SMART PARKING SYSTEM FOR TRACING WRONGLY PARKED VEHICLES & AVAILABLE PARKING SLOT RECOMMENDATIONS

Project report submitted in partial fulfilment of the requirement for the degree of Bachelor of Technology

in

Computer Science and Engineering/Information Technology

By

Aditya Srivastava (191426)

Under the supervision of

Dr. Shubham Goel
Assistant Professor, CSE

to

Department of Computer Science & Engineering and Information Technology
Jaypee University of Information Technology Waknaghat, Solan-173234, Himachal Pradesh

CANDIDATE'S DECLARATION

I hereby declare that the work presented in this report entitled " Smart parking system for tracing wrongly parked vehicles & available parking slot recommendations " in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology in Computer Science and Engineering/Information Technology** submitted in the department of Computer Science & Engineering and Information Technology, Jaypee University of Information Technology, Waknaghat is an authentic record of my own work carried out over a period from July 2022 to May 2023 under the supervision of Dr. Shubham Goel, Assistant Professor Computer Science and Engineering/ Information Department. The matter embodied in the report has, not been submitted for the award of any other degree or diploma.

Aditya Srivastava (191426)

This is to certify that the above statement made by the candidate is true to the best of my knowledge.

Dr. Shubham Goel
Assistant Professor
Computer Science and Engineering/ Information Department
Dated:

ACKNOWLEDGEMENT

To begin, we would like to express our heartfelt gratitude to almighty God for his heavenly grace, which enabled us to successfully complete the project work.

We are extremely grateful and wish to express my deep gratitude to Supervisor **Dr. Shubham Goel, Assistant Professor,** Department of CSE & IT Jaypee University of Information Technology, Waknaghat. His never-ending patience, intellectual direction, persistent encouragement, constant and vigorous supervision, constructive criticism, helpful suggestions, and reading numerous versions and revising them at all stages allowed this project to be completed. We would like to express our heartiest gratitude to Dr. Shubham Goel**,** Department of CSE & IT, for his kind help to finish our project.

We would also like to express our gratitude to everyone who has assisted us in making this project a success, whether directly or indirectly. In this unusual scenario, we'd like to express our gratitude to the different staff members, both teaching and non-teaching, who have provided us with valuable assistance and assisted our project. Finally, we must express our gratitude for our parents' unwavering support and patience.

Aditya Srivastava (191426)

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ABSTRACT

At the present age, with the onset of economic boom, the number of vehicles on the roads nowadays is constantly increasing. Consequently, finding a parking spot to park a car can sometimes become a lot more time consuming and stressful but will increase even more in the coming future. Current trends suggest getting a proper parking spot at the proper location and on schedule can not only improve efficiency while out for work, shopping or other exclusive activities but also curb the wastage of fuel and reduction in pollution caused to cruising at lower speeds. Thus, recommendations for viable parking spots enable users to have a hassle-free experience. By reducing cruising time and congestion and, in turn, aid in reducing pollution, fuel consumption and increasing parking revenue in smart cities. Therefore, for building smart cities, reliable and fast information on parking availability and occupancy has become essential. Recommendations help users to decide whether the products and services are worth their money and time. The knowledge of availability of the parking spaces can help the users to make their decisions by planning their trip according to the congestion levels. Additionally, vehicles that are parked illegally, taking up more space than is necessary contribute to the current shortage of parking spaces Thus, as the machine or system learns via practise and evaluating the data, the work of determining whether a journey is worthwhile for the user or not can be entirely transformed and automated utilising the algorithms. By this project, we aim to propose a system that assists drivers to find parking space and reduce traffic congestion.

Chapter 01: INTRODUCTION

1.1 Introduction

The problem of parking is a significant issue in cities globally, which can lead to frustration for both drivers and parking lot operators. Searching for a parking spot can be a stressful and time-consuming task, particularly during peak hours, and this may result in congestion, pollution, and safety risks. Furthermore, improperly parked vehicles can create inconvenience and safety hazards for other drivers and pedestrians.

Effective management of parking spaces is crucial for viable urban planning and development. For projects like smart cities, the aim is to digitise every step of the individual be it travel, banking, entertainment, etc. Thus, provide people with more robust, sustainable and environment friendly solutions to problems like traffic congestion, parking occupancy recommendation and illegal parking detection.

Sustainable urban planning and development depend on effective parking lot management. The objective of projects like building smart cities is to digitise every facet of people's lives, including travel, banking, and entertainment, among other things. By using this strategy, people can find solutions to issues like traffic congestion, increasing parking occupancy, and spotting unlawful parking that are more durable, sustainable, and environmentally friendly.

Cities also employ smart parking technologies as a means of economic development. First of all, these systems can shorten the time it takes for cars to find a parking space, which can minimize traffic congestion, fuel consumption, and environmental pollution. Second, shorter parking spot idle times translate into more parking revenue if drivers can locate a spot quickly. Smart parking systems can also assist in identifying illegal parking, which may result in a fine. The flow of data and urban mobility may both rise as a result of fewer cars cruising for parking spaces, increasing the city's capacity.

Cities are using smart parking technologies more and more as a means of stimulating the economy. First off, these systems can cut down on the time drivers spend looking for parking, which will reduce traffic jams, fuel consumption, and environmental pollution. Second, if cars can find a spot quickly, shorter idle times for parking spots lead to higher parking revenue. Additionally, smart parking systems assist in identifying illegal parking, which may incur a fine. The flow of data and urban mobility may improve by reducing the number of vehicles circling seeking parking places, improving the city's capacity.

The lack of facilities, such as an ideal parking occupancy prediction system, which would significantly lighten the burden on the transportation authorities, contributes to the problem of cruising congestion. Other contributing factors include ineffective parking pricing, inappropriate information systems, and insufficient parking availability. To meet the rising demand for parking, accurate forecasting of approved unoccupied parking spaces and their costs based on a variety of characteristics is necessary.

The lack of amenities like a precise parking occupancy prediction system, which might lessen the load on transportation authorities, is one of the causes of cruising congestion. Limited parking availability, poor information systems, and inadequate parking charges are additional contributing problems. There is a need for exact forecasting of the number of available parking places and their associated costs, which can be established based on a number of parameters, in order to handle the rising demand for parking.

IoT and AI technologies are the foundation of smart parking. It provides real-time access to parking occupancy and availability, forecasts peak and off-peak hours, creates dynamic pricing based on traffic, and allows parking operators access to large amounts of real-time data and reporting. The concept of Smart Mobility, is a subpart of the much larger smart city project where it promotes more efficient, economical & environment friendly transportation. Hence, making the trip flexible, clean, effective and thus safe and pleasant for the people. This hassle-free and faster approach is a smart technology solution to provide for smart city infrastructure and the transport ecosystem.

Smart parking solutions will substantially aid the development of smart cities and increase the efficiency of local governments. Smart parking will be a growing business that is essential to the success of smart cities given the ongoing urban growth both today and in the future. Numerous options will be provided by smart parking to let communities provide their residents with services that will help them save time and money. The same methods will also help to lessen traffic and improve the efficiency of the city.

The use of intelligent parking technologies will considerably advance the concept of smart cities and improve the efficiency of local governments. Smart parking will emerge as a crucial and expanding business to support the success of smart cities in the present and the future due to the ongoing growth of metropolitan areas. Smart parking provides a range of choices that enable municipalities to provide their people time and money-saving services while easing traffic and enhancing overall city efficiency.

1.2 Problem Statement

Both sensor-based and vision-based smart parking technologies prove to be effective in providing solutions but from a scalability and cost perspective, a vision-based system would be desirable. Vision-based systems prove to be a better option due to their ability to recognise obstacles and vehicles. These characteristics can be leveraged to create a more complex system. The majority of these techniques rely on specific visual tactics created for the situation, which makes them inapplicable to several parking lots.

This work provides a widely applicable, useful, and scalable method for real-time parking occupancy detection built on deep convolutional neural networks (CNN). The following is a recommended strategy for parking detection, CNNs are a deep learning approach that can be applied to address problems that need a high level of abstraction to fix issues, such as vision.

Vision-based smart parking systems are preferred due to cost and scalability, although both sensor-based and vision-based technologies have proven effective in providing solutions. A more complex system can be developed by using vision-based systems, which are advantageous as they can identify obstacles and vehicles. Nevertheless, several of these methods depend on particular visual strategies intended for a specific parking lot, rendering them inappropriate for other parking zones. A method that utilizes deep convolutional neural networks (CNNs) is presented in this study for detecting real-time parking occupancy, which is widely applicable, practical, and scalable. Vision-based parking detection can be achieved using CNNs, which are a deep learning technique capable of solving problems that demand a high level of abstraction.

Additionally, few research papers consider the problem of vehicles breaking parking rules and regulations, which causes congestion in the parking lot due to irresponsible and irregular parking. The majority of research papers concentrate on methods for detecting available parking places. The major goal of this project was to create an integrated system that tracks and recognises improperly parked vehicles in addition to recommending to users the closest accessible parking spot. Most research papers propose solutions for vacant parking spot detection but a very few consider vehicles that violate parking space rules and regulations. Thus, creating congestion in the parking lot due to irregular and irresponsible parking. The main focus of this project was to build an integrated system that can recommend parking space which user is nearest to and trace wrongly parked vehicles.

1.3 Objective

Objectives of the project:

- To create a working prototype of a dynamic smart parking system that can identify any available parking spaces on a lot as well as any vehicles being parked illegally.
- If a system could identify vehicles that were being parked illegally, the effectiveness of using parking spots could be increased by either notifying the owner of the vehicle or a parking enforcement officer.
- The main objective of this project is to offer sustainable parking options for urban areas in order to improve traffic flow and lessen gridlock.
- On-street parking charging systems are less dynamic and may not account for rapid changes in circumstances, which can result in inappropriate street congestion and ineffective on-street parking space management.
- The absence of real-time or forecasted information about the occupancy levels of parking lots. Cruising and searching times may be reduced with advance knowledge of occupancy levels.
- Knowledge of parking costs in advance (if expensive or do not fit into regular budget of the parkers) may encourage the use of public transportation over private transportation

- Automatic number-plate recognition (ANPR) is a technique that reads car licence plates using optical character recognition on photographs to produce vehicle location data. It can be utilised in many different public places to perform a range of tasks, such as automatic toll tax collection, parking lot systems, and automatic vehicle parking systems.

1.4 Methodology

In these experiments, two main datasets are utilised. Each had a different way effectively labelling, solving, or dealing with problems. And each demonstrated the single-shot detection method used in this project's accuracy as well as its limitations.

The CNR dataset includes parking lots with fixed camera angles and generally good resolution.

Behind other vehicles, trees, or other impediments, cars may adopt alternative stances or experience slight occlusion. Further back in the image, cars are smaller and may have fewer meaningful features extracted than those in the foreground. The CNR dataset does not, however, identify each and every vehicle in an image; in fact, a set of ground truth bounding box labels frequently omits a number of vehicles per parking lot image. The CNR dataset's bounding box annotations do not completely enclose the automobiles, which is another flaw.

Cars may occasionally take alternative places or experience partial obstruction as a result of being blocked by other vehicles, trees, or other obstructions. The size and number of distinguishable features of cars in the background of a photograph may differ from those in the front. Additionally, because some cars are frequently excluded from the ground truth bounding box labels for each parking lot image, the CNR dataset might not be able to detect every vehicle in an image. The CNR dataset's bounding box annotations may not completely enclose the cars, which is another drawback.

The fourth detection layer, the most recent YOLO version three, adjusted image sizing, and all evaluated permutations of models are covered in the detection findings. The accuracy was determined based on the prediction error in all of the accuracy % charts.

i.e., Accuracy = (1 - |predicted - actual| / actual) x 100

The robust detection algorithm based on deep learning techniques with good accuracy is what the suggested method aims to convey. By using the provided parking lot data to train the model, the suggested method may identify a parked automobile in an image or video. This demonstrates that the success rate of convolutional neural networks will be comparable to that of earlier, more conventional techniques. When the camera is installed by the user, the system will be able to detect the presence of cars in the parking lot based on the direction of the camera.

At our Institute, we gathered pictures of the five parking lots on the two opposite sides of the administrative building and of others on the two opposite sides of the hotel. The temporary security camera, which is positioned above the Hom Krun coffee shop and at the hotel in a way that it covers every parking space, is used to gather the photographs. The VLC media player, via which the movies are captured, can be used to access this camera. Every day, the videos are shot under various lighting circumstances. From the video footage, we took pictures of the two distinct parking lots. We trained the model using 900 photos we obtained from the parking lot.

We labelled photos with the labels "Empty" and "Occupied," respectively.

We used the open-source LabelIng software to label the image. Software that is user-friendly makes it simple to annotate photographs. First, the programme some predefined classes that need to be updated to match our classes,

The classes are "Empty" and "Occupied," respectively. The programme is configured to YOLO format, and we noted in the pictures when there isn't a car in a specific position.

"Empty" and "Occupied" where there is a car. information about the boundary boxes

The two classes we annotated are saved in the txt format, which will save

the bounding boxes' coordinates.

1.5 Technical Requirements

- Python Integrated Development Environment like
  Anaconda (Jupyter Notebook), PyCharm
- Libraries including Scikit learn, OpenCV, YOLOv3,
  YOLOv5 OpenCV, PyTorch, PaddleOCR, NorFair

Chapter 02: LITERATURE SURVEY

This section primarily attempts to provide a look at the state-of-the-art in terms of what smart parking options are available now and what their benefits and drawbacks are. We viewed the idea of numerous solutions being provided based on the used car identification method in the context of smart parking as a smart city application. The employment of deep learning methods in conjunction with vision-based smart parking systems is then described in greater detail. Finally, we outline the privacy interests that should be taken into account when creating a vision-based solution that handles sensitive data. We used several search phrases, such as IoT AND Smart parking AND camera, IoT AND smart parking, smart parking AND camera, illegal parking AND deep learning, and to evaluate the literature on IEEE, ACM, and ScienceDirect.

Parking occupancy and availability forecasting and pricing have been identified as crucial elements in reducing traffic and time spent cruising for parking. In the last ten years, a number of parking occupancy prediction models and pricing schemes have been created to help parking management deal with a variety of issues, including traffic, long trip times, and price overheads brought on by improper parking management. The following two subsections provide a report on the work done in the field of parking prediction and pricing.

Images of cars may not accurately reflect their position due to changes in posture or partial blockages from objects like other cars or trees. In addition, smaller cars in the background could have less noticeable features than those in the foreground. Nevertheless, not all vehicles may be detected by the CNR dataset, and each parking lot image may have multiple cars that are not included in the ground truth bounding box labels. Another restriction is the possibility that the bounding boxes annotated in the CNR dataset do not completely include the automobiles.

The administration of parking lots effectively depends heavily on methods for detecting occupancy in parking spaces. The time it takes to discover an empty spot in a parking lot can be greatly reduced by knowing in real-time whether there are any available free parking spots and informing the users.

Techniques for detecting parking space occupancy are crucial to effective parking lot management. Real-time information regarding the availability of open parking spots is essential for efficient parking lot management because it can significantly minimise the time it takes users to find an empty place.

Ground sensors are frequently used in parking lots to assess the condition of the individual spaces. This calls for the installation and upkeep of sensors in each parking space, which could be costly, especially in parking lots with a large number of available spaces.

Deep CNNs make the suggested solution robust to partial occlusions that cause a disruption, the existence of shadows demonstrates an excellent generalisation in a variety of lighting conditions. In reality, the results' quality is preserved when Parking lots and many different scenarios were taken into consideration as opposed to those employed during the training period. The CNRPark dataset includes images taken on various days and in various lighting conditions, as well as instances of occlusion and shadow that make the occupancy detection task more challenging. The proposed dataset has been thoroughly and manually annotated, and it has been made available to the scientific community for developing new car park occupancy detection algorithms.

The proposed technique ensures robustness to partial occlusions, which might result in interruptions, by using Deep CNNs. Additionally, the model exhibits superb generalisation under various lighting scenarios, including the presence of shadows. Notably, even when used in parking lots and other situations not experienced during the training time, the suggested approach maintains its effectiveness. Images from the CNRPark dataset that were taken in various lighting situations, with occlusion, and in the shadow further complicate the process of detecting occupancy. Researchers looking to create new car park occupancy detection algorithms may now access the information, which has been thoroughly and manually annotated.

Convolutional Neural Networks are utilised in a Deep Learning method that is very successful for vision applications (CNN). A CNN is made up of a sizable number of hidden layers, each of which uses the input to perform calculations on the output, which is then passed on as input to the next layer. The presence of convolutional layers, which are better able to model and detect the spatial correlation of surrounding pixels than typical fully connected layers, distinguishes CNNs from traditional neural networks. The classes that the network was trained on are the final outputs of the CNN for a classification problem. On the one hand, the training step can be time-consuming and computationally expensive.

Deep Learning employs Convolutional Neural Networks (CNNs), a potent method for visual applications. In CNNs, the input is processed by a number of hidden layers, which then pass the output to the next layer. Convolutional layers in CNNs, as opposed to standard neural networks, are excellent in modelling and identifying spatial relationships between pixels. The class that the CNN was trained on is the final result for a classification task. Training can, however, be time- and money-consuming computationally.

The majority of the parking spaces nearest to the building are monitored by just one camera, however the parking spaces farthest from the structure are monitored by multiple cameras due to the angle of view and perspective of the camera module employed.

Due to the angle of view and viewpoint of the camera module used, the bulk of the parking spots closest to the building are only observed by one camera, but the parking spaces farthest from the structure are observed by numerous cameras.

Using this redundancy, we choose the confidence value of the camera that has the best view of that parking space in order to handle various obstacle problems (for instance, trees).

This redundancy allows us to tackle various obstruction problems (for example, trees) by selecting the confidence value of the camera that has the greatest view of that parking space.

Instead of using ground sensors, smart cameras offer two important benefits: reduced cost and greater versatility. A Raspberry Pi camera module costs around 80e, and an outdoor camera cabinet with pole support costs roughly the same.

Smart cameras offer two significant advantages over ground sensors: lower cost and more versatility. An outdoor camera cabinet with pole support costs about the same as an 80e Raspberry Pi camera module.

The system that we developed periodically takes a picture of a section of the parking lot and, for each parking place, uses a trained CNN to ascertain whether or not it is occupied.

Our system periodically takes a photo of a piece of the parking lot and uses a trained CNN to determine whether or not each parking space is occupied.

A mask that recognises the different parking places filters images taken by cameras. The mask was carefully constructed once and for all. Figure 1 depicts examples of masks created for two distinct cameras. Using the created masks, each frame is automatically split at runtime into the patches (the area of the original image that contains a single parking space) corresponding to the parking spaces that that camera is watching.

The captured images are subjected to a filter through a mask that identifies the different parking spaces, and the mask is meticulously created. Figure 1 displays examples of masks created for two distinct cameras. During runtime, the frames are automatically divided into patches, which correspond to the parking spaces visible to that camera, using the predetermined masks.

Many machine learning models, including ensemble, time series models, such as ARMA and ARIMA, and regression trees, support vector machines, and random forests. To date, methods for predicting parking availability or occupancy have been used. Queuing theory has been used to predict waiting times before occupancy in the parking lot in addition to machine learning techniques.

Methods for estimating parking availability or occupancy have been used up to this point. Along with machine learning techniques, queueing theory has been used to forecast the amount of time people will wait in the parking lot before it fills up.

While events, traffic, vacation time, and rains have a secondary influence, neural networks-based prediction systems for parking space availability have demonstrated the importance of a number of primary criteria, including time of day, day of the week, location, and temperature. For the Berlin pilot region, Tiedemann et al. created a parking space occupancy prediction algorithm that blends Neural Gas vector quantization with raw data chronology into data threads. Additionally, this prediction system's accuracy was enhanced by combining machine learning clustering with the original temporal relationships of the raw data. On data sets from San Francisco, California, and Melbourne, Australia, parking availability has been predicted using a variety of machine learning techniques, including regression trees, neural networks, and support vector regression.

Neural networks-based parking space availability prediction algorithms have shown the significance of a number of major criteria, including time of day, day of the week, location, and temperature. Events, traffic, vacation time, and precipitation have a secondary influence. Tiedemann et al. developed a parking space occupancy prediction method for the Berlin pilot region that combines Neural Gas vector quantization with raw data chronology into data threads. The accuracy of the prediction method was also improved by incorporating the original temporal correlations of the raw data with machine learning clustering. Parking availability has been forecasted using a range of machine learning methods, including regression trees, neural networks, and support vector regression, on data sets from Melbourne, Australia, and San Francisco, California.

Regression tree, a less computationally costly approach, achieved the highest prediction accuracy in this investigation when compared to the other two algorithms. The availability of parking spaces has also been accurately and quickly predicted using a Bayesian regularised neural network. Support vector regression, ARIMA models, and recurrent neural networks, in addition to Bayesian regularised neural networks, have also been employed in this study. The trade-off between possible forecast accuracy and a thorough temporal and spatial representation of parking spot availability has been shown using the SFpark data using various spatial-temporal clustering approaches. Parking availability has also been predicted using a multivariate autoregressive model for the cities of San Francisco and Los Angeles.

When compared to the other two algorithms in this study, regression tree, a less computationally intensive approach, produced the highest prediction accuracy. Using a Bayesian regularised neural network, the availability of parking spaces has also been promptly and reliably anticipated. In addition to Bayesian regularised neural networks, other techniques such as support vector regression, ARIMA models, and recurrent neural networks have also been used in this study. The SFpark data have been used to demonstrate the trade-off between potential prediction accuracy and a full temporal and spatial description of parking spot availability. A multivariate autoregressive model has also been used to estimate parking availability for the cities of San Francisco and Los Angeles.

2.1 Internet of Things & Smart City

Today's technology is what propels the creation of a better future, where it has facilitated successful outcomes in a variety of fields like health care, business, and education.

The Internet of Things is a notion that has garnered a lot of traction and interest in recent years (IoT). According to Pureswaran et al, the Internet of Things (IoT) is a network of devices linked to a centralized cloud with the goal of developing into a distributed many-to-many connectivity technique.

By the year 2020, there will likely be more than 25 billion devices linked to the Internet. The main cause of this is the rise in the number of modern gadgets that support the idea of the smart city and home. Today, compact, inexpensive sensors are utilized to automate a variety of processes. For instance, smart parking systems can automate the detection of open parking spaces or the ventilation process in buildings by monitoring temperature and humidity.

The lack of facilities, such as an ideal parking occupancy prediction system, which would significantly lighten the burden on the transportation authorities, contributes to the problem of cruising congestion. Other contributing factors include ineffective parking pricing, inappropriate information systems, and insufficient parking availability. When resources are limited and there are huge demands, pricing becomes very important. Therefore, Seattle's severe parking issue can be resolved by implementing an effective dynamic pricing system for its on-street parking system. To meet the rising demand for parking, accurate forecasting of approved unoccupied parking spaces and their costs based on a variety of characteristics is necessary. For establishing future predictions, which are crucial to calculating prices, pricing models should take into account both historical and present data. The issue of cruising congestion is made worse by the lack of amenities like a reliable parking occupancy forecast system, which would greatly lessen the pressure on transportation authorities. Other contributing factors include inadequate information systems, insufficient parking supply, and ineffective parking pricing. When resources are in short supply and demand is high, pricing becomes important. As a result, Seattle's urgent parking problem can be solved by introducing a dynamic pricing structure for on-street parking. To keep up with the growing demand for parking, precise forecasting of vacant parking spaces' pricing based on multiple variables is required. Price determination relies heavily on future projections made by pricing models, which should take into account both historical and present data.

Due to the population's rapid growth, parking and vehicular traffic have emerged as major concerns. Searching for parking spaces takes a lot of time in public areas with thousands of tourists. A lot of human labour is also necessary to maintain the current parking structure. Furthermore, there is no way to tell if a vacant parking space is open or not. A number of nations will implement the smart parking system. In India, Bangalore is most likely to see the implementation of this kind of parking system soon.

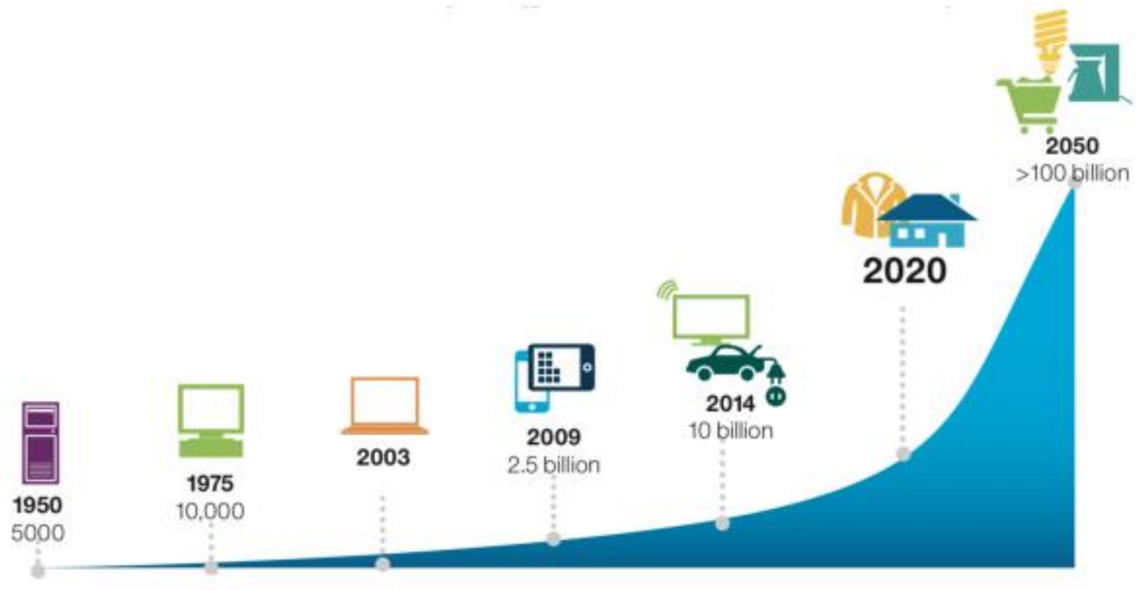

Fig. 2.1 Future Scope of IoT

AlHarbi et al. emphasise that smart cities improve cities by addressing issues and fostering a sustainable environment. The authors continue by saying that these improvements for the smart city can be made in smart parking by, for instance, lowering pollution and traffic congestion or watching for and providing suggestions for parking spots.

In-ground sensors:

The in-ground sensors of Smart Parking monitor each parking space and send the occupancy status to SmartSpot gateways. These gateways then relay the live status information to the SmartCloud platform, enabling real-time parking information to be viewed on multiple devices.

Before installation, we make sure that each sensor meets our strict functional standards, allowing them to operate with high accuracy in a variety of operational environments, and we can customize their behavior to meet the specific requirements of each parking space.

Smart Parking offers a wide range of services, including bay monitoring, car counting systems, fixed and mobile automatic number plate recognition (ANPR), and guidance signage, all based on a modular approach, for large-scale sites.

Sensors with a surface mount:

For exposed sites where core drilling into the ground might not be an option, such as thin surfaces covering cabling and services, membranes, roof tops, and wharfs, Smart Parking also provides the option of surface-mount sensors. In addition to functioning identically like their in-ground counterparts, these sensors can be equipped with a fluro collar for increased visibility in locations with heavier foot traffic.

Overhead indicator sensors:

Off-street parking management is made easy, affordable, and extremely effective with the Smart Parking overhead indicator system.

Drivers now have a completely new multi-storey parking experience thanks to this technology, which offers highly visible, color-coded LED overhead guidance indicators that are dynamically regulated by your SmartPark business rules. Users can now quickly determine whether entire rows of parking bays are available.

Every single bay transmits its current status to SmartCloud, which can then use it to generate capacity and guiding signs as well as reporting and analytics for the entire parking lot.

2.2 Object Detection using Deep Learning

Despite recent developments in deep learning, there is still tremendous room for improvement and contribution. In recent years, deep learning has been increasingly used in vision-based systems for object recognition. Deep learning operates in a way that precludes classifying the objects without a trained model. The same method can be applied to a youngster, who needs training time until they can recognise the alphabet's different characters and learn to read.

Although deep learning has made significant progress recently, there is still a lot of room for improvement and innovation. Deep learning methods are being used more frequently in vision-based object recognition systems. Deep learning cannot accurately categorise things without a trained model. Similar to how a youngster learning to read needs practise in order to recognise the various alphabetic characters, this process might be linked to that.

Convolutional neural network (CNN) can assist in effectively recognising patterns in the image while managing a vision-based solution where object recognition is required. According to Amato et al., CNN uses a sizable number of hidden layers to process input and produce a result as an output. A large number of hidden layers increase the output's detection accuracy when determining what the identified items are. Amato et al. go on to say that it can be quite costly from a computational and temporal standpoint to train a model for object classification. It takes a lot of iterations for the network to find and comprehend the layers in the neural network, hence it needs a good graphics unit to do the training.

When managing a vision-based solution for object recognition, convolutional neural networks (CNN) can help in efficiently recognising patterns in the image. Amato et al. claim that CNN processes input through a significant number of hidden layers and outputs the result. When determining what the identified items are in the output, a large number of hidden layers improve detection accuracy. Amato et al. continue by stating that training an object categorization model can be quite time and computationally expensive. The network needs a strong graphics unit to perform the training since finding and understanding the layers in the neural network requires many iterations.

Redmond et al. contrast different object identification techniques with their model, dubbed YOLOv3. The YOLOv3 model is an advancement over the YOLOv1 and YOLOv2 variants. The comparison's goal was to assess how well the various models handled inference time and effectiveness.

There are several machine learning techniques, however existing proposals have limitations. Proposals Limitations The trip's goal, the impact of parking information, heterogeneity, revenue earned, the location, weekday versus weekend, and approved versus denied parking requests are not taken into account.

Although there are many machine learning techniques, the current proposals have some drawbacks. Limitations Propositions The purpose of the journey, the effect of parking data, heterogeneity, revenue earned, the location, weekday versus weekend, and accepted versus denied parking requests are not taken into consideration.

The pricing structure is not flexible enough in terms of day-to-day and intraday scales.

The plan did not take cancellation of requests, the effect of cross-priced parking periods, the time of day, geographical considerations, parking types, parking time limits, or the day of the week into account.

The pricing system isn't sufficiently adaptable to daily and intraday scales.

The influence of cross-priced parking hours, time of day, geographical considerations, parking types, parking time constraints, or day of the week were not taken into account in the design.

The departure time, traffic jams, and occupancy-based time-varying step parking rates were not modelled in the scheme. There are missing elements like money produced, parking costs, parking types, and parking time restrictions.

The approach did not model departure time, traffic backups, or occupancy-based time-varying step parking prices. Elements like revenue generated, parking costs, parking types, and parking time limits are absent.

Using SFpark data, a variety of ML algorithms, including Decision trees, Random forests, Support vector machines, and gradient boosting, have also been used to estimate parking availability. Grid search has also been used to select the most effective model out of the group. Deep learning with Recurrent Neural Networks (RNN) was used to estimate the occupancy rate of parking spaces in Birmingham, UK. Along with RNN, this work also uses meta heuristics based on GA and ES.

2.3 YOLOv3 vs YOLOv5

The well-known object detection technique YOLOv3 (You Only Look Once version 3) is employed in computer vision. It is a deep neural network that can locate and detect objects in real-time video and image streams. A single neural network is applied to the entire image by dividing it into a grid of cells in YOLOv3, which then predicts the bounding boxes and class probabilities for the objects that are present in each cell.

In comparison to YOLOv2, YOLOv3 offers a number of improvements, such as a larger input image size, additional convolutional layers, and the use of skip connections to enhance feature representation. While real-time performance is maintained, these improvements lead to an increase in accuracy and detection performance.

The real-time object identification method known as YOLOv5, which was created by Ultralytics, is the replacement for YOLOv4. In comparison to YOLOv4, it is quicker and more accurate. Scaled-YOLOv4, a more compact and effective variant of YOLOv4, is the architecture on which YOLOv5 is built. It utilises a separate backbone network, CSPDarknet, which is faster and more efficient in using memory.

YOLOv5 is available in a variety of variations, from compact ones for embedded devices to huge models for powerful GPUs. It is capable of real-time detection of a wide variety of things, including humans, automobiles, animals, and more.

YOLOv5 is available in a variety of variations, from compact ones for embedded devices to huge models for powerful GPUs. It is capable of real-time detection of a wide variety of things, including humans, automobiles, animals, and more. A sizable dataset named COCO

(Common Objects in Context), which includes more than 330,000 photos and 2.5 million instances of objects labelled with more than 80 categories, is used to train YOLOv5.
The University of Washington's YOLOv3 and YOLOv5 object identification models were created by the same team. The main variations between the two are as follows:

Model architecture: YOLOv5 is faster and more accurate since it has a new design than YOLOv3. The CSPNet (Cross-Stage Partial Network) backbone used by YOLOv5 improves accuracy while using less compute and memory.

Performance: YOLOv5 performs better than YOLOv3 in terms of speed and accuracy. The creators claim that YOLOv5 performs at the cutting edge on a number of benchmark datasets, including COCO and PASCAL VOC.
Training: Compared to YOLOv3, YOLOv5 features a more straightforward training approach. Due to the single-stage training method used, the entire dataset is used to train the model from beginning to end. The model is first trained on a smaller dataset for YOLOv3, on the other hand, and is then fine-tuned on the entire dataset.

Size: When compared to YOLOv3, YOLOv5 is smaller. The YOLOv5 model is about 27 MB in size, compared to the YOLOv3 model's size of about 237 MB.

YOLOv3, an earlier model that has been extensively utilised, is accessible in a number of deep learning frameworks, including TensorFlow, PyTorch, and Darknet. These frameworks also support the more recent YOLOv5 paradigm.

Joseph Redmon and Alexey Bochkovskiy from the University of Washington and the Moscow Institute of Physics and Technology respectively developed YOLOv3 and YOLOv5, both of which are state-of-the-art object detection models.

Due to its high accuracy and real-time detection capabilities, YOLOv3 quickly gained popularity as one of the most popular object detection models after its release in 2018. A fully convolutional neural network (CNN) and an anchor-based approach are utilized to forecast bounding boxes and class probabilities for objects in an image. With 106 layers, YOLOv3 is capable of detecting more than 80 types of objects. The model can detect objects at different scales within an image using a feature called spatial pyramid pooling, included in it.

An improvement over YOLOv3, YOLOv5 was released in 2020. Several new features, including a new backbone architecture called CSPNet and a modified anchor box approach called anchor-free detection, are incorporated into its architecture, which is similar to YOLOv3. There are four variants of YOLOv5, namely YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x, which increase in complexity and accuracy. In terms of both speed and accuracy, YOLOv5 has been shown to outperform YOLOv3 and can detect over 80 classes of objects.

YOLOv5 is generally faster than YOLOv3 in terms of speed because of its simplified architecture and optimized code. The accuracy of the models, however, can vary depending on the dataset and specific use case. In certain benchmark tests, YOLOv5 has demonstrated superior performance compared to YOLOv3, although the variance is not consistently substantial.

Overall, YOLOv3 and YOLOv5 are both effective object identification algorithms with unique advantages and disadvantages. The precise constraints of the task at hand, such as the size of the dataset, the desired precision, and the hardware available, will determine which model should be used.

2.4 Vision-based smart parking solution

A deep CNN designed especially for smart cameras, according to Carrara et al., can be used to offer a decentralised and effective solution for visual parking lot occupancy monitoring. The CNRPark-EXT dataset is the main contribution of this work. This dataset contains 150 000 labelled images of parking spaces that are both full and vacant, shot in a variety of lighting and weather conditions. The authors use two cameras to obtain data for training from various angles and perspectives. By doing this, they may make a mask that makes it possible to crop the entire images into individual patches. The authors used both the mAlexNet and AlexNet designs from CNN.

Visual parking lot occupancy monitoring can be efficiently decentralized using a deep CNN specifically designed for smart cameras, as suggested by Carrara et al. This work's primary contribution is the CNRPark-EXT dataset. There are 150,000 labeled images of parking spaces in this dataset, which show both occupied and unoccupied spots and were taken under various lighting and weather conditions. To obtain training data from various angles and perspectives, the authors use two cameras. They may create a mask that enables them to divide the entire image into separate patches by doing so. Both the mAlexNet and AlexNet designs from CNN were utilized by the authors.

Valipour et al. provide an alternative approach for a vision-based smart parking system. The proposed system consists of three components: a camera, a server, and a front-end application.

The camera takes pictures of a parking lot and sends them to the server through the Internet or a local wireless network. a server, a database, and a detection module also an online service. It is the server's responsibility to collect and provide camera images, transfer the detection result to the detection module, and store that information in the database. The front-end application, which presents information on available parking spaces, is the third component.

Through the Internet or a local wireless network, the camera captures pictures of a parking lot and transmits them to the server. An online service, a server, a database, and a detection module as well. The server is responsible for collecting and providing camera images, transferring the detection results to the detection module, and storing that information in the database. The third component is the front-end application that displays information about available parking spaces.

Nyambal et al. present an alternative, connected solution. The dataset used consists of 782 images from two parking lots at the University of the Witwatersrand. A single parking space is depicted in each of the patches that have been created on each image. Coordinates for parking spaces are stored in a JSON. The experiment's authors trained the dataset using AlexNet and LeNet, two CNN architectures.

An alternative, connected solution is presented by Nyambal et al. There are 782 images in the dataset which were taken from two parking lots at the University of the Witwatersrand. Each image contains patches, and each patch depicts a single parking space. A JSON stores the coordinates for parking spaces. Two CNN architectures, AlexNet and LeNet, were used by the experiment's authors to train the dataset.

2.5 Camera & Surveillance

Today, cameras are mostly employed for surveillance and safety reasons, such as to determine whether someone is permitted. It's possible that individuals entered a forbidden location. In recent years, cameras have been created to perform more complex tasks, like analyzing photos and extracting meaningful information. As a result, sensitive information is frequently included in the information collected from photos, which is problematic from an ethical standpoint. Mostly used for surveillance and safety purposes, cameras are employed to ascertain whether someone is authorized. Individuals may have entered a prohibited area. Cameras have evolved in recent years to perform more complex tasks such as analyzing photos and extracting valuable information. Frequently, the information collected from photos includes sensitive information, which is problematic from an ethical standpoint.

One of the key requirements in residences, commercial, and industrial facilities is parking lot surveillance. To prevent car theft, damage, and unwanted intrusions, it is essential to have surveillance in parking lots. Modern parking management systems have adopted smart parking solutions such as automated valet parking robots, parking sensors, and parking-routing-information-systems (PRIS). Surveillance plays a crucial role in automated parking solutions, such as during the allotment of parking spaces and automated parking. Deploying highly efficient and advanced surveillance networks is certainly essential in smart parking systems. To ensure consistent connectivity and high availability for modern parking lot surveillance systems, VERSITRON offers a wide range of products.

2.6 ANPR (Automatic number plate recognition)

In some countries, License Plate Recognition (LPR) is another term used for Automatic Number Plate Recognition (ANPR). Optical character recognition (OCR) technology is used to automatically read and recognize license plate characters from images or videos captured by cameras.

Vehicle identification is required for various applications such as law enforcement, toll collection, parking management, and others, which makes ANPR systems widely used. Specialized software processes an image of the license plate captured by a camera to extract its characters. A comparison is made between these characters and a registered license plate database to check if the vehicle is authorized to access a certain service or enter a specific area.

Convolutional neural networks (CNNs) and deep learning algorithms, which can boost recognition accuracy and speed, have considerably advanced ANPR technology in recent years. As it can be used to track the movement of people and vehicles, ANPR technology also raises privacy and surveillance issues.

Automatic Number Plate Recognition (ANPR) functions by employing cameras to take pictures of vehicle number plates, which are then processed using image-processing methods to reveal the plate's alphanumeric characters. Usually, the procedure consists of multiple steps:

Image Acquisition: The ANPR system uses cameras that are either fixed or mounted on vehicles to take pictures of licence plates.

Image Pre-processing: Any distortions, noise, or reflections that can obstruct the recognition process are removed from the collected images during pre-processing. This could entail changing the contrast and brightness, adding filters, or employing image-enhancing techniques.

Plate Localization: The ANPR system employs algorithms to find and isolate the number plate within the image once the image has been pre-processed. This may entail determining the location, dimensions, and orientation of the plate.

Character Segmentation: Following localization of the number plate, the system divides up each character and extracts them as independent images.

Optical Character Recognition (OCR): The last step is identifying the alphanumeric characters on the plate using OCR algorithms. To train the system to recognise various typefaces and character styles, this can entail employing machine learning techniques.

Numerous uses for ANPR systems exist, including toll collection, parking management, and law enforcement. The ANPR system's accuracy is influenced by a number of variables, including the calibre of the camera, the lighting, and the efficiency of the character recognition and image processing algorithms.

The use of ANPR (Automatic Number Plate Recognition) technology in a smart parking system has a number of advantages, such as:

Effective parking management: ANPR technology can assist in automating the parking management process, from locating empty parking spaces to watching for vehicle entry and exit.

Increased revenue: Parking operators who use ANPR technology can better manage their parking inventory, generating more money by making the most of available parking spaces.

Enhanced security: By recognising and tracking vehicles entering and leaving the parking lot, and alerting security staff in case of any suspicious activity, ANPR technology can be utilised to improve the security of parking facilities.

ANPR technology makes it possible to route vehicles to available parking spaces quickly and effectively, which cuts down on both the time spent hunting for a spot and the level of congestion in the parking area.

ANPR technology can offer users a seamless and trouble-free parking experience with automatic entrance and exit, as well as simple payment alternatives.

ANPR technology is a crucial part of a smart parking system since it may help maximise the use of parking spaces while also enhancing security and user experience.

Even though ANPR technology is widely used and offers a number of advantages, there are still some issues with its application. Some of the typical issues include:

Issues with accuracy: ANPR systems can occasionally have trouble correctly reading licence plates, particularly if the plates are dusty, damaged, or hidden by other items or shadows.

Cost: Because ANPR technology requires specialised cameras, software, and hardware, implementing it can be costly.

Privacy issues: ANPR systems have the capacity to record and store a lot of information, including photographs of cars and their drivers as well as licence plate numbers. Concerns concerning data security and privacy are raised by this.

Maintenance: In order to maintain the accuracy and dependability of ANPR systems, frequent maintenance is required, such as camera cleaning and software updates.

Weather: Unfavourable weather conditions, including persistent rain or heavy snow, might reduce the accuracy of ANPR systems.

ANPR systems may produce false positive findings, classifying a vehicle as being in violation when it is not.

Integration: If there are multiple manufacturers involved, integrating ANPR technology with other smart parking system components can be difficult.

The management of parking systems has been successfully managed using the powerful technology known as automated number plate recognition (ANPR). Numerous advantages are provided, including increased revenue collection, improved security, improved parking efficiency, and reduced manual labour. However, there are some drawbacks to ANPR technology, such as privacy concerns, high implementation and maintenance costs, and errors in number plate recognition caused by blurry images or damaged number plates. Despite these difficulties, ANPR technology in smart parking systems has more advantages than disadvantages. An improved user experience and a revolution in parking management are both possible with the adoption of ANPR technology.

Chapter 03: SYSTEM DEVELOPMENT

Deep learning, which is derived from artificial neural network technology, is now a hot topic in computing and is widely employed in a variety of industries, including cybersecurity, healthcare, image identification, and many others. However, developing a good DL model is a challenging task because real-world situations and data are dynamic and changing. Additionally, the aim is to propose a viable solution that can be used as a reference by both industry and academia.

3.1 Construct a conceptual framework

The technique begins with defining the problem area, acquiring information about the issue, and generating research questions. In addition, a literature study is done to evaluate the relevant work. The assessment of the literature aids in pinpointing the knowledge gaps that must be filled in order to advance our field of study.

3.2 Develop a system architecture

The next step in the research methodology is the development of a system architecture. By defining the system architecture, this step aims to give guidance to our prototype development process. The system architecture outlines the many system functionalities that must be represented in our prototype. In order to quantify and confirm the needs later on in the study process, they should be established now.

3.3 Analyse & Design the system

The third phase is to design the prototype, which entails determining which components are necessary in order for the prototype to have all the functionalities based on the criteria. Iteratively, the system is examined at this stage to determine whether it satisfies all functional criteria. At this point in the research technique, some of the important parts for the prototype—including a hardware and a software component—have been selected. In this step, the data transfer method and display platform are chosen.

3.4 Build the system

This process entails creating software and joining various parts in accordance with the system design, which is discussed in Section 3.3. To achieve a high level of accuracy in image analysis, it is quite usual to gather data (pictures) and build a model based on the data. As a result, we might need to gather data for our prototype's model-training. To train a model, one must first gather a new dataset, which could take some time. Vehicles are typical objects, and there are numerous open datasets with thousands of images of them. Furthermore, many individuals have prepared these datasets with various article identification 14 models and shared their outcomes. Rather than gathering a new dataset and preparing another item recognition model, we rather chose to utilize a portion of the accessible pre-prepared models and pick one of them in view of the exhibition on their vehicle identification exactness.

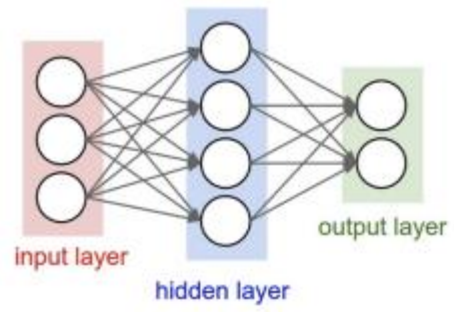

Fig. 3.1 Convolutional Neural Network

A crucial prerequisite for the CNN technique is data training. A data set including photos of the desired object must be gathered before object detection may begin. Each object in an image should have its own label to help identify it. After labelling, the data set is prepared for training. In order to identify and specify the commonalities among all the images during training, the data is altered in the hidden layers. These parameters give a specific description of the object or objects; they aid in understanding what the particular object looks like.

YOLO

You Only Look Once (YOLO) is a method for object recognition that employs a convolutional neural network to identify items in a picture and classify their type. YOLO divides the entire image into smaller grids and then iteratively searches for connections between the various grids to identify objects and determine their bounding boxes.

Several bounding boxes are predicted on an object throughout this procedure, but each bounding box has a score that is eventually combined into a single box for each object with the greatest score. Last but not least, once the thing is discovered, a classification is made on it to identify what it is.

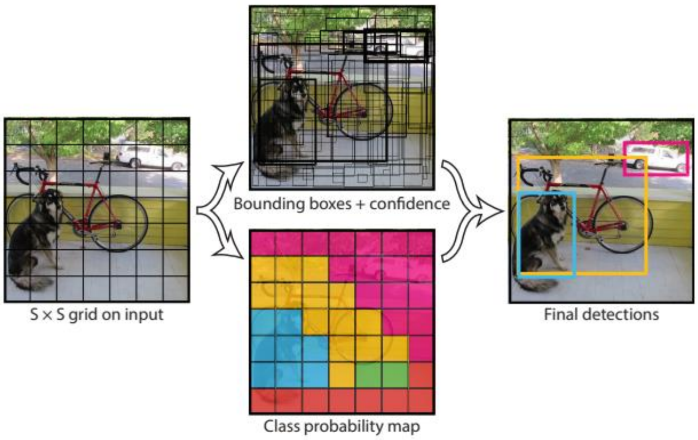

Fig. 3.2 YOLO model detection as regression problem

ANPR (Automatic number plate recognition)

Important elements of the LPR parking system

Core elements of the majority of ANPR-based parking management systems include:

The ANPR cameras

The main purpose of ANPR cameras is surveillance. For instance, they can record a legible image of a fast car's licence plate. OCR (Optical Character Recognition) and infrared illumination technology enable this. To verify and monitor the collected data, a database—typically cloud-based—is used to store it.

ANPR Software

Analysing the images of the collected licence plates is done by ANPR software. It reads, logs, and compares the licence plates to a database. The number plates are scanned in real time, the location of the car is determined, and the driver's information is extracted using sophisticated picture processing.

An effective approach for recognising Indian car number plates has been developed in the proposed algorithm. We can manage loud, dimly lit, crooked, and number plates with unusual fonts. In the pre-processing stage of this work, several image processing techniques are used, including morphological transformation, Gaussian smoothing, Gaussian thresholding, and the Sobel edge detection method. Following number plate segmentation and border-following contour application, contours are then filtered based on character dimensions and spatial localization. Optical Character Recognition (OCR) is the last step we take to identify the retrieved characters. The database is used to store the identified texts after which they are sorted and made searchable.

The owner's vehicle will be easily recognised in modest institutions, housing societies, and apartments thanks to this project.

Chapter 04: PERFORMANCE ANALYSIS

The accuracy of identifying the parking lot status is one significant statistic that will be assessed. Appropriate test cases need to be defined in order to gauge this prototype feature. The readers should be able to access all evaluation findings and all executed test cases. Due to problems that need to be fixed, some assessment results may fail or be inconclusive during the initial run. This research approach has the capacity to iterate, which may be useful for solving issues, fixing mistakes, and running failed test cases again. The prototype's compliance with the specifications is confirmed by observation and evaluation, in any case, more significantly, the result of this step will add to tending to the examination questions.
There are two benefits to employing vision-based systems over sensor-based ones: adaptability and efficiency.
reduced price. A smart camera can be used in place of one ground sensor per parking space used, which lowers the price. The accuracy of this method when compared to other systems is much superior to the others. Consequently, it's preferable to use this system as opposed to the others. select the vision-based systems for outcomes that are highly accurate. The aforementioned benefits can be used to conduct video surveillance operations and
be utilised for video tracking of moving autos, face recognition, and people recognition plus people.

4.1 Dataset

The CNRPark+EXT dataset, which was made on a parking garage with 164 spaces, has around 150,000 explained pictures (patches) of empty and involved stopping places. CNRPark+EXT expands CNRPark, a preliminary dataset made up of 12,000 photos from 2 cameras taken over the course of various days in July 2015.
The additional subset, known as CNR-EXT, consists of photographs taken between November 2015 and February 2016 in a variety of weather conditions by 9 cameras with diverse vantage points and viewing angles. CNR-EXT records a variety of lighting conditions, including partial occlusion patterns brought on by obstacles like trees, lampposts, and other vehicles, as well as partial or complete shadowing of the vehicles.

camera	camera A	camera B	
class	free	busy	
slot_id			
weather	sunny	overcast	rainy
capture_date	yyyy-mm-dd		
cam_id	1-9		
w_id	s	o	r
capture_time	hh.mm		

Table 4.1 List of all the features in the dataset

4.2 Analysis

It is discussed and decided upon which object detection methods to utilise, what hardware to use, and how the data will be communicated.

Similar to human brain networks, convolutional neural networks (ConvNets or CNNs) networks that are constructed using neurons and weights. In light of this, employing Convolutional Neural Networks are capable of learning the task with ease. In order to recognise the occupancy of the parking place in real-time, this is combined with the current algorithm. This Contains the real-time quality, accuracy, efficiency, and scalability answer identifying the parking area There are various types of convolutional neural networks. a multi-layered network that is built so that it can recognise visual patterns in a picture with just a little pre-processing. The methods of learning, Convolutional neural networks, in particular, offer a solution to issues such as detecting parking occupancy.

This deep learning technique offers a solution that performs admirably and is good for disruptions like partial occlusions, the existence of shadows, and a variety of lighting situations. When taken into account with parking occupancy detection and environment, which are completely different from the data used to train the model, the results show some quality. Since it requires processing resources during the classification step, an embedded environment like the Raspberry Pi is a good fit. A convolutional neural network is made up of a lot of hidden layers, each of which performs mathematical operations on the input image to produce the output image that was supplied as input to the network.

Vehicle detection

Several deep learning architectures, some of which have already been utilised in other smart parking solutions, can be employed to recognise automobiles. AlexNet is one of the most popular deep learning architectures. The great item classification accuracy of this architecture makes it stand out. Identifying the types of things in an image without providing any information about where they are in the image is what object classification and recognition mean. To designate parking spaces, object classification is insufficient. To designate parking spaces, it is also necessary to determine the positions of the automobiles. AlexNet is therefore not the right architecture for our system.

There are a few profound learning designs that can be utilized to both distinguish and confine an item in a picture. Consequences be damned is one of the freshest profound learning structures which stands apart with high exactness and a very quick discovery process. The quick discovery process lessens the requirement for figuring power and it is a significant variable when all picture handling is performed locally. These highlights demonstrate that Consequences be damned is a proper decision for vehicle discovery. There are various variants of Just go for it, where we decided to work with YOLOv3 since it is the latest rendition of the Consequences be damned design and contributes with an expanded exhibition contrasted with the more established adaptations of Just go for it.

The You Look Only Once (YOLO) method is one of the quicker object recognition algorithms.

recognition. However, it is not yet the most precise algorithm for object recognition and therefore there will be less loss in terms of accuracy and can be selected for real-time recognition accuracy.

YOLO 9000 used to be the quickest and one of the most popular in previous years. Precise algorithm. However, it was not the most accurate algorithm for a few years. compared to other algorithms like SSD and RetinaNet, the best for accuracy. Then, YOLOv3, the following version of YOLO, was published with a few modifications to the internal architecture of the Darknet.

The YOLOv3 algorithm's ability to do detections at three different scales is regarded as its most crucial component. A "1 x 1" kernel is used as a feature map to produce the output by the fully convolutional neural network. The YOLOv3 architecture performs object detection at three different sizes and three different architectural layers.

The ability of the YOLOv3 algorithm to do detections at three distinct scales is seen to be its most important feature. The output of the fully convolutional neural network is produced using a "1 x 1" kernel as a feature map. Using three different sizes and three different architectural levels, the YOLOv3 architecture detects objects.

In earlier years, YOLO 9000 was both one of the fastest and most widely used. Exact algorithm For a few years, though, it wasn't the most precise algorithm. The most accurate algorithm when compared to others like SSD and RetinaNet. Then, YOLOv3, the successor to YOLO, was released with a few changes to the Darknet's internal architecture.

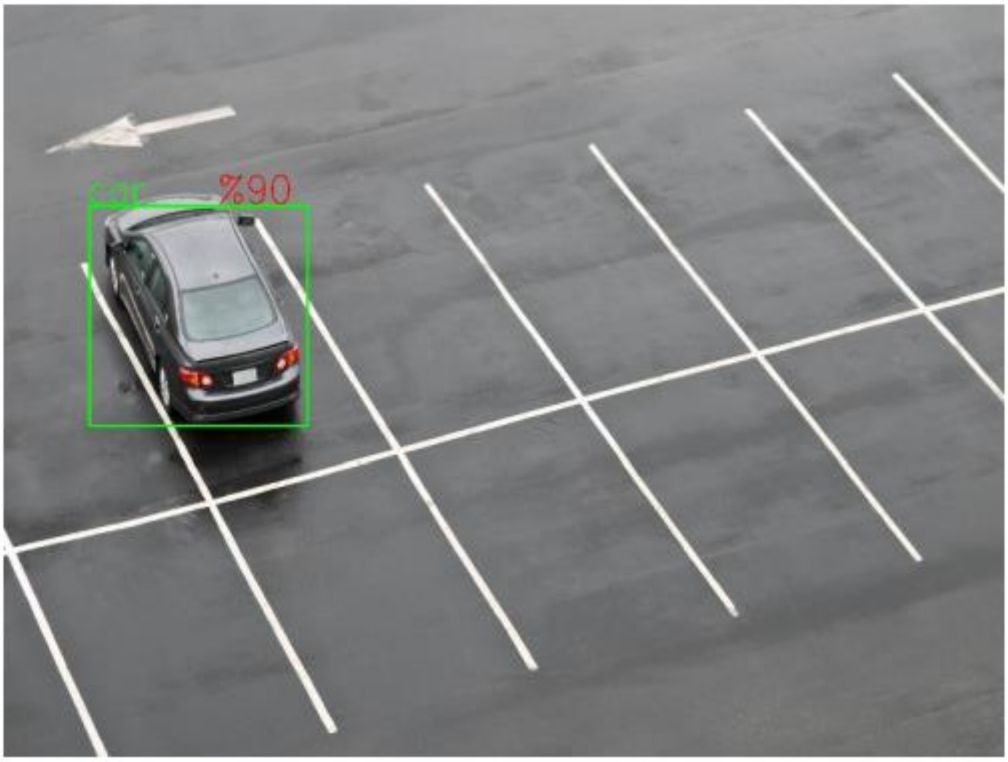

Fig. 4.1 Detected a parked vehicle

The graphic shows how YOLOv3 recognises an automobile in the image and delivers its position, object type, and confidence value. The training dataset has a significant impact on the object detection algorithm's accuracy. Although it would take longer, a dataset that includes photographs of automobiles that were captured in various weather, lighting, and angular circumstances will likely produce superior results. Therefore, building a new dataset is outside the purview of our investigation.

Parking spot occupancy detection

When the framework has the places of the parking spaces, it can decide the condition of the parking spaces by estimating how much a parking space's bouncing box covers with a vehicle's jumping box. To gauge this covering, Convergence Over Association, otherwise called Jaccard file can be utilized. Intersection over union is estimated by finding a region where two boxes crossover and partitioning the covering by the area covered by the two boxes.

The system may determine whether a parking space is occupied or not by comparing the IoU value for each detected vehicle's bounding box with the bounding box of the previously stored parking slot. The parking spot can be considered to be free when the IoU value is low, such as 0.10, because the vehicle does not take up much of the space. The parking spot can be considered to be occupied if the IoU values are high, like 0.80, as this indicates that the car has taken up the majority of the space. These threshold values are predicated on the fact that the bounding box coordinates span a little area around the vehicle in addition to the vehicle itself. Consequently, a vehicle's jumping box that covers a little piece of the following parking space would be permitted for this situation, nonetheless, it won't be permitted when the worth is higher since it is viewed as possessing the other parking space. One more direct requirement toward being considered for parking space location is covering between the parking spaces bouncing boxes. Because of the way that the area of bouncing boxes are bigger than the actual vehicles, there might be a cross-over in parking spaces' jumping boxes close to one another.

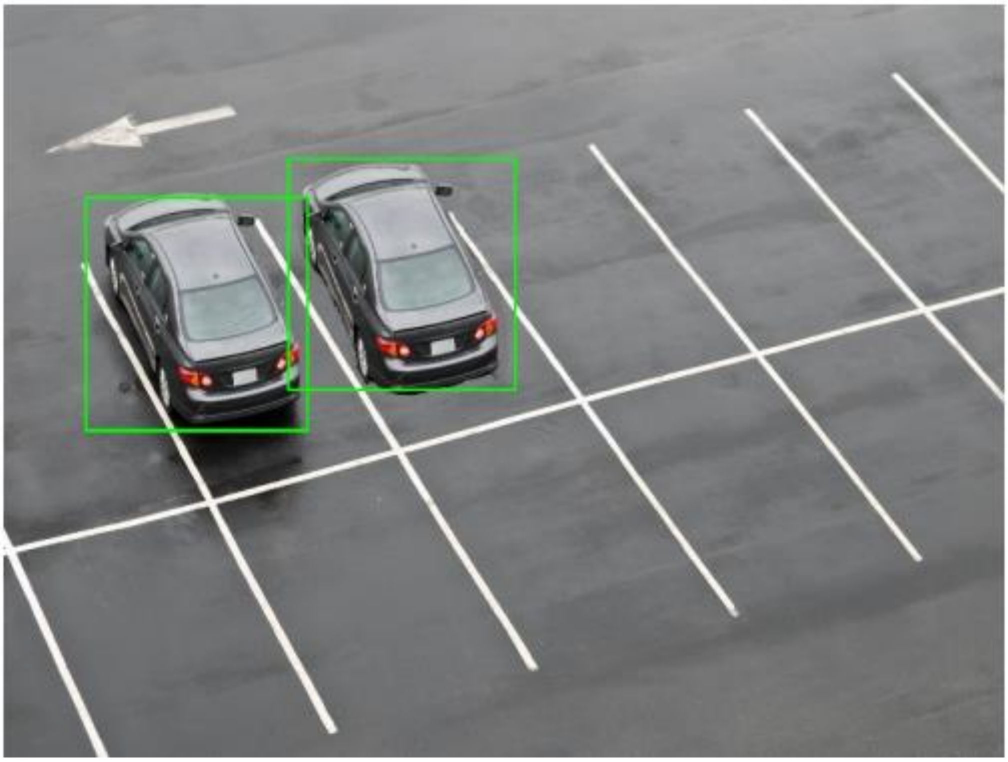

Fig. 4.2 Multiple parked vehicles detected

there is a crossover on the identified parking spaces. the covering region might increment relying upon the place of the camera connected with the parking spaces. At the point when one of the parking spaces is involved and the other one is empty, the jumping box of the identified vehicle might be covered with both bouncing boxes of these two parking spaces. To turn away this issue, the IoU worth of each parking space with contiguous parking spaces ought to be determined. This worth can be put away along with the pixel area of each recognized parking space and can be utilized to identify involved parking spaces. A parking space ought to be vacant on the off chance that the IoU esteem between the parking space and the identified vehicle is under 0.10. Be that as it may, this edge esteem should be expanded assuming there is cross-over between bouncing boxes of parking spaces. For example, assuming the IoU for two parking spaces is 0.30, the new edge esteem that will be utilized for stopping inhabitants' discovery ought to be (0.10+0.3 = 0.4) 0.4. Because of contrasts between the size of vehicles, the limit worth ought to be expanded, e.g., 0.10 is utilized in this model. The decision of the limit esteem relies exceptionally upon the point of the camera. Catching a picture when the camera is pointed from the front of the vehicles will bring about a little IoU esteem. Nonetheless, catching a picture from the side of the vehicles will bring about a high IoU esteem since every vehicle that is remaining close to one another is covering a piece of the other vehicle, subsequently, the limit should be expanded to not foresee mistakenly.

The fact that there are many types of automobiles is a crucial factor that needs to be taken into account when determining the average value. As previously said, the detected vehicle could be a motorcycle, truck, car, or bus. We assume that compared to other vehicle types, vehicles are the most prevalent. The average parking place location should only be calculated when a car is the detected vehicle because of this.

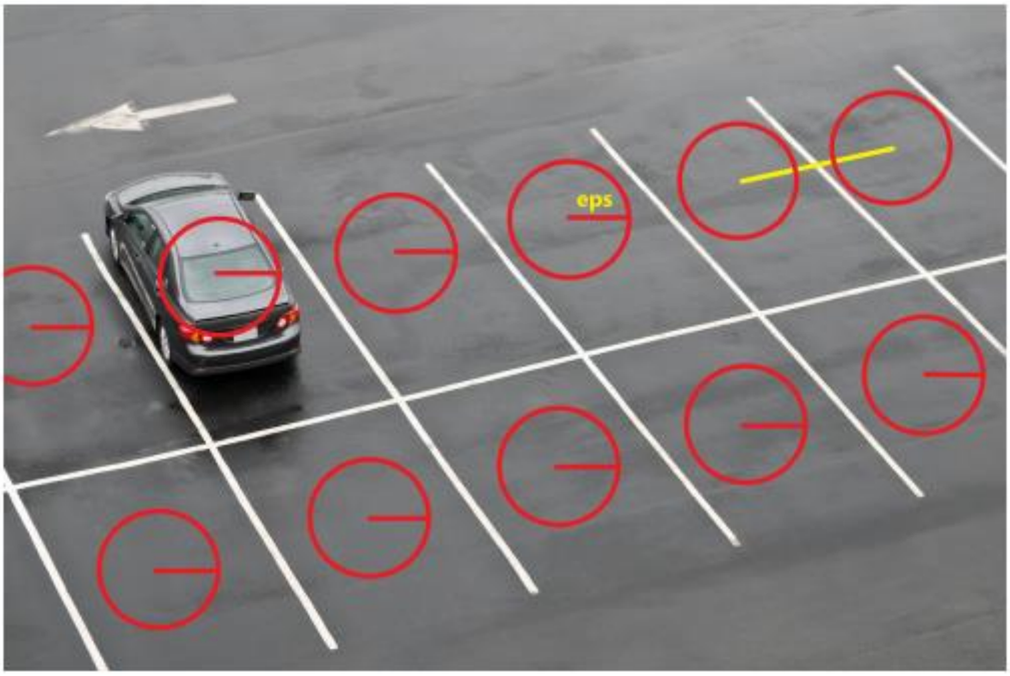

Fig. 4.3 Detecting the vacant spaces

Cluster analysis

The framework can proceed to work and characterize all the parking spaces and ascertain a typical size for each parking space in view of the pixel directions of distinguished vehicles. Notwithstanding, it is important that every one of the vehicles are left appropriately. In a circumstance where a vehicle is left mistakenly, for example twofold left, the pixel directions of the vehicle might be characterized as a parking space. The framework can't recognize which vehicles are left accurately and which vehicles are left wrongfully. To accomplish this objective, an AI approach can be valuable. Because of the way that it isn't known which vehicle is left accurately, a solo learning calculation will be a sensible decision to work on the discovery of parking spaces by not considering those vehicles that are unlawfully left. The reason for utilizing unaided learning is to recognize gatherings of vehicles that are accurately left and that are left in a similar spot in light of the positions and leaving recurrence of identified vehicles. Specifically, we accept that the recurrence of accurately left vehicles will be higher contrasted with wrongfully left vehicles. As per the objective and the presumptions, an unaided AI branch bunch examination is a reasonable arrangement. By executing a bunching calculation, the information that has not been marked, characterized or sorted can be gathered.

Illegal Parking Detection

All of the available parking spaces will be located based on the clustering result. We made the decision to employ the same technique we employed to determine whether parking places were occupied in order to find automobiles that were parked illegally. A detected vehicle may be deemed to be illegally parked (double parked) if its bounding box overlaps with two or more parking spaces and the overlap value exceeds the overlap between the parking spaces.

The convolutional neural network-based monitoring system performs well in areas with a high density of illegal parking. Below are the findings from the field test.

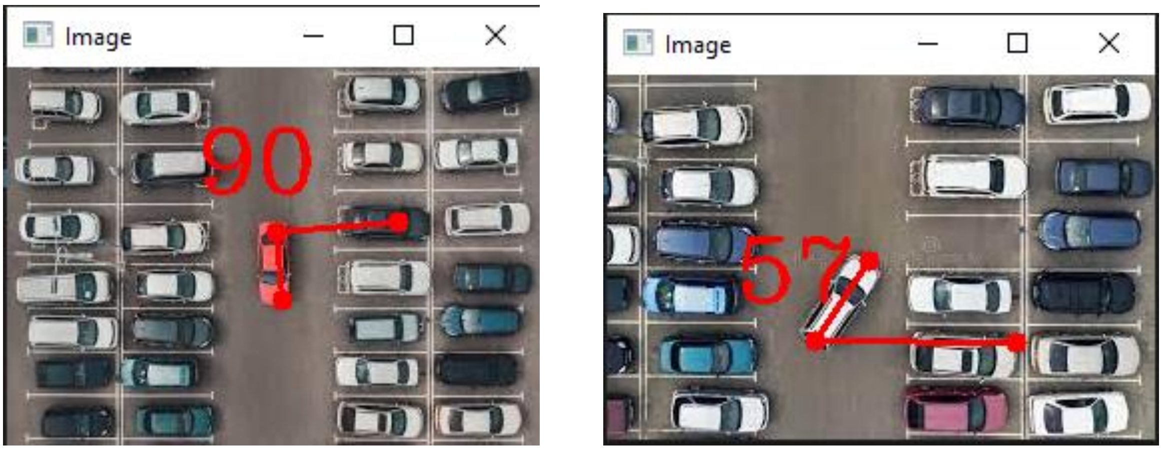

Fig. 4.4 Angle calculation for classifying wrongly parked vehicles

4.3 Methods and Techniques

To gain a broad understanding of the system's various subproblems, we created an issue breakdown tree. Each subproblem has a set of tasks that must be completed in order to solve it. The four subproblems of parking spot detection, data transmission, hardware selection and configuration, and integration were derived from the main issue.

We developed an issue breakdown tree to acquire a thorough grasp of the system's different subproblems. There are a number of actions that must be carried out in order to address each subproblem. The primary issue gave rise to the four subproblems of parking spot detection, data transmission, hardware selection and configuration, and integration.

In order to get a complete understanding of the various subproblems with the system, we created an issue breakdown tree. Each subproblem requires a different set of steps to be taken in order to be solved. Parking spot detection, data transmission, hardware selection and configuration, and integration are the four subproblems that stemmed from the main problem.

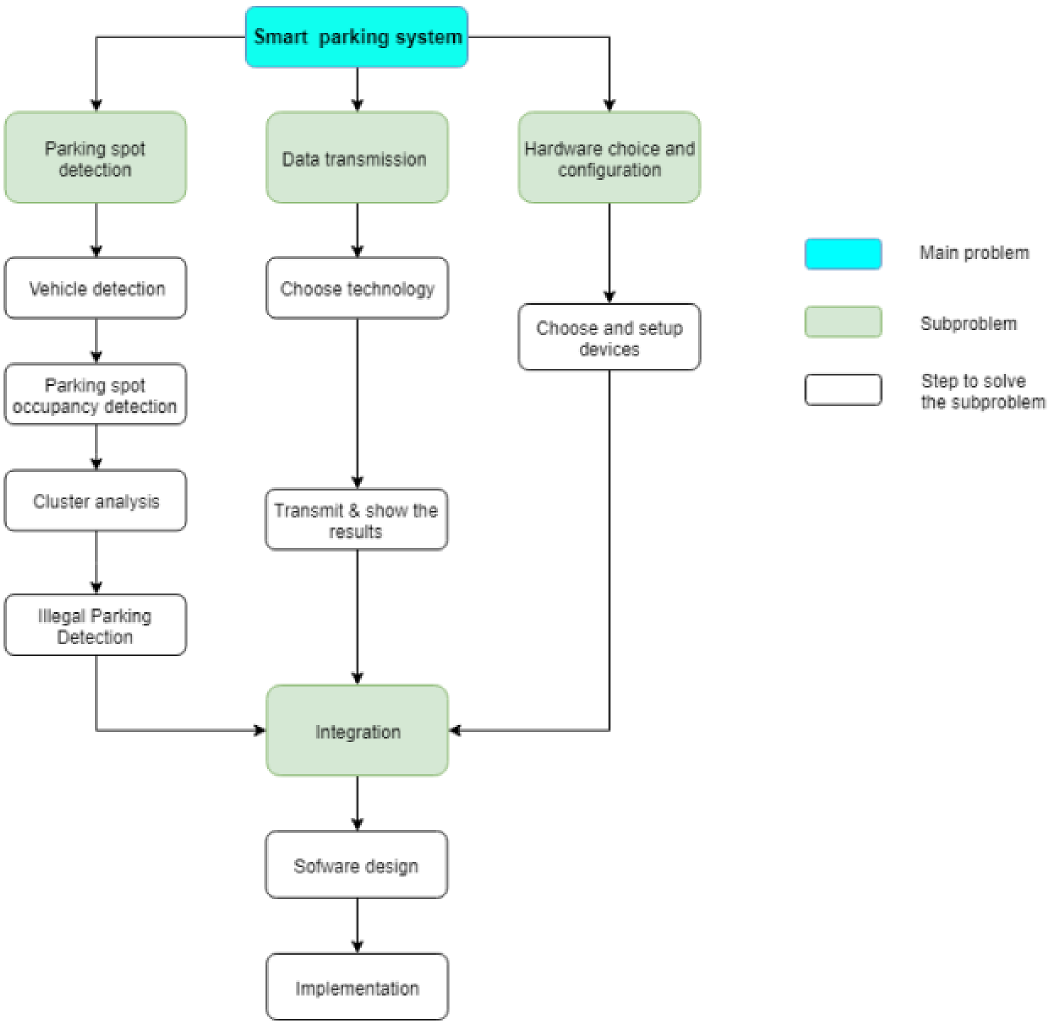

Fig. 4.5 Methodology for system development

Parking spot detection

Parking spaces should be automatically detected in order to construct a dynamic smart parking system. The use of an object detection algorithm can be used to complete this task.

Vehicle detection utilising deep learning technology has been selected as the method for finding parking slots. The method that was picked was based on how easily it could find parking spaces in a parking lot. 22 parking spots are primarily indicated by the location of the parked cars on a parking lot. Additionally, knowledge of the positions of the vehicles may be helpful in identifying vehicles that have been parked illegally.

Line detection is an additional method for finding parking spaces. The problem with this method is that with time, the lines could get lost or blurry. We contend that this method must be combined with another technique in order to assess the condition of the parking spaces and identify automobiles parked illegally. Vehicle detection has thus been chosen as the method for locating parking spaces. Different approaches to deep learning can be applied to the detection of vehicles.

Another technique for locating parking spaces is line detection. This method has the drawback that the lines could become muddled or lost over time. We argue that in order to evaluate the state of the parking spaces and detect vehicles parked unlawfully, this method must be used in conjunction with another strategy. Determining parking places has thus been done using vehicle detection. The detection of vehicles can use a variety of deep learning techniques.

Line detection is another method for detecting parking spaces. The disadvantage of this approach is that the lines could blur or disappear with time. We argue that this method must be used in conjunction with another tactic in order to assess the condition of the parking spaces and identify vehicles parked illegally. Vehicle detection has therefore been used to determine parking spaces. Several deep learning techniques can be used for vehicle detection.

Building a dynamic smart parking system requires the automatic detection of parking spaces. This task can be finished by using an object detection method. The approach for locating parking spaces has been chosen, and it makes use of deep learning technology for vehicle detection. Based on how quickly it could locate parking spaces in a parking lot, the strategy was chosen. The placement of the parked cars on a parking lot serves as the primary indicator of the 22 parking slots. Additionally, understanding the locations of the vehicles may be useful in spotting those that have been unlawfully parked.

Chapter 05: CONCLUSIONS

5.1 Conclusion

The modelling was done by using Python 3.8 and its necessary libraries. Code was performed by all the team members on their respective systems. More complex and advanced algorithms would be helpful in evaluating the performance of the model at a significant rate.

It was agreed to conduct the test on a parking lot with 14 spaces in order to evaluate the prototype. We used our own vehicles to conduct the tests. We repeatedly parked the cars in each parking space during the evaluation process. Additionally, unlawful parking was practised repeatedly in several locations. Vehicle detection, parking place occupancy detection, illegal parking, cluster analysis, and data transfer are the six primary components of the prototype evaluation.

Fig. 5.1 Parking lot used for performing system evaluation

The system was able to identify two parked vehicles in the parking lot. Based on where the identified vehicles are, the system creates two parking slots and records their locations in two different lines. The temporary location of the parking space is contained in the first file, and the coordinates of each detected car are contained in the second file, which together provide the dataset for the clustering analysis.

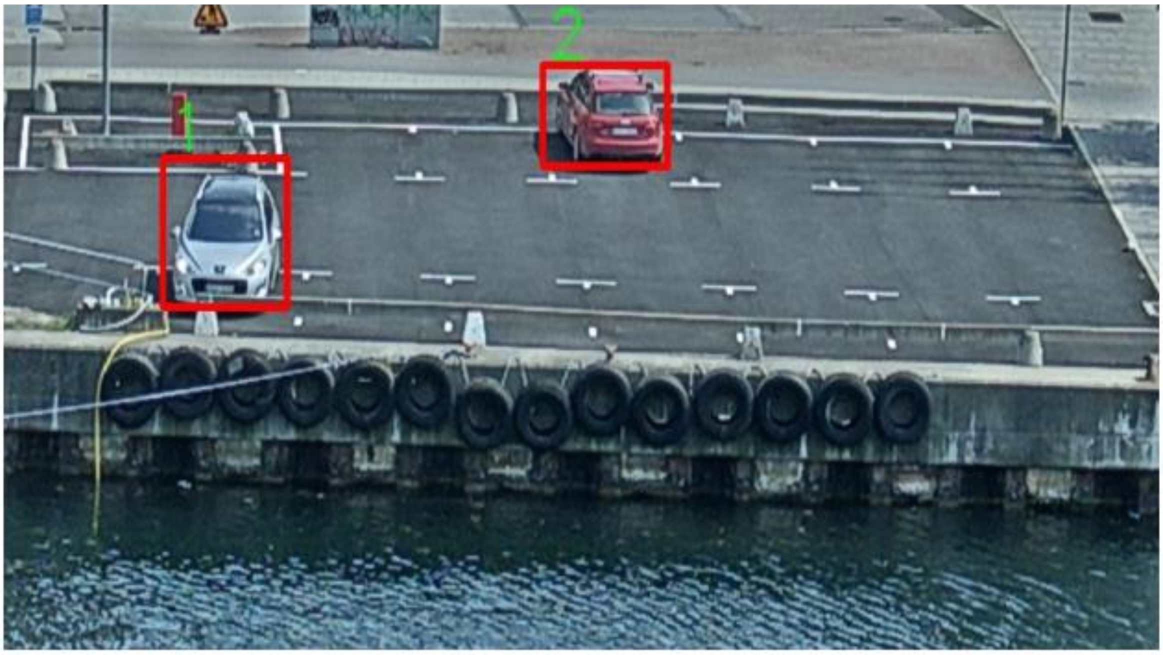

Fig. 5.2 Multiple parked vehicles detected

At the point when the conceivable parking spaces had been all left on, the framework had the option to characterize all the 14 accessible leaving spots.The size of the jumping boxes isn't something similar, albeit the recognized vehicle was no different for all bouncing boxes, with the exception of 36 for jumping box number 7. The extents of the bouncing boxes are vigorously reliant upon the region that the vehicle possesses in the picture. On the off chance that the caught picture contains a marginally side perspective on the vehicle, the involved region will be higher than in another picture, which contains just the front or back perspective on a similar vehicle. Likewise, the framework had the option to identify the involved and vacant parking spaces. The framework denotes the involved spots with a red bouncing box, while the vacant spots are set apart with a green jumping box.

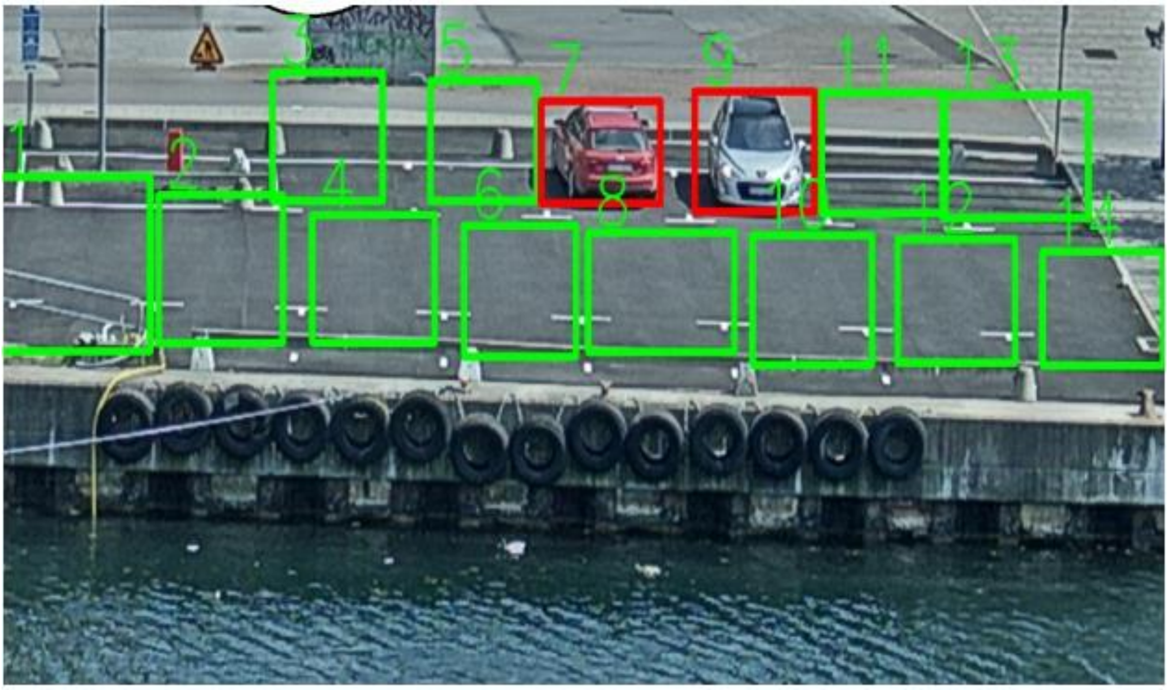

Fig. 5.3 Classifying parking spots before clustering analysis

Due to insufficient data collection, the system was unable to perform a clustering analysis on the parking spot data, so a vehicle that was parked illegally was not considered to be doing so. However, both parking spots could be marked by the system.

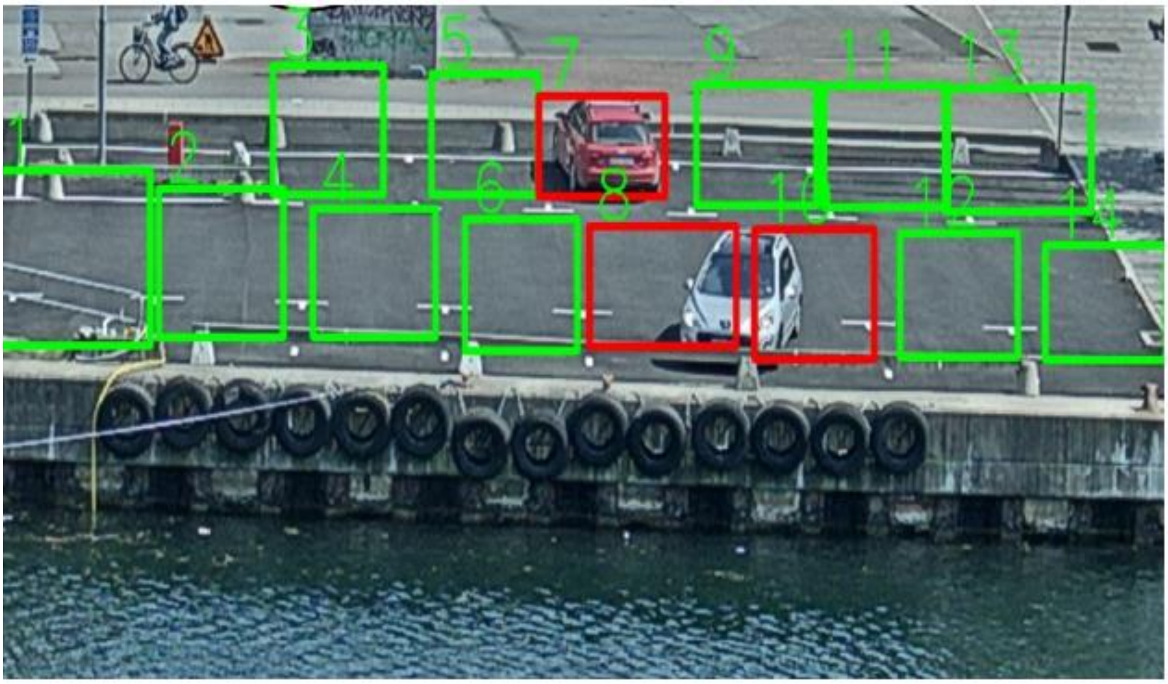

Fig. 5.4 Illegal parking classification before clustering analysis

The system carried out a clustering analysis after gathering a specific volume of data. The car was parked twice in each parking space due to the time constraints, with the exception of parking slot 7, which was out of control. Data from legally and improperly parked automobiles are included in the dataset that is used for clustering. During the evaluation process, we took 29 pictures, 26 of which were taken when the car was parked legally and 3 of which were taken when it was parked improperly. While various parking spaces are classified as clusters, the three black dots, which reflect illegal parking data, are outliers. The 14 parking spaces are represented by the 14 clusters that the system defined.

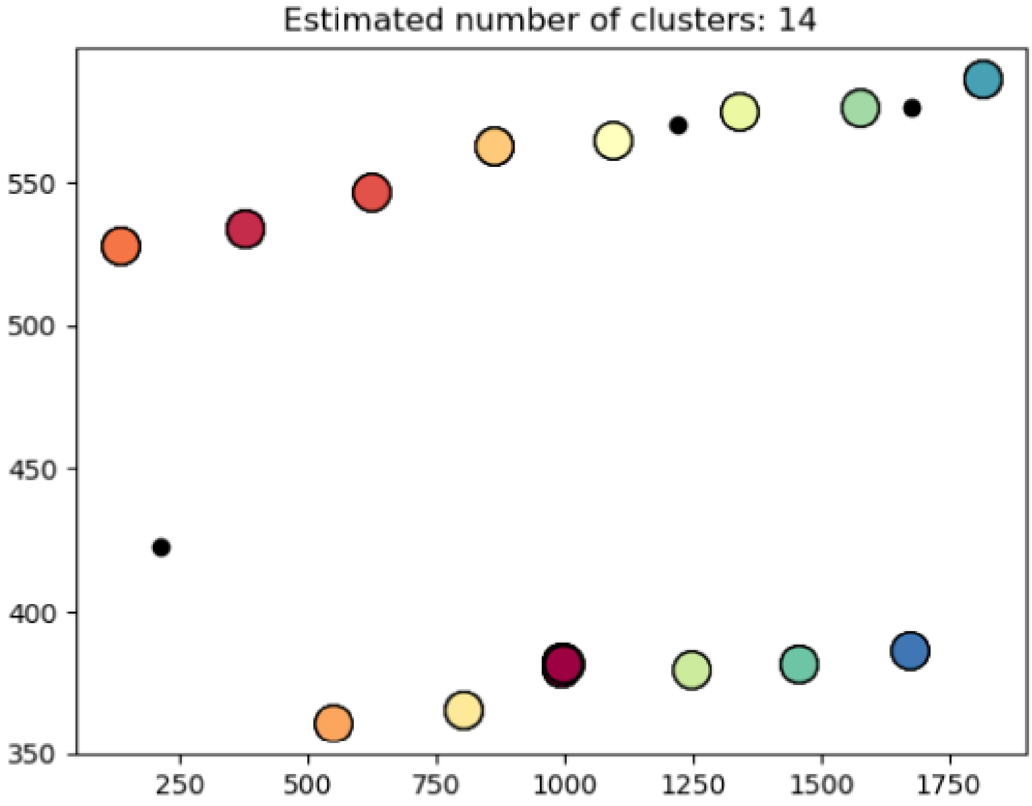

Fig. 5.5 Clustering result

After clustering has been completed, parking places are determined by averaging all samples that make up the same group. Additionally, the dataset was cleaned up by removing the unlawfully parked cars that were identified as outliers. The final positioning of the parking spaces is determined by how the coloured dots clustered. Following the cluster analysis, the system keeps track of available and occupied parking spaces without having to recalculate for every new vehicle it finds. The cluster analysis revealed two occupied parking spots.

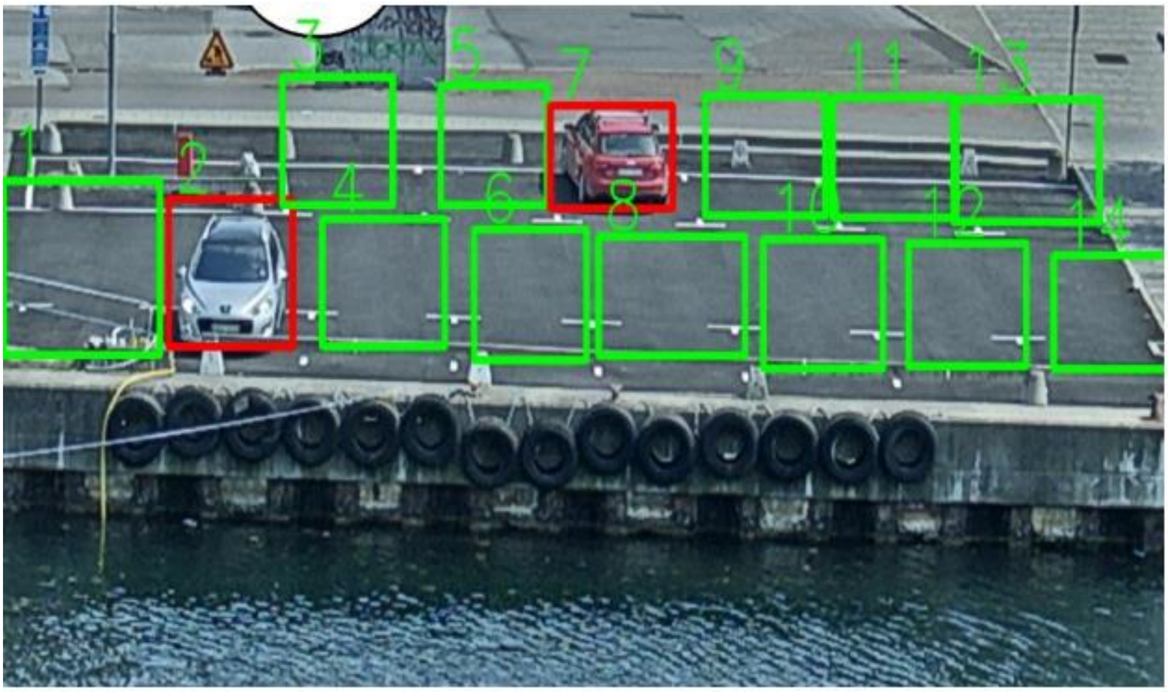

Fig. 5.6 Multiple parked vehicles detected after clustering

The algorithm was able to label automobiles that were parked illegally with a blue bounding box after the parking slots were defined and the cluster analysis was completed.

a circumstance in which a car is double-parked. Additionally, the system flagged these two as occupied because the vehicle occupied both parking spaces.

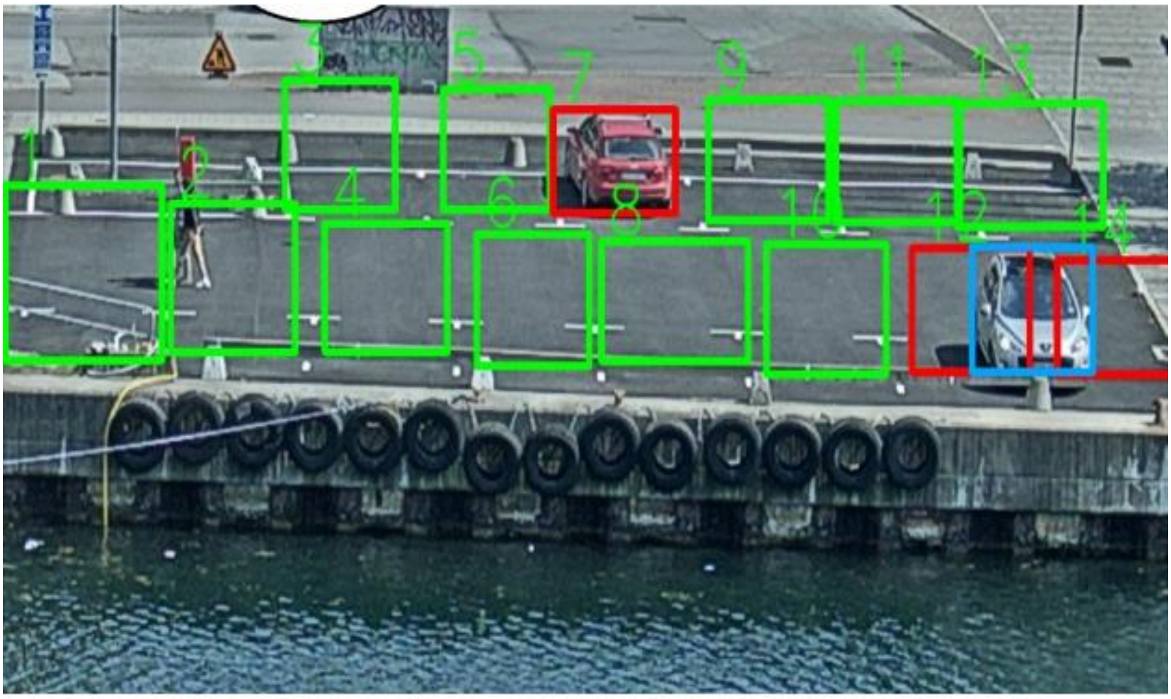

Fig. 5.7 Double parking occupied by vehicle after clustering

Results from five parking lots at our Institute, namely parking lots 1, 2, 3, 4, and 5, are tested. The parking lot's occupancy is first detected by the YOLOv3 detector, but because our institute's parking lot is in quadrilateral form and takes the shape of squares and rectangles, the bounding boxes of the parking lot are drawn manually using OpenCV python code and saved in an xml format. By overlapping the output data of the YOLOv3 detector with the bounding boxes, we can then determine whether the parking lot is occupied or empty.

5.2 Application

The goal of this study was to create a model of an original cunning leaving framework to determine whether there are any empty parking spaces in a parking garage and whether any vehicles have been left in an improper manner. The successful outcomes of our research show that it is capable of identifying automobiles and parking places where they are being parked. Furthermore, when the vehicle was double left, it was possible to identify a wrongly left vehicle. The Consequences be damned design was used to identify the vehicles, and it provided adequate execution and the ability to distinguish the vehicles with ease. Additionally, the grouping examination produced a favourable result with the ability to recognise illegally left vehicles as exceptions. The exceptions that deal with the illegally parked automobiles were identified and eliminated so that this information wouldn't take up much parking space. In any case, information on legal parking spots was conveniently gathered into one category.

Furthermore, no vision-based system has been employed in prior research to identify illegal parking on a parking lot. The majority of research publications on smart parking have concentrated on figuring out how to construct vision-based systems and what level of accuracy can be attained. In our work, we've developed a system prototype that can spot illegal parking.

Due to the modern technology sector's ongoing development, automated equipment is currently gradually displacing manual labour in a number of industries. The automation sector has reduced production costs while enhancing quality of life. Artificial intelligence is widely applied in many different industries, especially in the highly automated production sector, where machine vision currently reigns supreme. Urban management is evolving steadily in the direction of information technology. In urban management, there are corresponding processing methods for unlawful parking, however the approach for spotting illegal parking using machine vision is still being researched.

5.3 Future Work

The prototype that was created for this thesis is still in its early stages. The vision-based smart parking solution study area has a lot more to offer and can do better in this area. The suggested approach primarily concentrates on the identification of illegally parked vehicles and developing a solution that can dynamically learn on its own over time. As a result, the necessity for system improvement should be taken into account. Additionally, it could be interesting to investigate the large variety of deep learning algorithms that are currently accessible to find a better method of vehicle detection than what is currently practised. Moreover, the profound learning structures rely on how the design is being prepared and what pictures are being utilized for preparing the models; consequently, a potential future work is to train another model. Also, since the effectiveness of the model relies upon how much the articles are prepared, it may very well be great to prepare just a single sort of item, which for this situation would be vehicles.

Because of the modest edge for playing out this task, assessing the framework was just performed during a restricted time, hence there is a requirement for assessing the framework further during a more extended time span and in various parking garages. The discoveries of vehicles in various weather patterns and light circumstances, e.g., when it is snowing or pouring and when it is dim or light outside, could influence the recognition. Subsequently, assessing the framework during various weather patterns and light circumstances is expected to assess the consistency of the framework.

The project's visualisation component, where data should be interpreted and visualised by either developing a user-friendly application or integrating the platform with an appropriate tool, has received little attention.

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Appendix

Parking space detection

```
def plot_detection(images,index = 0 , figsize=(33,64)):
  photo = cv2.imread(images[index])
  detected = yolo.detect_image(PILImage.fromarray(photo))
  f = plt.figure(figsize=figsize)
  sp = f.add_subplot(1, 2, 1)
  sp.axis('Off')
  plt.imshow(photo)
  sp = f.add_subplot(1, 2, 2)
  sp.axis('Off')
  plt.imshow(detected)
```

Outline parking spaces

```
def create_boxes(images):
  data  = pd.DataFrame()#[],columns =["x1","y1","x2","y2", "score","class","file"])
  for i in range(len(images)):
    out_boxes, out_scores, out_classes, labels = yolo.find_objects(PILImage.open(images[i]))
    out_boxes = out_boxes.reshape((len(labels),4))
    df  = pd.DataFrame(out_boxes , columns =["y1","x2","y2","x1"])

#     {"y1":out_boxes,"x2","y2","x1"}
    df["score"] = out_scores
    df["class"] =out_classes
    df["frame"] = i
    df["labels"] = np.arange(len(df))
    data = data.append(df, ignore_index=True)

  data["xc"] = (data["x1"] + data["x2"])/2
  data["yc"] = (data["y1"] + data["y2"])/2
  data["w"] =  data["x1"] -data["x2"]
  data["b"] = data["y2"] - data["y1"]
  data["a"]= data["w"] *data["b"]
  data["d"] =  np.sqrt(data["b"]*data["b"]  + data["w"]*data["w"] )
  data = data[["labels", 'x1', 'y1', 'x2', 'y2',  'xc', 'yc', 'w',  'd' , 'b', 'score', 'class', 'frame' ,'a']]
#   mask = data["class"].apply(lambda x: x in [2, 5, 7])
#   data = data[mask]
  return data
```

Finding available parking spaces

```
def look_for_slots(data, img=[],PRUNE_TH = 3, plot = True,
                                PRUNE_STEP =  10,
                                MERGE_STEP =  20,
                                MERGE_TH =  0.65):


  n_fr = data["frame"].nunique()
  cols = ["labels", 'x1', 'y1', 'x2', 'y2',  'xc', 'yc', 'w' , 'b',"class",'a' ]
  base_col = ['x1', 'y1', 'x2', 'y2',  'xc', 'yc', 'w' , 'b']
  slots  = data[data["frame"] == 0 ][cols]
  slots["found"] = 1
  def plot_images():
    df = slots[['x1', 'y1', 'x2', 'y2',"found","labels" ]]
    df["class"] ="empty"
    msk = df["labels"].isin(id_map.values())
    df.loc[msk,"class"] = "occupy"
    nw_df = new[['x1', 'y1', 'x2', 'y2',"labels" ]]
    nw_df["class"] = "new"
    nw_df["found"]=1
    df = df.append(nw_df,  sort=True).reset_index(drop=True)
    df["found"] = df["found"].astype(int)
    plot_frame( img[i], df[["y1","x2","y2","x1"]].values,  df["class"].values, df["found"], df["labels"])
#   out_boxes,  out_classes, found, labels
# "empty":"#4a148c","occupy":"#f44336", "new":"#7cb342","del":"#80deea"
  print("LOOKING FOR PARKING SLOTS INSIDE IMAGE FRAMES")
```

Determination of angle between vehicles for illegal parking detection

```
def gradient(pt1,pt2):
    return (pt2[1]-pt1[1])/(pt2[0]-pt1[0])

def getAngle(pointsList):
    pt1, pt2, pt3 = pointsList[-3:]
    m1 = gradient(pt1,pt2)
    m2 = gradient(pt1,pt3)
    angR = math.atan((m2-m1)/(1+(m2*m1)))
    angD = round(math.degrees(angR))
    cv2.putText(img,str(angD),(pt1[0]-40,pt1[1]-20),cv2.FONT_HERSHEY_COMPLEX,
                1.5,(0,0,255),2)
```