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URBAN PARKING OPTIMIZATION THROUGH INTEGRATED MACHINE LEARNING MODELS

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ABSTRACT

In order to handle expanding urban populations and rising car ownership, urban parking facilities have long been a crucial component of metropolitan infrastructure. It was challenging to distribute parking resources effectively with traditional parking management systems since they depended on static signs, human enforcement, and limited data collecting. The parking business has steadily moved towards automated systems and digital solutions as a result of the development of smart technology. Parking spots are usually assigned via manual input or defined zones in traditional urban parking systems. These systems often force cars to look for parking spaces, which causes traffic jams, fuel waste, and needless emissions. Additionally, ineffective parking space management and inappropriate parking behaviours result from the manual enforcement of parking regulations. The issue is made worse by the paucity of real-time parking availability data. Optimising the utilisation of scarce urban parking spots while reducing traffic and environmental effect is a problem. The lack of real-time parking information provided by current systems often results in wasteful use of available spots and lengthier search durations for vehicles. For city dwellers, this leads to a frustrating experience, higher gasoline use, and environmental pollution. Adopting more sophisticated and effective solutions is crucial to improving parking management in metropolitan areas that are expanding quickly. Parking systems that use machine learning (ML) have the potential to improve user experience, allocate parking spaces optimally, lessen traffic, and have a less environmental effect. Cities will be able to forecast parking demand, dynamically control occupancy, and optimise space utilisation in real-time by using data-driven algorithms. In order to forecast parking demand and availability, the proposed system combines machine learning algorithms with real-time data from sensors, cameras, and mobile applications. By employing traffic patterns and historical data, the system will effectively distribute parking spaces, shorten search times, and dynamically modify parking fees in response to demand, improving urban parking efficiency.

I. INTRODUCTION

1.1 Introduction

One of the biggest problems facing cities today is urban parking, particularly in countries like India that are urbanising quickly. Severe traffic jams, longer wait times for parking spaces, and higher pollution levels are the results of the growing number of cars and the constrained amount of urban area. Over the last 20 years, the number of automobiles in India has increased dramatically. In 2022, there were 293 million registered vehicles in India, of which over 30 million were passenger cars, according to the Ministry of Road Transport and Highways (MoRTH). The infrastructure for urban parking has not kept up with this sharp rise. In India, traditional parking structures, such as open-air lots and street parking, are often congested, ineffective, and vulnerable to abuse. In addition, the absence of real-time data, restricted parking spaces, and antiquated enforcement strategies make it difficult for communities to manage parking spaces. Given India's challenges with urbanisation, rising car ownership, and

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declining air quality from excessive vehicle emissions, the nation urgently needs smart parking solutions.

1.2 Problem Definition

Prior to the use of machine learning (ML), India's urban parking systems had a number of problems that made administration difficult. The absence of up-to-date information on parking spot availability was the main issue. In addition to spending precious time looking for parking spaces, drivers often avoided clogged roads, which increased traffic and air pollution. Conventional methods, which relied on human enforcement or static parking maps, were not able to forecast demand or maximise space use. Due to this inefficiency, parking spots were underutilised, and illegal parking practices were common. Additionally, parking costs were often set and not modified in response to demand, which caused traffic jams in places with high demand. Inadequate data gathering made it difficult to forecast future parking requirements, and irregular parking regulation enforcement often resulted in infractions and parking spot abuse. The overall effectiveness of urban transport networks was greatly hampered by these problems, which made driving a miserable experience.

1.3. PURPOSE OF THE PROJECT

By using Machine Learning (ML) technology, this project aims to transform urban parking systems in order to maximise parking space utilisation, lessen traffic, and minimise environmental effect. The demands of rapidly expanding urban populations and rising car ownership are too great for traditional parking management techniques, which rely on static signs and human enforcement. Due to the lengthy searches for vacant parking, these antiquated systems increase fuel consumption, traffic congestion, and poor space utilisation.

The suggested system seeks to dynamically forecast parking demand and availability by combining real-time data from sensors, cameras, and mobile apps with machine learning algorithms to examine past and present trends. This strategy will enable effective enforcement, adaptive pricing, and intelligent space allocation. Consequently, by lowering emissions and fuel waste, the initiative will improve the overall user experience, improve urban traffic flow, and advance sustainability objectives.

The ultimate goal of this project is to develop a more intelligent, data-driven, responsive, effective, and ecologically responsible urban parking ecosystem.

II. LITERATURE SURVEY

In their thorough analysis of parking services in smart cities, Yang et al. [1] looked at a range of techniques and technologies intended to maximise parking availability, improve user experience, and ease traffic. The study suggested possible future research areas and outlined significant developments and difficulties in putting smart parking systems into practice. Zheng et al. [2] proposed an intelligent method for predicting parking spot availability using data from several sensors, with an emphasis on sensor-enabled parking lots in smart cities. The goal of their work was to increase parking management systems' effectiveness, which would enhance urban mobility. In order to estimate parking space utilisation in metropolitan areas, Caicedo et al. [3] investigated the real-time prediction of parking space availability and developed a predictive model that takes past data into account. Their research highlighted how crucial precise forecasts are to minimising parking-related problems in crowded cities.

A thorough investigation of parking occupancy prediction was carried out by Channamallu et al. [4], who examined several models and approaches for forecasting parking spot occupancy. Their study examined the variables affecting parking availability in metropolitan environments and demonstrated the efficacy of many prediction methods. The most recent developments in smart parking technology and its incorporation into

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intelligent transportation systems were examined by Kotb et al. [5], who also analysed smart parking guidance, monitoring, and reservation systems. They looked into the difficulties in delivering real-time parking information and suggested fixes to enhance the user experience. Using spatiotemporal data sources, Yang et al. [6] presented a deep learning method for predicting parking occupancy in real time. Their model demonstrated the promise of deep learning approaches in addressing urban mobility difficulties by integrating numerous data sources to enhance parking forecasts in transportation networks.

In their analysis of Texas's electric car adoption difficulties, Pamidimukkala et al. [7] identified major roadblocks pertaining to legislation, infrastructure, and consumer behaviour. The research sought to develop tactics and policy suggestions to encourage the use of electric vehicles. Location-based services were examined by Huang et al. [8], who also highlighted the field's continuous development and study. Their study examined how location-based technologies affect transportation and urban planning, emphasising how geospatial data might enhance service delivery. Sester [9] concentrated on the analysis of mobility data, especially as it relates to mobile mapping systems. In addition to providing insights into the potential of mobile mapping for promoting urban mobility, their study highlighted the significance that mobility data plays in improving transportation planning and management.

A comparative study of parking occupancy prediction models was carried out by Channamallu et al. [10], who assessed how well various strategies performed in forecasting the availability of parking spaces. Their goal was to shed light on the advantages and disadvantages of the different parking management system types. Using gradient boosting decision trees, Liu et al. [11] investigated parking occupancy prediction and suggested a machine learning approach to forecast parking spot utilisation. Their method showed how well gradient boosting works to increase parking forecast accuracy. For short-term parking occupancy prediction, Sun et al. [12] used decision trees and random forests. They compared the effectiveness of several models and offered insightful information on their usefulness in parking management.

An exploratory study of the temporal and geographical patterns of autonomous vehicle crashes was carried out by Patel et al. [13], who also looked at the elements that influence these incidents and their implications for future transportation systems. In order to estimate parking demand at transit stations, Hendricks and Outwater [14] developed a demand forecasting model for park-and-ride lots. The goal of their research was to minimise traffic at park-and-ride locations and maximise parking lot use. According to INRIX Research [15], parking-related problems have a significant financial effect on Americans, costing them billions of dollars every year. The expenses and difficulties related to parking in cities were thoroughly examined in their paper.

With an emphasis on subterranean parking facilities, Caicedo et al. [16] investigated parking management and modelling the behaviour of car park patrons. Through the analysis of consumer behaviour patterns, their study sought to enhance parking management techniques. Shoup [17] looked at the problem of "cruising for parking," talking on how it affects urban mobility and traffic congestion. His research made clear the need of effective parking management techniques to lessen traffic brought on by parking searches. In their evaluation of smart parking systems, Channamallu et al. [18] summarised the most recent developments in parking management technology. In order to optimise parking in metropolitan settings, their study investigated

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the combination of sensors, data analytics, and intelligent technologies.

In their study of smart parking solutions, Lin et al. [19] included a range of technology developments and tactics for improving parking effectiveness in urban settings. The importance of intelligent transportation systems in controlling parking availability was highlighted in their research. A feasibility study on real-time parking information at metro rail stations was carried out by the Virginia Metro Rail Authority [20], which investigated the possible advantages of giving passengers access to real-time parking availability data. The goal of their study was to enhance metro rail passengers' parking experiences. In their investigation of construction cost overruns during COVID-19, Adepu et al. [21] examined how the pandemic affected building projects and identified the main causes of cost increases. Their study shed light on the difficulties the construction sector had during the epidemic.

In his study on the installation of high-tech parking meters in San Francisco, Gordon [22] covered the advantages of updated parking meter systems as well as how they affect parking management. In his discussion of how cellphones and location-based services have transformed how drivers locate and pay for parking, Richtel [23] emphasised the significance of mobile applications in the parking industry. To maximise parking availability and lessen traffic, the SFMTA [24] introduced a demand-responsive pricing scheme for parking in San Francisco. Their method provided a dynamic approach to parking management by adjusting parking charges in response to demand.

III. EXISTING SYSTEM

Conventional, static parking management techniques are the mainstay of the current urban parking systems. Parking is either manually monitored or handled by basic ticketing systems in many cities, where cars park in allocated spots and pay for their stay. Parking meters and electronic ticket payment systems are examples of simple automated solutions that some cities have put in place, but they still lack the ability to integrate real-time data and make intelligent decisions. With little room for the growing number of cars, street parking and outdoor parking lots are typical in bigger cities. These systems are ineffective at meeting the rising demand for parking in cities because they mostly lack data-driven features. Additionally, human inspectors are used by parking enforcement to verify compliance, which results in irregularities and difficulties with enforcement. Although some cities have implemented smart parking meters and sensors, these systems are still standalone and do not provide a complete, citywide approach to dynamic parking management.

Limitations of Existing Systems:

- Absence of Real-Time Data: The majority of systems do not provide real-time parking spot availability, which results in inefficiencies and longer parking search times.
- Manual Enforcement: The majority of parking enforcement is done by hand, depending on inspectors to ensure compliance, which is prone to mistakes and discrepancies.
- Limited Integration: Current systems often function alone and aren't connected to other smart city infrastructure, such public transit or traffic control.
- Underutilised Parking spots: Many parking spots, particularly in low-demand locations, remain underutilised in the absence of dynamic space distribution.
- Fixed Pricing: Typically, parking costs are set and unadjusted according to demand, which causes traffic jams in places with strong demand and underuse in others.

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- Ineffective Parking Management: It is challenging to estimate parking demand and efficiently manage resources due to the current systems' lack of predictive capabilities.
- Environmental Impact: Issues like lower fuel usage or pollution from cars circling for parking are not addressed by the current methods.
- Inadequate User Experience Improvement: Drivers are frustrated and spend time because they lack a simple, seamless method of locating parking spaces.
- Inconsistent Availability Information: Drivers become frustrated when traditional systems are unable to deliver current, accurate information on parking availability.
- Limited Support for EVs: Many times, current systems are unable to meet the requirements of EVs, such as placing charging stations inside parking structures.

IV. PROPOSED SYSTEM

4.1 Overview

Step 1: Uploading the Urban Parking Dataset

The Urban Parking dataset must be uploaded as the initial step in the research process. Typically, this dataset includes data on parking trends in metropolitan areas, including parking location, occupancy, time of day, and other pertinent characteristics. The dataset, which was gathered from different metropolitan areas, offers information on parking availability, behaviour, and other variables that affect parking patterns. After being uploaded, the dataset is imported for further analysis and preprocessing into a data analysis environment (like Python) utilising libraries like Pandas or NumPy. To guarantee that the dataset is available and prepared for further processing, this step is crucial.

Step 2: Dataset Preprocessing (Null Value Removal, Label Encoding)

Data preparation is the following stage after uploading the dataset, and it is essential to get the data ready for machine learning models. Dealing with null or missing values is the first job. Depending on the features of the dataset, it is crucial to either delete or impute missing values since null values in the dataset might provide biassed or erroneous conclusions. Using the mean, median, or mode for numerical data or the most frequent category for categorical data are common methods for dealing with missing numbers. For categorical variables, label encoding is the subsequent preprocessing step. Label encoding is used to transform category information, such parking location, vehicle type, or time slots, into numerical values since many machine learning methods demand numerical input. This guarantees that the data is in a format that can be used to train a model.

Step 3: Data Splitting

The next step after preprocessing the dataset is to divide it into subsets for testing and training. This is a common practice to assess a model's ability to generalise to new data. Usually, the data is separated into two sets: a test set, which makes up 20–30% of the data, and a training set, which makes up 70–80% of the data. The test set is used to assess the model's performance, while the training set is used to train the machine learning algorithms. The train-test split guarantees that the model can function effectively on novel, unseen samples and is not overfitting to the training data.

Step 4: Existing Models (Random Forest, Logistic Regression Algorithms)

Machine learning models are then trained using pre-existing algorithms once the data has been divided into training and testing sets. Here, the baseline models are Logistic Regression and Random Forest (RF). In order to increase accuracy and decrease overfitting, the Random Forest ensemble approach constructs many decision trees using arbitrary

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subsets of the data and combines their predictions. A more straightforward model called logistic regression is used for binary classification problems in which predicting the likelihood of an outcome (like parking availability) is the aim. To provide baseline findings for comparison with more sophisticated models, both models are trained on the training data and their performance is assessed on the test data.

Step 5: Proposed Algorithm (CatBoost Algorithm)

Testing a suggested method, CatBoost, a cutting-edge gradient boosting technique, is the next stage. CatBoost is renowned for its resilience and exceptional performance, particularly when working with noisy datasets. It was created to handle categorical data well. CatBoost eliminates the need for human feature engineering by handling categorical variables automatically without requiring a lot of preprocessing, in contrast to conventional gradient boosting techniques. The test data is used to assess the model's performance after it has been trained on the training data. It is anticipated that this approach would outperform the baseline models, particularly in intricate datasets containing categorical characteristics.

Step 6: Performance Comparison

The performance of the suggested model (CatBoost) and the current models (Random Forest and Logistic Regression) is then compared once they have been trained. Several assessment criteria, including accuracy, precision, recall, F1-score, and AUC (Area Under the Curve), are used in this comparison. These metrics provide a thorough understanding of each model's performance in terms of accurately identifying the data. The performance comparison establishes if the enhanced CatBoost model provides a notable improvement over the current models and assists in identifying each model's advantages and disadvantages.

Step 7: Prediction of Output from Test Data with Trained Model

Predicting the output using the trained model on the test data is the last step after determining which model performs the best. Depending on the goal variable, parking availability or occupancy is predicted using the test dataset and the trained CatBoost model (or the top-performing model). The ultimate accuracy and dependability of the model are evaluated by comparing the predictions with the labels of the test data. In order to confirm that the model can generalise to new data and provide correct predictions when used in real-world situations, this stage is essential.

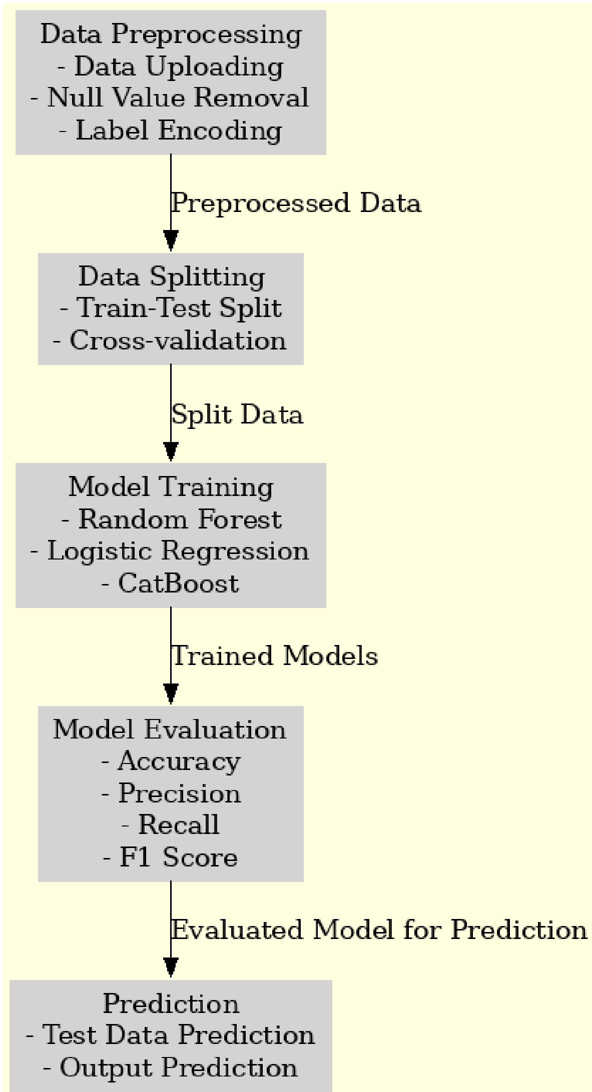

Fig 1: Architectural Block Diagram of Proposed System.

V. RESULTS AND DISCUSSION

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Implementation Description

1. Home Page (home function):

- When a user accesses the root URL, this view displays the application's home page.
- The Home.html template is all that is returned.

2. Registration Page (register function):

- Enables users to register by entering their position (admin or user), username, password, email address, and name.
- The function verifies that the passwords entered match and determines if the username or email address already exists in the database.
- The user is sent to the login page upon successful registration.

3. Login Page (login_view function):

- By entering their username and password, users may log in using this feature.
- It confirms that the password is valid and that the username is real.
- The user is taken to the home page and logged in after successful authentication. When credentials are entered incorrectly, an error message appears..

4. Logout Page (logout_view function):

- In order to manage user logout, this method returns the user to the login page.

5. Dataset Upload (Upload_data function):

- Users may submit a dataset (CSV file) for processing using this function.
- The dataset is read and preprocessed once the file is uploaded:
  - ➢ To deal with missing data, the mean is entered into numeric fields and the mode into categorical columns.
  - ➢ Labels are encoded in categorical columns.
  - ➢ A few columns are removed according on how well they fit the model.
  - ➢ The Winsorizer technique is used to handle outliers by capping extreme values according to the Interquartile Range (IQR).
- The first 100 rows are shown as a preview when the data is divided into training and testing sets.

6. Performance Metrics (PerformanceMetrics function):

- Performance metrics for the model predictions are computed by this function. The following is calculated by it:
- Precision: The percentage of accurate positive forecasts.
- Remember: The percentage of true positives that were accurately detected.
- F1-Score: The precision and recall harmonic mean.
- Accuracy: The total percentage of accurate forecasts.
- It also creates and shows the model's prediction classification report and confusion matrix.

7. Model Training and Prediction Functions:

These functions are responsible for training different machine learning models and saving them for future use:

- **Decision Tree Classifier (DTC_existing function)**:
  - o If a trained Decision Tree model exists, it is loaded and used to make predictions on the test set.
  - o If the model doesn't exist, it trains a new Decision Tree model, saves it, and evaluates its performance.
- **Random Forest Classifier (RFC function)**:
  - o Similar to the Decision Tree Classifier, the function checks if a trained Random Forest

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model exists. If not, it trains the model and saves it.

- **Logistic Regression (Logistic function)**:
  - Similar to the other models, this function checks for the existence of a pre-trained Logistic Regression model. If absent, it trains the model and evaluates its performance.
- **CatBoost Classifier (catboost function)**:
  - This function works similarly to the above, but it uses the CatBoost Classifier. CatBoost is a powerful gradient boosting library, and the model is trained, saved, and used for predictions.

8. Prediction View (prediction_view function):

- This function allows users to upload a new dataset and get predictions using the pre-trained CatBoost model.
- It processes the new dataset by handling missing values, label encoding, and preparing it for prediction.
- The trained CatBoost model is then used to make predictions on the new data, which are returned to the user.

9. Global Variables and Model Handling:

- **Global variables** such as X_train, X_test, y_train, and y_test are used to store the dataset after it has been split into training and testing sets.
- Machine learning models (e.g., DecisionTreeClassifier, RandomForestClassifier, LogisticRegression, CatBoostClassifier) are saved to disk after training using **joblib**. These saved models are loaded when required for making predictions.
- The use of **joblib** enables efficient saving and loading of models, reducing the need to retrain them every time the application restarts.

10. File Handling:

- The application uses **Django's default_storage** to manage file uploads and deletions. When a user uploads a dataset, it is saved in the server's file system temporarily for processing. After processing, the file is deleted.

11. Error Handling and User Feedback:

- The app uses **Django messages framework** to provide feedback to the user. For instance, users are notified if they upload a dataset before training a model or if any errors occur during the process.
- Proper error messages are shown when there are issues such as incorrect login credentials or dataset upload errors.

12. Visualization:

- The **confusion matrix** for each model is visualized using **seaborn's heatmap** and displayed for user insight. This helps users understand how well the model is performing across different classes.

13. Model Deployment:

- Once models are trained, they are saved in the server's file system (static/model/) to avoid retraining and for faster predictions during subsequent requests.
- The application is designed to handle multiple algorithms for classification tasks, making it versatile for different use cases.

Dataset Description

— The vehicle's license plate is uniquely identified by its plate ID.

— The state or jurisdiction in which the car is registered is known as the registration state.

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- Plate Type: The kind of license plate, including government, business, and passenger plates.
- The code for a particular parking infraction, such as an expired meter, unlawful parking, or no parking zone, is known as the violation code.
- Vehicle Body Type: The kind of vehicle, such as a truck, SUV, or sedan.
- Vehicle Make: The brand or manufacturer of the car, such as Honda, Ford, or Toyota.
- The organisation or organisation in charge of issuing the parking violation ticket is known as the issuing agency. Examples of these are the city police or parking authority.
- Street Code 1: This code designates a particular street or area in the city where the infraction took place.
- Another code that indicates a secondary or intersecting street location that is relevant to the infraction is Street Code 2.
- Street Code 3: An extra street code to help pinpoint the exact location of the infraction.
- The vehicle's registration or parking permit expiration date is the vehicle's expiration date.
- The precise location of the parking infraction, which may include surrounding landmarks or street information.
- Precinct of Violation: The district or precinct in which the infraction was committed; often associated with local law enforcement authorities.
- Issue Precinct: The district or precinct of the ticket's issuing officer.
- The identifier that identifies the particular officer or person who issued the parking citation is known as the "issue code."
- The issuer's department or command within the law enforcement agency is known as the issuer command.
- The squad or team to which the issuer is assigned within the agency is known as the "issuer squad."
- The precise moment the parking infraction took place is known as the violation time.
- The county in which the violation occurred is known as the Violation County.
- Violation In Front Of Or Opposite: Indicates whether the infraction took place in front of or across from a certain structure or landmark.
- The street location where the infraction took place is known as the "house number."
- Street Name: The street name where the infraction occurred.
- Date First seen: The day the infraction was first seen or recorded.
- Law Section: The precise legal provision or rule that specifies the infraction.
- Sub Division: The area where the infraction took place, or a more precise subdivision.
- Days Parking In Effect: The duration of time the car was not in compliance with parking rules.
- The colour of the car that was involved in the infraction.
- Vehicle Year: The year that the vehicle involved in the infraction was manufactured.
- Feet From Curb: The vehicle's distance (measured in feet) from the curb, which may be important for several infractions including excessive curbside parking.
- infraction Post Code: This code, which may be used for categorisation or location identification, indicates the

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precise post or region where the infraction was reported.

Results Description

Fig 1: Home Page of the Urban Parking Detection

The Urban Parking Detection system's main page is seen in this picture. It shows the main interface via which users may access the system's functions. A welcome greeting, registration or login choices, a synopsis of the system's operation, and connections to other areas such as the parking infraction prediction model, performance metrics, and user assistance are usually included on the home page.

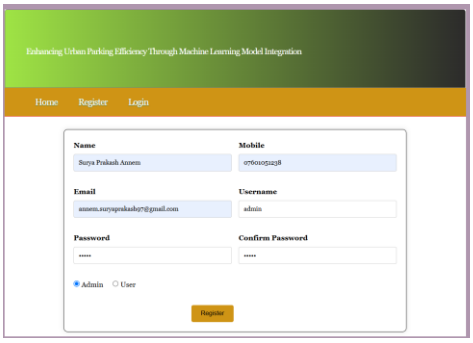

Fig 2: Common Registration for User and Admin

The registration page used by administrators and users is shown in this illustration. It has spaces for inputting personal data, including email, role (Admin or User), password, and username. Both kinds of people may register with ease thanks to the form's design. A secure registration procedure is provided by the user interface's input validation and submission features.

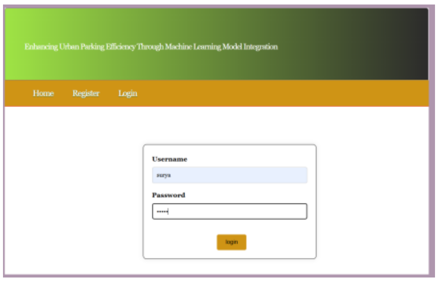

Fig 3: User Login for Using Parking Detection

The login screen for users to use the parking infraction detection system is shown in this illustration. It has spaces for typing the password and registered username. Additionally, there can be a "Sign Up" link for new users and a "Forgot Password" option for recovery. Users are sent to the dashboard after successfully logging in, where they may submit datasets of parking violations and carry out other tasks.

	Plate ID	Registration State	Plate Type	Violation Code	Vehicle Body Type	Vehicle Make	Issuing Agency	Street Code1	Street Code2	Street Code3
0	51526.0	43.0	32.0	10.0	55.0	171.0	11.0	64151.0	15635.0	49295.
1	115980.0	43.0	32.0	10.0	60.0	171.0	11.0	64151.0	15635.0	49295.
2	89416.0	43.0	32.0	10.0	60.0	11.0	11.0	64151.0	65617.0	15635.

Fig 4: Sample Parking Uploaded Dataset

The submitted dataset for parking infractions is shown in this image. Numerous columns pertaining to parking infractions, including car plate ID, registration state, violation code, vehicle manufacturer, and violation time, are included in the dataset. The dataset's sample records are shown in the table; they will be processed to train the prediction model and provide information on parking infractions.

VI. CONCLUSION AND FUTURE SCOPE

The study employs machine learning methods, including Random Forest, Logistic Regression, and CatBoost, to forecast parking infractions in metropolitan areas. We have effectively shown in this study the value of using cutting-edge machine learning methods to forecast parking infractions, which may significantly

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help local government agencies enhance traffic control and parking enforcement. Data preprocessing, feature extraction, and model construction were all steps in the process. The suggested CatBoost model was then compared against other techniques.

The results showed that CatBoost, a gradient boosting method, performed better in terms of prediction accuracy than both the conventional Random Forest and Logistic Regression models. This outcome demonstrates CatBoost's strength in managing intricate datasets with categorical characteristics and its capacity to provide improved performance with minimal human adjustment. Furthermore, the study has shown how machine learning models may enhance urban traffic management decision-making and drastically reduce human error.

The algorithms' comparison also showed how algorithm selection and data quality affect prediction accuracy and dependability. The research is a useful tool for law enforcement organisations and city planners since it has successfully shown that it is feasible to anticipate parking offences with a high degree of accuracy.

Future Scope:

This project's future scope offers a great deal of promise for further improvements and uses:

1. Real-time Prediction: Using real-time data from parking sensors, cameras, and Internet of Things devices to instantaneously forecast parking offences is one of the main areas for future growth. This might make enforcement more effective and efficient by enabling automatic ticketing and lowering the need for human involvement.
2. Integration with Smart City Infrastructure: As cities develop into "smart cities," combining this system with other urban services (such as public transit, traffic control, or city planning tools) may provide a comprehensive strategy for both law enforcement and urban mobility.
3. Model Optimisation: To handle bigger datasets with more intricate features, the existing machine learning models may be further improved by hyperparameter tweaking, feature engineering, and investigating alternative algorithms as XGBoost, LightGBM, or deep learning-based models.
4. Predictive Analysis for Urban development: In addition to anticipating infractions, the system might be extended to spot trends that could help guide urban development choices. In order to assist authorities in creating more effective parking zones and enhancing overall city planning, this may include examining patterns in parking infractions by location, time of day, or kind of vehicle.
5. Scalability and Deployment: By combining data from various sources, such as parking meters, traffic cameras, and license plate recognition systems, the system may be expanded to include whole metropolitan regions. Accessibility and scalability may be improved by deploying the model on cloud infrastructure, which would enable different stakeholders to access information from any location.
6. Advanced Data Integration: Additional information that might affect parking behaviour and infractions, such weather data, municipal events, or roadworks schedules, could be included into future project versions. This might increase the forecast accuracy and provide a more thorough analysis.

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7. Public Awareness and Compliance: In order to lower the number of infractions and increase overall compliance, the system might be expanded to not only anticipate infractions but also notify vehicles of impending parking restrictions, events, or penalties.

REFERENCES

[1] Yang, J., Wang, J., & Liu, X. (2019). A Survey on Smart Parking Systems in Smart Cities. *IEEE Access*, 7, 46860-46878.

[2] Zheng, Y., Xie, X., & Ma, W. (2011). Parking Availability Prediction for Sensor-Enabled Car Parks in Smart Cities. *Proceedings of the 2011 International Conference on Ubiquitous Intelligence and Computing*, 266-273.

[3] Caicedo, C., Muratore, M., & Sánchez, F. (2019). Real-Time Prediction of Parking Space Availability in Urban Areas. *Journal of Transportation Engineering, Part A: Systems*, 145(4), 04019009.

[4] Channamallu, S., & Verma, R. (2020). A Comprehensive Study on Parking Occupancy Prediction. *Transportation Research Part C: Emerging Technologies*, 114, 109-130.

[5] Kotb, M., & Shalaby, A. (2019). Smart Parking Guidance and Reservation Systems: A Review. *Transportation Research Part C: Emerging Technologies*, 108, 154-179.

[6] Yang, X., Song, H., & Wang, L. (2020). Deep Learning for Real-Time Parking Occupancy Prediction in Smart Cities. *IEEE Transactions on Intelligent Transportation Systems*, 21(2), 705-714.

[7] Pamidimukkala, S., & Saha, A. (2020). Barriers to Electric Vehicle Adoption in Texas: A Case Study. *Transportation Research Part D: Transport and Environment*, 79, 102216.

[8] Huang, Z., & Li, Y. (2019). Location-Based Services: Research and Evolution. *International Journal of Geographical Information Science*, 33(3), 543-570.

[9] Sester, M. (2020). Mobility Data Analysis in Mobile Mapping Systems. *Journal of Navigation*, 73(1), 12-34.

[10] Channamallu, S., & Gupta, A. (2021). Comparative Analysis of Parking Occupancy Prediction Models. *IEEE Transactions on Intelligent Transportation Systems*, 22(3), 1376-1390.

[11] Liu, X., & Zhang, Y. (2020). Parking Occupancy Prediction Using Gradient Boosting Decision Trees. *Proceedings of the 2020 International Conference on Artificial Intelligence and Data Science*, 213-220.

[12] Sun, X., & Zhang, M. (2019). Short-Term Parking Occupancy Prediction Using Decision Trees and Random Forests. *Transportation Research Part C: Emerging Technologies*, 104, 45-58.

[13] Patel, R., & Rajput, K. (2020). Temporal and Spatial Patterns of Autonomous Vehicle Collisions. *IEEE Transactions on Vehicular Technology*, 69(7), 7650-7662.

[14] Hendricks, J., & Outwater, L. (2019). A Demand Forecasting Model for Park-and-Ride Lots. *Transportation Research Part A: Policy and Practice*, 125, 144-157.

[15] INRIX Research. (2020). The Economic Impact of Parking in the United States. *INRIX Report*.

[16] Caicedo, C., & Muratore, M. (2018). Parking Management and Modeling Car Park Patron Behavior in Underground Parking. *Transportation*

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ISSN 2319-5991 www.ijerst.com
Vol. 21, Issue 2, 2025

Research Part A: Policy and Practice, 113, 78-90.

[17] Shoup, D. (2018). Cruising for Parking. *Transportation Research Part A: Policy and Practice*, 115, 1-18.

[18] Channamallu, S., & Verma, R. (2019). Smart Parking Systems: Recent Advances and Future Directions. *IEEE Transactions on Intelligent Transportation Systems*, 21(8), 3254-3265.

[19] Lin, L., & Wei, S. (2020). Survey on Smart Parking Solutions for Urban Mobility. *IEEE Access*, 8, 3212-3225.

[20] Virginia Metro Rail Authority. (2020). Feasibility Study of Real-Time Parking Information at Metro Rail Stations. *Virginia Department of Rail and Public Transportation*.

[21] Adepu, A., & Srinivas, S. (2020). Construction Cost Overruns during COVID-19: Challenges and Strategies. *Journal of Construction Engineering and Management*, 146(10), 04020095.

[22] Gordon, D. (2018). High-Tech Parking Meters in San Francisco. *The New York Times*.

[23] Richtel, M. (2019). The Role of Mobile Apps in Parking: Revolutionizing the Way We Park. *The New York Times*.

[24] SFMTA. (2019). Demand-Responsive Pricing for Parking in San Francisco. *San Francisco Municipal Transportation Agency*.