incorrectly identified as empty

Real-Time Latency L

$$L = \frac{T_{current} - T_{\ last\ update}}{N} \tag{3}$$

Where T

Total T Total is the total time the system runs in seconds, and the number of detections per second is how many vehicles can be detected per unit time

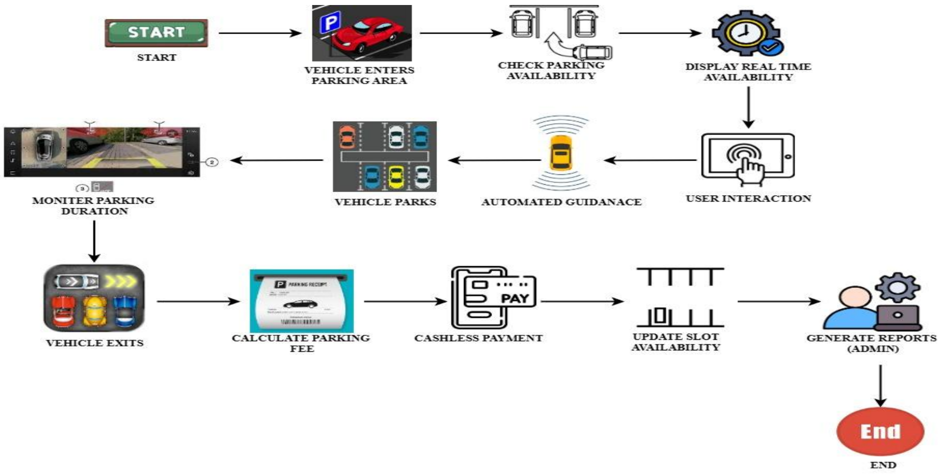

Fig.1 Yolov11 model training

Dataset: The current research dataset includes three datasets, the PASCAL VOC dataset, the COCO dataset, and the PKLot dataset. PASCAL VOC and COCO data sets are the common data sets used for object detection. These data sets contain 20 categories and 80 categories, respectively. This experiment only utilizes three data sets, namely, car, bus, and truck. The PKLot dataset, provides an image dataset for parking space classification. The data used in this paper is a picture of the parking lot of the Pontifical Catholic University of Parana (PUCPR) in Brazil. The PKLot dataset PUCPR is included in different days. Images in different lighting conditions, including sunny, rainy, and cloudy conditions. It provides the original image and the corresponding annotation file.

The architecture of YOLOv11 represents a major step forward compared to previous versions, especially YOLOv8. With a focus on enhancing both computational efficiency and detection accuracy, YOLOv11 is tailored for real-time tasks like vehicle detection, where speed and precision are paramount The backbone of YOLOv11 is central to the model's ability to extract meaningful features from an input image at multiple scales. It consists of a series of convolutional layers and custom-designed blocks that generate feature maps at various resolutions. The backbone uses the C3k2 block for improved efficiency and retains the Spatial Pyramid Pooling Fast (SPPF) **block** from earlier versions. The introduction of the C2PSA block further improves the model's focus on specific regions of interest within the image, making it better at detecting small and partially occluded objects.
Convolutional Layers: The architecture begins with convolutional layers that progressively down sample the image, reducing its spatial resolution while increasing the depth of feature maps. These layers are designed to capture progressively higher-level features from the image

Conv**1**: Applies a 3x3 convolution with 64 filters and a stride of 2 to down sample the input image.

Conv2: Follows with another 3x3 convolution, this time with 128 filters, further reducing the spatial resolution. SPPF and C2PSA Blocks: The SPPF block spatial pools the features at different scales for the model to gather context information at multiple resolutions. In turn, the C2PSA block applies spatial attention that causes the model to pay attention to the most relevant features hence increasing detection accuracy in object detection where the objects are small or occluded.

4.1 Neck

The neck of YOLOv11 is responsible for aggregating feature maps from different layers and resolutions, ensuring that they are suitable for object detection. YOLOv11's neck incorporates the C3k2 block to improve the speed and efficiency of feature aggregation. Feature Aggregation: The neck applies upsampling to feature maps from lower layers, followed by concatenation with higher-resolution feature maps. This helps the model combine detailed information from multiple scales. Feature Upsample: Upsampling is applied to the feature maps to increase their resolution, allowing the network to handle fine-grained details. Feature Concat: The upsampled features are then concatenated with lower-resolution features to maintain context across various scales.C3k2 Block in the Neck: After concatenation, the C3k2 block processes the aggregated features efficiently. This ensures that feature maps from different layers are merged effectively without increasing computational load significantly. Spatial Attention: The incorporation of the C2PSA block in the neck helps YOLOv11 focus on the most relevant areas of the image. This is particularly important in environments where there are overlapping objects, as it allows the model to identify and prioritize the most important regions for detection.

4.2 Head

The head of YOLOv11 is responsible for generating the final predictions, including bounding boxes, class labels, and confidence scores. Its outputs predictions at multiple scales to account for objects of different sizes, making the model versatile in detecting both large and small vehicles.

Detection Layers: YOLOv11 employs detection layers at three different scales—P3, P4, and P5. Each scale processes feature maps of different resolutions, allowing the model to detect objects of varying sizes effectively . P3: Detects smaller objects by processing low-resolution feature maps.P4: Focuses on medium-sized objects with higher-resolution maps.P5: Targets larger objects using the highest-resolution feature maps. Each detection layer generates bounding boxes, class labels, and confidence scores, ensuring that YOLOv11 can accurately localize and classify objects in the image. Overall, YOLOv11's architecture integrates efficient feature extraction, aggregation, and detection, with improvements in computational efficiency and accuracy. These advancements make it particularly well-suited for tasks like vehicle detection in real-time applications, where both speed and precision are , equation (4)

$$x_{normalized} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{4}$$

Supervised Learning (Classification for Availability Prediction): Supervised learning employs the use of various algorithms such as Decision Trees or Support Vector Machines (SVM) for determining the availability of parking spaces. The availability prediction logistic regression classification equation is (5) :

$$P(y = 1|X) = \frac{1}{1+e^{-z}} \tag{5}$$

4.3 Clustering for Unsupervised Learning

In instances where labelled data is not accessible, one can resort to unsupervised techniques such as K-Means clustering. The aim is to reduce the total distance of each point from the center of its assigned cluster, by squaring the distances. The equation for K-Means objective function is (6):

$$J = \sum_{i=1}^{N} \sum_{K=1}^{K} r_{ik} \; ||x_i - \mu_k||^2 \tag{6}$$

4.4 Reinforcement Learning for Dynamic Optimization:

Reinforcement learning involves an agent (the parking system) performing a series of actions (namely directing cars to their respective parking spots) in order to achieve the maximum possible long-term reward (which is minimizing the time spent in searching for parking). The equation that is generally referred to as the Bellman equation, which is used to update Q-values in a Q-learning system, is (7) :

$$Q(s,a) = Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right] \tag{7}$$

4.5 Traffic Flow Prediction (Regression Models)

Regression models including linear regression can be applied for predicting the traffic flows as well as the volume of parking. A linear regression model for predicting traffic flow y is stated as (8) :

$$\boldsymbol{y} = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n + b \tag{8}$$

4.6 Long-Term Demand Prediction (Time Series Forecasting)

In order to forecast the requirement of long term parking, one can deploy time series forecasting models viz. ARIMA, LSTM etc. The prediction equation of the ARIMA model is defined as (9) :

$$\boldsymbol{y_t = c + \sum_{i=1}^{p} \emptyset_i y_{t-i} + \sum_{j=1}^{q} \theta_j \, \epsilon_{t-j} + \epsilon_t} \tag{9}$$

4.7 Performance Evaluation (Accuracy Metrics)

The performance of the parking prediction model can be evaluated using metrics like accuracy, precision, recall, and F1-score equation (10). For a binary classification problem (e.g., predicting parking availability), the F1-score is calculated as:

$$F1 = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{10}$$

5. Result and Discussions

Highly predictive of parking occupancy in a college campus garage, random forest, and decision trees (linear regression and SVR as well) and yolov11 were among the evaluated models in the comparative analysis with reference to strength-weakness analysis.

5.1 Regression analysis

The machine learning models were actually explored with continuous hourly occupancy, revealing differences in performance and appropriateness of each model. The figure 2 presents the R^2 score of the models before the hourly occupancy pre-processing. Octal occupancy was studied as a continuous variable in relation to the performance metrics and applicability of the machine learning models. One can see the R^2 score of the models prior to pre-processing the hourly occupancy in figure 1.

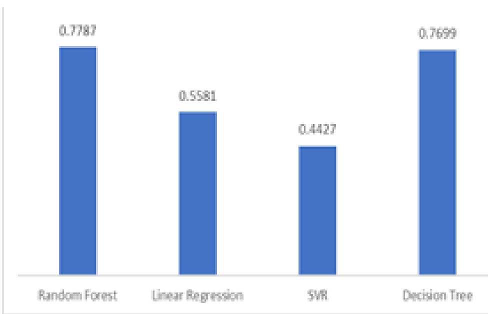

Fig.2 R^2 score of models

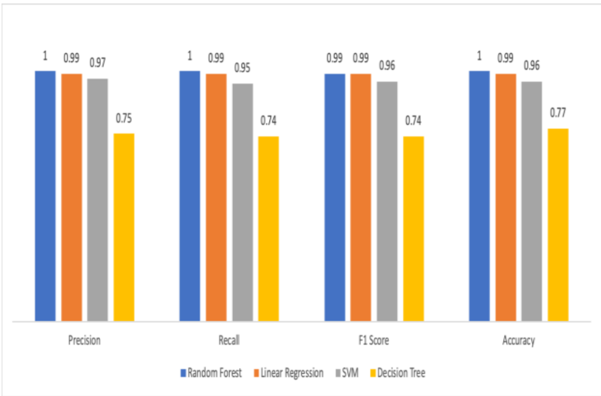

Fig 3. Results of prediction models

5.2 Classification analysis

The bar chart in figure 3 and 4 makes a comparison for four machine learning models (random forest, linear regression, SVM, and decision tree) on four performance-based metrics- precision, recall, F1 score, and accuracy. In sum, random forests and linear regression did well on some metrics, which indicates their worth as models for the particular dataset. SVM also performed really well, especially in recall and the F1 Score. While still showing good performance, the lagging decision tree model needs some fine tuning to really improve recall but may do better on precision and overall accuracy. The findings suggest that the types of plans related to advanced strategy traffic optimizations and congestion management significantly improve mobility. Intelligent Traffic Management Systems (ITMS) greatly reduce travel delays by flexibly adapting traffic signals to real-time data changes.

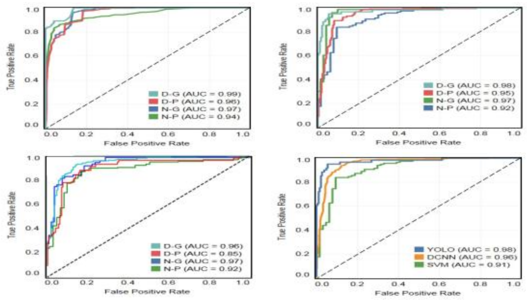

Fig 4. ROC curves based on different prevailing conditions derived from YOLO, DCNN, SVM and combined all conditions for each algorithm

The real integration of alternative modes of transportation, such as carpooling and public transit, showed measurable improvement in terms of decreased occurrence of usage by single-occupancy vehicles, thus improving the congestion. Smart infrastructures and data-driven policies enhanced the traffic flow and safety. Furthermore, emissions decreased through lesser idling periods. But the findings have some challenges, such as high initial costs and public adoption. Thus, congestion management advocated effective sustainability and efficient transportation systems.

6. Conclusion

To conclude, improving campus parking using machine learning and decrease congestion as a result is a response to the growing problems of many universities as well as urban planners. Machine learning techniques including predictive analytics, classification, and reinforcement learning techniques may be used to determine curb space occupancy, control the number of parked cars, and ease traffic congestion respectively. However, habiting these models machine learning incorporates collected input information from real time systems like sensors, G P S, and even mobile phones to study the movement of cars, their waiting time and occupancy levels giving room for easing space congestion and improving movement of cars. In additional these systems can be implemented to be implemented to changing environments which makes them very flexible and scalable as well. The introduction of machine learning in parking management systems can help lower traffic jams, improve on the campus activities and aid the efforts of sustainable development by reducing emissions produced by waiting cars. Also, such systems may prove to be useful in ensuring future infrastructure improvements. Nevertheless, there are still concerns regarding issues such as data collection, user privacy as well as system integration, but the advantages of introducing machine learning to improve campus parking services are greater than these concerns. Upgrading technology means more sophisticated and better intelligence in solving issues such as congestion and parking due to internal or external factors.

7. Future Enhancement

Future enhancements for optimizing campus parking through machine learning could revolutionize the parking experience. Integrating autonomous vehicles with machine learning models could enable these vehicles to autonomously search for and park in available spaces, reducing congestion. Additionally, real-time dynamic pricing, powered by ML, could adjust parking fees based on demand, encouraging drivers to park in less crowded areas. Synchronizing parking space detection with smart traffic signals could optimize traffic flow by directing drivers efficiently to available spots, further minimizing congestion. Advanced predictive analytics, incorporating historical data and factors like weather or events, could offer more accurate parking availability predictions, helping drivers plan ahead. Integrating these systems into mobile apps could provide personalized recommendations, real-time notifications, and parking reservations. Machine learning could also support parking space-sharing models, utilizing underused spaces during off-peak hours. Finally, linking parking systems with IoT devices and campus infrastructure could create a seamless, multimodal transport solution, optimizing space usage and reducing congestion.

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