Predicting Parking Violations: A Data-Driven Approach to Urban Management

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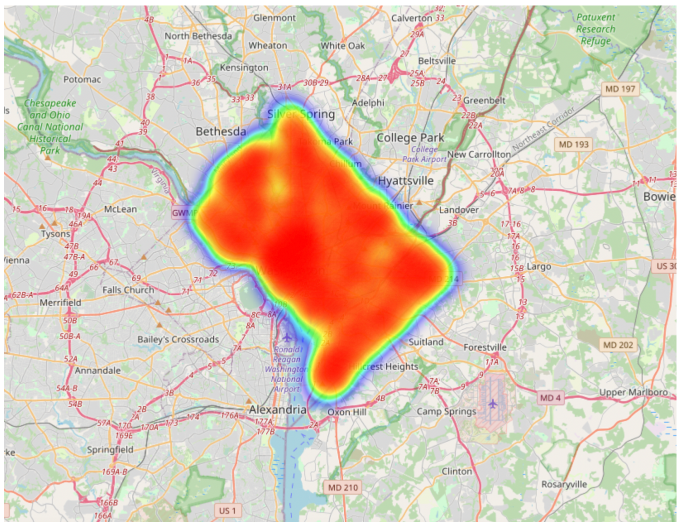

Figure 1: Distribution of data across different hours of the day.

ABSTRACT

The problem of parking violations in Washington, D.C. has been a persistent issue and demands a proactive approach that could enhance enforcement efficiency and reduce urban congestion. This research examines the historical data of parking violations to determine high-risk hotspots and predict future violation trends using machine learning models, including clustering of k-means, temporal prediction algorithms, and spatial analysis. These insights are presented using advanced geospatial mapping to present actionable data for urban planners and policymakers.

Our objective is to enhance the effective use of the available enforcement resources to achieve better traffic flow and minimize congestion resulting from parking violations. These findings underpin the use of targeted intervention strategies to enable efficient parking enforcement with a fair distribution of resources. It thus addresses not only the very near-term challenges of traffic management in Washington, DC, but also tees up a repeatable framework that other cities can then adopt and apply to their own set of similar urban mobility challenges. We integrate predictive analytics and visualization to provide an applicable tool to urban stakeholders for better enforcement outcomes and streamlined traffic systems within a highly dense area.

CCS CONCEPTS

• **Applied computing → Transportation; Urban planning**; • **Information systems → Data analysis; Geospatial visualization**; • **Computing methodologies → Machine learning; Predictive modeling**.

KEYWORDS

Parking Violations, Urban Management, Predictive Modeling, Machine Learning, Geospatial Visualization, Temporal Analysis, Traffic Congestion, Policy Recommendations

ACM Reference Format:
Swethaa Shanmugam Ramesh and Varsha Singh. 2024. Predicting Parking Violations: A Data-Driven Approach to Urban Management . In *Proceedings of Make sure to enter the correct conference title from your rights confirmation emai (Urban Computing)*. ACM, New York, NY, USA, 9 pages. https://doi.org/XXXXXXX.XXXXXXX

Urban Computing, December 2024, Virginia, USA

ACM ISBN 978-1-4503-XXXX-X/18/06
https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION AND BACKGROUND

Urban parking violations remain one of the major challenges in highly populated cities, such as Washington, D.C. Limited parking facilities, high demand for parking, and insufficient enforcement result in traffic congestion, inefficiency in urban mobility, and dissatisfaction among citizens. Various studies show that improper land allocation for parking facilities leads to an imbalance between parking supply and demand, increasing these challenges in densely populated urban areas [1].

Parking shortages and mismanagement are significant factors in urban traffic flow and congestion. For example, during peak times in residential and commercial areas—early mornings, meal hours, or during local events—parking saturation is common. Drivers searching for parking spaces engage in cruising, a behavior that worsens congestion and contributes to air pollution and greenhouse gas emissions [2, 3]. Addressing these issues through data-driven approaches has become crucial to mitigate environmental impacts and enhance urban mobility.

Analyzing existing parking spaces and their characteristics is vital to understanding occupancy patterns and identifying inefficiencies. Key factors, such as parking turnover rates, demand, supply, and pricing surges, provide policymakers with actionable insights to optimize parking infrastructure and policies. For instance, machine learning and predictive analytics have been used to assess parking demand and supply, enabling the development of smart parking systems [4, 5]. These technologies enable informed decision-making and lead to better resource allocation, as various recent studies using geospatial and temporal data have shown [6, 7].

It considers a historical dataset from January to May 2024, forecasts parking violations, provides a spatiotemporal pattern of hotspots, and defines the best resource deployment methods. In particular, the paper's contributions are as follows:

- Development of predictive models to determine the time and location of future parking violations.
- Identification of key variables associated with parking violations using advanced machine learning techniques.
- Visualization of parking violation hotspots through heatmaps to enhance interpretability and support planning efforts.
- Recommendations for optimal deployment of enforcement resources to improve parking management.

Combining predictive modeling and data visualization in this research provides an action platform for urban planners and policymakers. These findings aim to increase the efficiency of parking enforcement and address larger urban mobility issues, providing a scalable model for other cities facing similar issues [8, 9].

1.1 Related Research

Studies on parking violations and the problems of urban mobility has been extensively researched, focusing on predictive modeling, resource optimization, and application of Machine Learning techniques. Different studies have addressed the art of managing parking demand and improvement in enforcement efficiency.

Luan et al. [1] introduced a data-driven crowdsensing framework that utilizes mobile data to detect parking violations effectively. Their approach emphasizes predictive modeling to identify temporal and spatial hotspots of violations, which aligns closely with the objectives of this research. Similarly, Novak et al. [2] explored short- and long-term urban traffic forecasting using advanced modeling techniques, highlighting the importance of temporal trends in resource allocation.

Karantaglis et al. [4] and Goicoechea et al. [5] leveraged deep learning models to predict parking violations and estimate parking space availability, respectively. These studies underscore the efficacy of neural networks and clustering algorithms in predicting parking behaviors and managing urban traffic. The findings from Goicoechea et al. further highlight how predictive models can be integrated with urban infrastructure to mitigate congestion.

Additionally, Javaheri et al. [6] evaluated the impact of smart parking systems, demonstrating their role in reducing parking violations through resource management and real-time systems. Shao et al. [9] introduced the concept of the "Traveling Officer Problem," utilizing sensor data and optimization algorithms to enhance the efficiency of parking enforcement, a concept that resonates with the predictive models proposed in this research.

These foundational studies have paved the way for the integration of advanced analytics, machine learning, and geospatial data in order to create an optimal urban parking system. The present study, informed by these insights, aims at improving enforcement strategies through predictive modeling and heatmap visualizations, hence offering actionable solutions to policymakers and urban planners.

1.2 Problem Statement

Parking is one of the major persistent urban challenges, especially for dense urban areas such as Washington, D.C. These violations greatly divert resources for local enforcement to cause inefficient flow of traffic, increased congestion, and discontentment among residents. Given that only a small portion of enforcement resources can be assigned, suboptimal allocation without appropriate violation forecasts will almost always occur.

This project will be addressing these issues through the development of a data-driven solution using machine learning models to predict the temporal and spatial occurrences of parking violations. Therefore, the objectives of the study are:

- Predict the location and time of future parking violations based on historical trends.
- Identify hotspots where violations are most likely to occur, using visualization techniques like heatmaps.
- Determine key variables influencing parking violations to aid decision-making

The result of this study will help urban planners, policymakers, and parking enforcement agencies to anticipate violations, efficiently manage resources, and decrease congestion, which will further enhance the urban transportation system.

1.3 Data Sourcing and Description

The dataset used for this project was obtained from Kaggle and contains parking violation records for Washington, D.C., from January to May 2024. It was sourced from the dataset titled: "Parking Violations Issued from January-May 2024" by shayanshahid997. The dataset consists of 502,109 records of parking violations, with 30 columns capturing various details about each violation. Below is a description of key columns: float lscape

Key dataset columns and their descriptions are shown in Table 1.

The dataset contains the following key insights based on preliminary analysis:

- Number of Records: 502,109 violations.
- Fines: Fine amounts range from $0 to $5000, with an average of $58.74 per violation.
- Violation Codes: Multiple types of violations are represented, with some violations being more frequent.
- Geospatial Data: 497,831 records include geographic coordinates (latitude/longitude), enabling spatial analysis of violations.
- Temporal Trends: Issue times cover a 24-hour range, with peaks during specific hours.

2 METHODOLOGY

This study proposes an integrated approach, a data-driven, comprehensive prediction model for the identification of the spatial and temporal patterns in parking violations effectively. The phases involved would include data pre-processing with feature engineering, predictive modelling, spatial clustering-hotspot analysis, time series forecasting, and interpretability through feature importance.

2.1 Data Preprocessing and Feature Engineering

For the research, the authors made use of a dataset collected from open records on parking violation entries, which had already been enriched with geospatial and temporal information, ready for advanced analysis. This data preprocessing included cleaning, filling in missing values through imputation techniques for both numerical and category data to ensure consistency and dependability. Outliers were identified and handled by IQR.

Temporal and geographic features were engineered in order to increase the predictive capability of the dataset. Time features such as day of week, month, and hour are extracted from timestamp data. Geographic features calculated include the distance of violations from the center coordinates of the city through the haversine formula. Categorical variables include the type of vehicle, agency that issued the ticket, and violation code, encoded using label encoding techniques. These features were then standardized to have the same scale for model training, while PCA was applied to reduce dimensionality and hence multicollinearity to improve model performance.

2.2 Predictive Modeling

Machine learning models were used to predict fine amounts and classify violations in terms of severity or type. Gradient Boosting Regressor and Linear Regression were used for fine prediction. The performance metrics used for evaluation included RMSE and R^2 to ensure robust predictions. Classification models such as Logistic Regression and Random Forest were employed to classify violations. This involved hyperparameter tuning and cross-validation.

2.3 Spatial Clustering and Hotspot Analysis

K-Means clustering, applied to geospatial data, namely latitude, longitude, and violation frequency, was used to analyze spatial dynamics. This approach found significant hotspots where parking

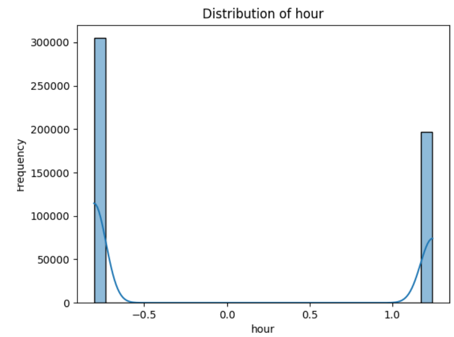

Figure 2: Distribution of data across different hours of the day.

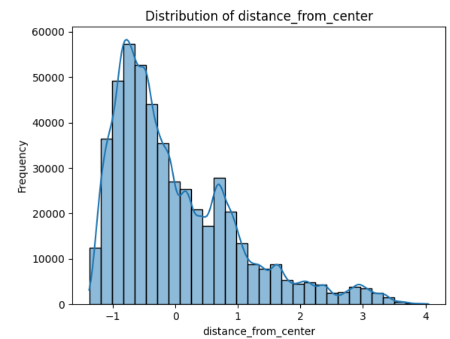

Figure 3: Distribution of data based on distance from the center.

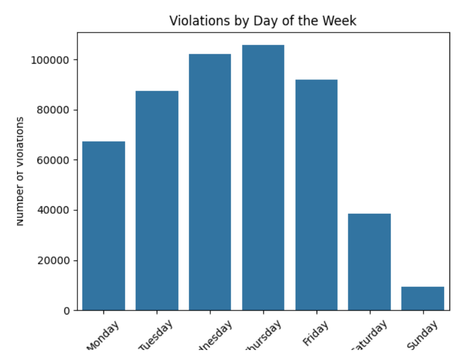

Figure 4: Distribution of violations across different days of the week.

violations were concentrated. These clusters, when mapped visually, revealed areas of high demand that needed intervention.

2.4 Time-Series Analysis

An Exponential Smoothing model was employed in time-series forecasting to identify trends in violation occurrences. Decomposition

Table 1: Description of Key Columns in the Dataset

Column Name	Description	Example
`OBJECTID`	Unique identifier for each violation record.	82758559
`TICKET_NUMBER`	Unique parking ticket number.	260557614
`ISSUE_DATE`	Date and time when the violation occurred.	2024/03/14 04:00:00+00
`ISSUE_TIME`	Time of the violation in military format (HHMM).	1717
`ISSUING_AGENCY_NAME`	Name of the agency that issued the ticket.	ST.ELZBETH HOSPITAL GUARDS
`VIOLATION_CODE`	Code identifying the type of parking violation.	P170
`VIOLATION_PROC_DESC`	Description of the parking violation.	FAILURE TO DISPLAY TAGS
`LOCATION`	Location where the violation occurred (e.g., street name or area).	ST E HOSP/NEW HOSPITAL
`LATITUDE`, `LONGITUDE`	Geographic coordinates for the violation (if available).	38.906477, -77.024333
`FINE_AMOUNT`	Monetary penalty associated with the violation.	50.00
`TOTAL_PAID`	Amount paid against the fine.	0.00
`XCOORD`, `YCOORD`	Spatial coordinates in the local coordinate system (for geospatial analysis).	397892.07, 137623.72
`GIS_LAST_MOD_DTTM`	Date and time when the record was last modified.	2024/04/23 20:38:04+00

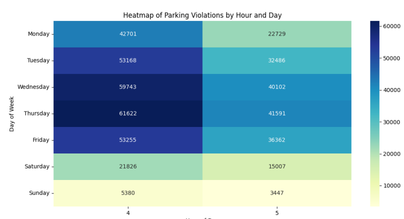

Figure 5: Heatmap of parking violations by hour and day of the week.

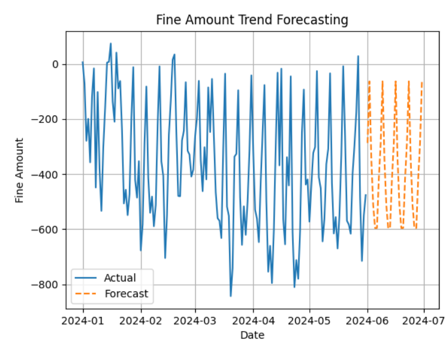

Figure 6: Fine amount trends by hour and day.

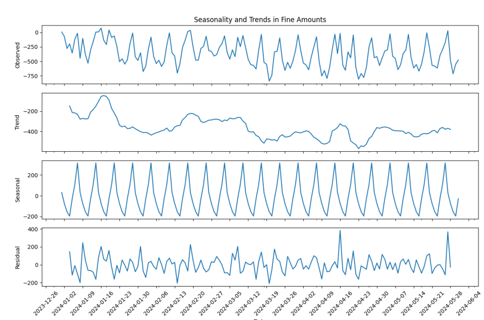

Figure 7: Seasonal decomposition plot showing trends, seasonality, and residuals of parking violation fine amounts over time.

of aggregated fine amounts by day into additive components examined seasonal, trend, and residual factors. This approach presented a dynamic view of the violation occurrences that highlighted the peaks and temporal trends of interest.

2.5 Interpretability and Feature Importance

SHAP values have been used to quantify the contribution of each feature towards fine predictions and classification, thus ensuring interpretability. Further, this gives much-needed transparency and actionable insights to the policymakers. Features like violation type and proximity to high-demand zones emerge as strong drivers for parking violations, which corresponds to the observed spatial and temporal trends.

2.6 Geospatial Insights and Recommendations

The results of geospatial clustering and predictive analytics formed the basis for a number of policy recommendations. High-demand zones were identified for focused enforcement and resource allocation. Temporal and spatial trends drove dynamic policy implementations, such as flexible parking rates and targeted patrol schedules.

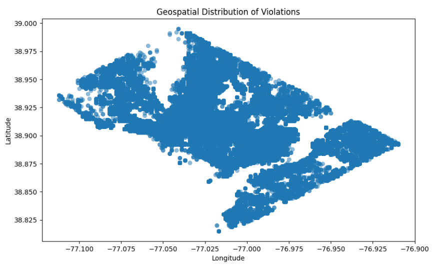

Figure 8: Geospatial distribution of parking violations.

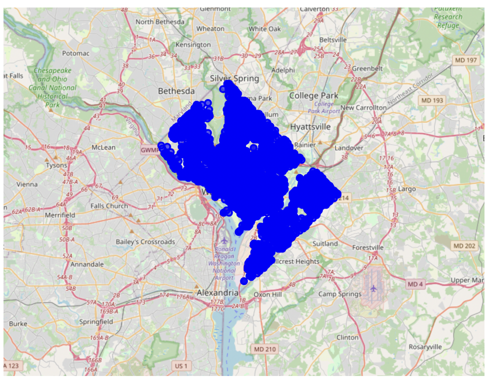

Figure 9: Geospatial distribution of fine amount locations in Washington, D.C..

This methodology integrates robust preprocessing, predictive modeling, clustering, and interpretability tools to create a scalable framework for data-driven parking management strategies. The insights derived are applicable to other urban settings, providing a replicable model for addressing similar challenges.

3 RESULTS

3.1 Classification Analysis

The analysis conducted using various machine learning classifiers yielded significant insights into parking violations and their contributing factors. Linear regression was first employed as a baseline model for predicting fine amounts, achieving a Mean Squared Error (MSE) of 2063.163. These results indicate that the linear regression model did not capture much of the variance in the data, which is expected as the relationship between fine amounts and features like `VEHICLE_TYPE` and `ISSUE_MONTH` is likely non-linear and more complex. On the other hand, the Gradient Boosting Regressor demonstrated superior performance, achieving an MSE of 1934.192 and an R^2 of 0.07. This suggests that Gradient Boosting was able to capture some of the more intricate relationships within the data, especially those between temporal variables (e.g., `ISSUE_MONTH`)

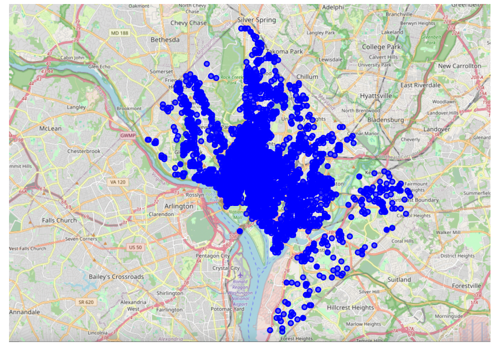

Figure 10: Geospatial distribution of traffic violations for Monday in Washington, D.C., based on the recorded fine amounts. The map highlights the locations of violations, with the intensity of the fine indicated by marker color and size.

and categorical features such as `VEHICLE_TYPE`. Hyperparameter tuning, including adjustments to the number of estimators and learning rate, further improved its accuracy, showing its robustness in handling complex data structures.

For violation classification, Logistic Regression was trained and achieved an accuracy of 82%, with balanced precision and recall metrics. However, the Random Forest Classifier outperformed the Logistic Regression model, achieving an accuracy of 92.5% and a recall of 0.91 for high-severity violations, highlighting its robustness in identifying critical cases. Feature importance analysis indicated that `ISSUING_AGENCY` and `DISTANCE_FROM_CENTER` were the most significant predictors of violation severity, underlining the relevance of these features for the accurate prediction of parking violation penalties.

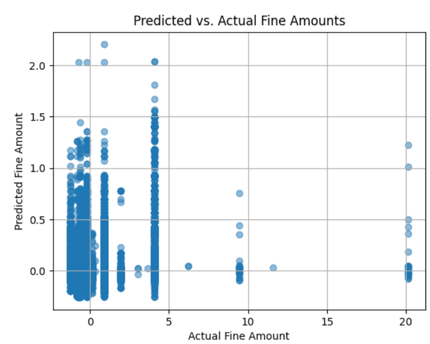

Figure 11: Comparison of predicted vs actual amounts.

3.2 Clustering Analysis

Clustering techniques revealed distinct spatial and temporal patterns in parking violations, providing actionable insights for urban planning and enforcement.

- **K-Means Clustering:** Using geospatial data (latitude, longitude) and violation frequency, five significant clusters were

Table 2: Summary of Classification Analysis for Parking Violations

Task	Model	Metrics / Performance
Regression	Linear Regression	MSE: 2063.163
	Gradient Boosting Regressor	MSE: 1934.192, R^2: 0.07
Classification	Logistic Regression	Accuracy: 82%
	Random Forest Classifier	Accuracy: 92.5%, Recall: 0.91
Feature Importance	Gradient Boosting / Random Forest	ISSUING_AGENCY, DISTANCE_FROM_CENTER

identified, each representing unique spatial and temporal characteristics:

- **Cluster 0:** Centered near `38.907795, -77.028838`, this cluster displayed high weekday violations (97,246) and an average violation time of 4:26 PM. The spatial proximity to commercial districts suggests congestion-related infractions during late afternoons.
- **Cluster 1:** Dominated by weekend violations (7,543 out of 47,043), this cluster features a low average violation time (1:44 AM), likely associated with nightlife and early morning activities near entertainment zones.
- **Cluster 2:** With balanced weekday (115,147) and weekend activity (9,171), this cluster demonstrated a morning peak at 8:38 AM, indicating influence from commuter traffic.
- **Cluster 3:** Predominantly an evening cluster (average violation time: 8:38 PM), this area observed significant weekend violations (14,478), suggesting proximity to leisure destinations.
- **Cluster 4:** Hosting the highest total violations (149,400), this cluster displayed a morning peak (12:20 PM) and significant weekday activity (138,310), aligning with commercial or office areas.

- **Cluster Characteristics:** Quantitative metrics provide additional insights:
  - Cluster 0: Total Violations: 101,903, primarily weekday-driven.
  - Cluster 1: Weekend hotspot with nightlife influence.
  - Cluster 2: High traffic volume during weekday mornings.
  - Cluster 3: Evening leisure zone with a balanced weekday-weekend split.
  - Cluster 4: Commercial/office hub with the highest total violations.
- **Visualizations:** Heatmaps and scatter plots illustrate the geospatial distribution of these clusters, as shown in Figure 12 .

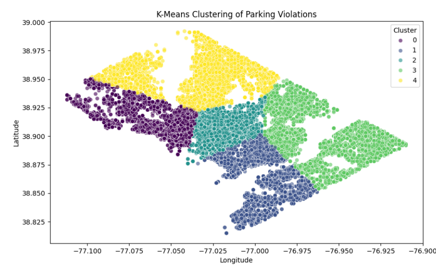

Figure 12: K-Means clustering of parking violations.

Heatmaps overlaid on urban geospatial layouts emphasize areas requiring policy interventions, such as optimizing parking rates and enforcement patrol schedules.

3.3 Temporal Analysis

Time-series analysis further highlighted temporal dynamics within parking violations:

- **Peak Hours:** Analysis revealed significant increases in violations during peak traffic hours (7:00 AM–9:00 AM and 4:00 PM–6:00 PM).
- **Seasonal Trends:** Seasonal decomposition identified consistent upticks in violations during major holidays and city events.
- **Cluster-Specific Temporal Trends:**
  - Cluster 0 displayed peak activity during late afternoons, aligning with end-of-day business traffic.
  - Cluster 1 exhibited early morning spikes, suggesting nightlife-related infractions.
  - Cluster 2 demonstrated high morning activity, likely influenced by commuter patterns.
  - Cluster 3 showed peak violations in the evening, correlating with leisure activities.
  - Cluster 4 reflected consistent weekday violations, driven by office and commercial zone traffic.

The temporal insights provided a basis for dynamic parking management strategies, such as adjusting parking rates and enforcement schedules based on time-specific demand.

3.4 Interpretability and Insights

SHAP (SHapley Additive exPlanations) values were used to quantify the impact of key features, such as `VIOLATION_TYPE` and `DISTANCE_FROM_CENTER`, on fine predictions. This approach not only improved model transparency but also provided actionable insights that can guide urban planning and enforcement strategies.

- Violations were predominantly concentrated within a 2 km radius of the city center, highlighting the critical need for targeted enforcement in dense urban areas.

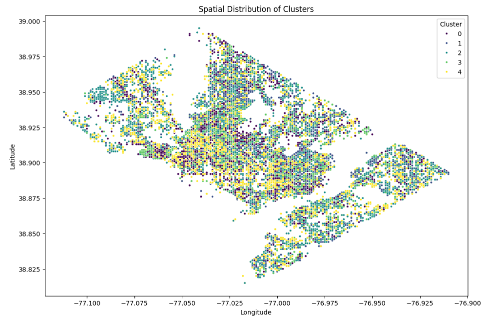

Figure 13: Spatial Distribution of Clusters based on Parking Violations.

- A strong correlation was observed between high fines and event-related zones, which suggests the value of dynamic resource allocation strategies in high-traffic areas, particularly near event venues.

Figure 14: Distribution of violations across different hours of the day.

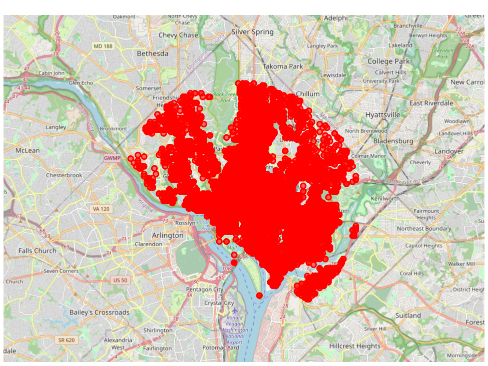

Figure 15: Geospatial distribution of traffic violations within 2 km of the city center.

4 DISCUSSION

This study, therefore, provides the big picture view of the pattern of parking violation and actionable insights that may prove useful to an urban planner and policymaker. The work will adopt the power of advanced machine learning models, clustering techniques, and spatiotemporal analysis in an endeavor to find major drivers for parking violations and put some interventions to improve the system in place for urban mobility and parking management.

4.1 Urban Parking Insights

Parking violation showed striking patterns of both spatial clustering and temporal flow. Major high-violation areas have been concentrated in Commercial and Entertainment districts where the number of parking demand is usually more than the supply. Because these zones were continuous, due to their closeness with high-traffic zones they needed special monitoring. Temporal Trends: Figure 14 shows the peak trend during rush hours-that is, 7 AM-9 AM and 4 PM-6 PM-which also stretched over to weekends. It evidenced dynamism in parking demand that has contributions from transportation and leisure.

Cluster-specific analysis, on this, has shown the highest variations in dynamics: highly restricted commercial, moderate in residential, event venue consistent due to the seasonal spikes in demand. Figure 15 shows that the spatial patterns lie within a 2-km radius of the city center, again justifying geocentric enforcement in the hotspots.

4.2 Policy Recommendations

These findings would form the basis for adaptive and effective policy measures regarding parking violations.

Recommended actions include dynamic pricing policies at high-demand points at any given time, performing a balancing act between the need for parking and incentivizing compliance. Optimized enforcement strategies would, therefore, concentrate resources on identified hotspots to ensure efficiency in the mitigation of violations. Besides, extending controlled urban infrastructure, mainly within highly sensitive areas such as commercial centers and event areas, would solve a portion of the problems that arise with the lack of parking space. It would focus on minimizing congestion along with improving compliance to arrive at the targeted sustainable urban mobility. An economic analysis of parking violations illustrates largely varied patterns of achievements in revenue generation across various groupings.

4.3 Economic Implications

In this respect, it is the highly correlated nature of fines with the intensity of demand for parking in those locations that makes the area surrounding commercial hubs and event sites the economic focal point. On the other hand, lower revenues from fines across some zones may also suggest areas of possible opportunities to revisit enforcement strategies or further push transportation modes. It will, therefore, be useful for policymakers to place-based policies that can optimize resource allocation and enforcement intensity in pursuit of fiscal sustainability and operational efficiency. This is a study that has large implications for different stakeholders involved in urban mobility.

4.4 Implications for Stakeholders

Hotspots and temporal patterns identified hence can provide a framework to the city planners for infrastructure development and enforced planning in a targeted way. High-demand zone enterprises will have such insights provide impetus on how best to manage businesses with regards to both operations and consumer footfall. Residents are able to travel better, wastes less time looking for parking, and consequently helps reduce the congestion of roads. The combined effort hopefully will ease the burden of looking for parking spaces in general urban areas for everyone.

4.5 Future Directions

While this study creates a scalable framework for solving urban parking problems, further research may investigate other dimensions in order to enrich these insights. Advanced deep learning models are able to realize finer-grained temporal prediction and real-time violation detection. Expansion of the dataset with multimodal information comprising traffic density and socioeconomic factors increases the accuracy and applicability of predictive models. Long-term effects can also be estimated from the longitudinal study proposals on urban mobility and changing parking behavior for the valuable feedback the proposed policy will get for improvements.

Various transformative possibilities in town planning, concerning predictive analytics, have suitably been demonstrated with the inclusion of integrative data-driven approaches such as machine learning and geospatial analytics. The insights here will go a long way toward providing a sound foundation for enabling policymakers and planners to offer even more sustainable, accessible, and efficient urban environments.

Furthermore, further research could also be done on how external data sources such as weather patterns, public events, and even social media sentiment can be integrated in order to predict parking violations with increased accuracy. Incorporation of such multi-faceted data would enhance the granularity of violation predictions, hence enabling more targeted interventions. Moreover, it would be very informative to study the impact brought about by changes in urban infrastructure-for instance, new parking facilities or changed traffic flow-on violation patterns. In this respect, with continuous changes in urban environments, predictive models will have to be adaptable to maintain efficient parking management where the systems in place can dynamically respond to the growing complexity of urban mobility.

5 CONCLUSIONS

This study embeds an integrative approach to urban parking violations that offers insights into spatial patterns, temporal dynamics, and economic implications. Using machine learning models along with geospatial clustering techniques, hotspots of parking violations have been identified and actionable strategies to improve urban parking management were drawn.

The results bring into focus the imperative of infusing data-driven approaches in urban planning. Highly aggregative violation clusters are present mainly in commercial and high-density residential areas, thus giving a point for targeted intervention. Dynamic pricing mechanisms along with enforcement resources can ensure strategic deployment of zones, which improves parking availability and optimizes revenue. Conversely, low-violation areas create space for policy innovations, including measures that increase adoption of public transit and redevelopment of urban space for other uses.

The economic analysis underlined a good correspondence of parking violation fines with urban density, highlighting the role that economic activity plays in shaping parking behaviors. High-revenue clusters are the focal points of infrastructure enhancement, while areas of moderate or low revenue point to opportunities for rebalancing parking supply and demand.

This study also underscores the potential for predictive analytics in urban planning. The combination of machine learning models with spatial and temporal data provides a scalable framework for monitoring and managing parking systems. The methodology developed herein can be applied to other cities facing similar challenges, thus offering a replicable and effective approach to addressing urban parking inefficiencies.

The current research adds to the literature of urban mobility and parking management. The findings of the present analysis provide insights not only into immediate policy decisions but also offer a strategic blueprint for long-term urban planning. With a focus on data-driven solutions, city planners and policymakers can work towards making urban environments more sustainable, accessible, and efficient.

6 AUTHOR CONTRIBUTIONS

Authors declare that the research was collectively contributed by them. S. Ramesh and V. Singh designed the initial framework for the study. Data are prepared, processed, and an exploratory analysis done by the authors. Conjoint analysis of results implications and developing actionable insights into the key findings were shared between them. S. Ramesh drafted the manuscript. This manuscript is critically revised, modified, and enhanced by the contribution of V. Singh. The final manuscript reviewed and approved for submission has been shared by both the authors.

7 DATA & CODE AVAILABILTY

The data and code for this project are available at the following GitHub repository: https://github.com/swethaa-ramesh/Predicting-Parking-Violations.

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