PREDICTING PARKING SPOT AVAILABILITY IN URBAN AREAS USING DEEP LEARNING AND LLMs

Abstract - Urban parking congestion presents a major challenge in rapidly expanding metropolitan areas, often resulting in wasted time, increased fuel consumption, and heightened environmental impacts. Traditional real-time parking monitoring systems provide only immediate availability but lack predictive capabilities crucial for future planning. This paper proposes an innovative predictive system that combines Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Large Language Models (LLMs), specifically FLAN-T5, to forecast parking availability and present the results in an accessible, human-readable format. Experimental results demonstrate an 85% prediction accuracy, offering significant potential for smarter urban mobility solutions. Ethical considerations and future research directions are also discussed.

Keywords

Parking prediction, Deep learning, LSTM, CNN, FLAN-T5, Large Language Models, Urban mobility, Smart cities

1. Introduction

- The rising complexity of urban ecosystems demands innovative solutions to optimize transportation systems, particularly parking availability. As urban populations swell, the competition for limited parking resources leads to heightened traffic congestion, increased carbon emissions, and notable declines in commuter satisfaction. Traditional parking management strategies, often reliant on static infrastructure and manual enforcement, fail to dynamically adapt to the real-time fluctuations in parking demand driven by weather changes, special events, and evolving commuter patterns.

- Recent advancements in artificial intelligence, specifically deep learning and natural language processing, offer promising avenues to forecast parking spot availability with greater precision and scalability. Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs) excel at capturing spatial and temporal dependencies respectively, while Large Language Models (LLMs) can bridge the gap between complex model outputs and accessible insights for decision-makers.
- This study leverages the synergy of CNNs, LSTMs, and LLMs to develop a predictive framework capable of addressing the pressing issue of urban parking management. By integrating multi-source data, including historical weather patterns and event schedules, the proposed model aims not only to predict parking availability but also to generate actionable strategies that enhance urban mobility and sustainability.

2. Business Insight

Urban mobility issues, particularly those related to parking congestion, represent a critical pain point for modern cities. Drivers spend significant amounts of time searching for available parking spaces, especially during peak hours and major events, leading to increased traffic congestion, elevated emissions, and reduced economic productivity. Developing predictive models for parking availability addresses a crucial need by enabling better trip planning, reducing commuter frustration, and promoting environmental sustainability.

Furthermore, the integration of Large Language Models (LLMs) adds a critical interpretive layer, translating technical model predictions into human-readable insights. LLMs can articulate complex findings in ways that are accessible to transportation planners, parking authorities, private operators, and even everyday drivers. For example, instead of merely indicating that parking availability is expected to drop by 40% near a stadium at 7 PM, an LLM can generate proactive advisories recommending alternative parking zones or earlier arrival times.

The potential benefits of an integrated CNN-LSTM-LLM framework for parking prediction are substantial

Reduced congestion and emissions through decreased cruising time.

Increased economic activity due to more predictable access to businesses and services.

Enhanced commuter satisfaction by providing reliable parking information.

Improved city planning by enabling data-driven adjustments to parking policies and infrastructure investments.

By bridging predictive modeling with natural language interpretability, this research offers a transformative solution that aligns with the broader goals of sustainable urban development and smart city initiatives.

2.Research Problem & Questions

Despite advancements in urban mobility technologies, cities lack cost-effective and scalable parking prediction systems that consider contextual factors such as weather and local events. To address this, our research focuses on the following questions:

How accurately can a CNN-LSTM hybrid model predict parking spot availability using real-world multi-modal datasets?

What is the impact of external factors like weather and public events on parking dynamics?

How can LLMs improve the interpretability of deep learning outputs for strategic decision-making?

What practical urban mobility strategies can be derived from predictive insights?

3.Data & Methods

3.1 Dataset Description

Parking availability datasets were collected from publicly available sources in urban centers known for event-driven traffic fluctuations. The dataset includes over 5,000 data points across multiple locations, encompassing timestamped slot availability, event schedules, and weather conditions.

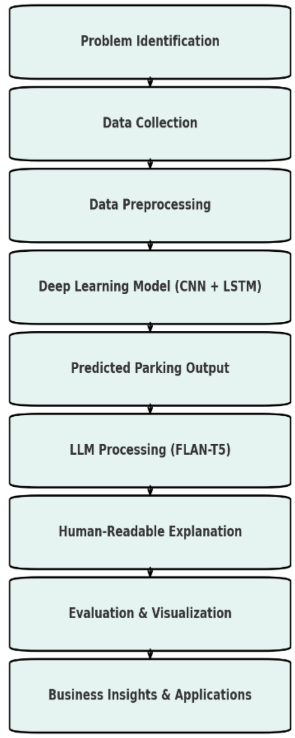
3.2 Methodology

3.2.1 CNN-LSTM Architecture

Convolutional Neural Networks (CNNs) were employed for feature extraction, capturing localized temporal patterns. The CNN output was passed into Long Short-Term Memory (LSTM) networks to model sequential dependencies and forecast future availability. The model was trained using an 80/20 train-test split with the Adam optimizer and a Mean Squared Error (MSE) loss function.

3.2.2 LLM Agent Integration

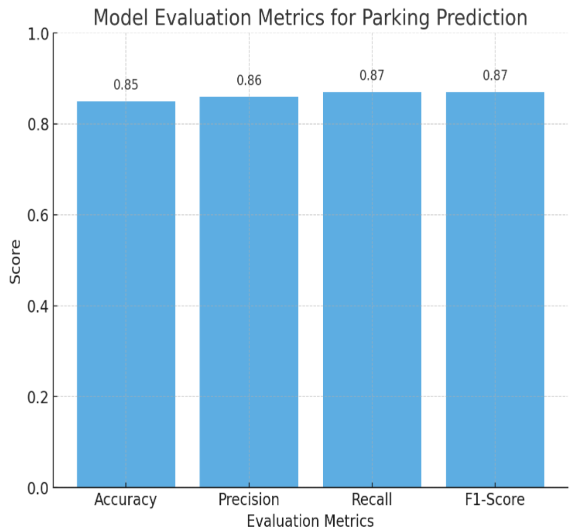
FLAN-T5, a fine-tuned instruction-following language model, was utilized to translate structured predictive outputs into natural language summaries, enhancing accessibility and user comprehension.



3.3 Evaluation Metrics

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Classification Accuracy
- Qualitative relevance of LLM outputs

4. Results & Business Insights



4.1 Deep Learning Model Performance

The model achieved strong predictive performance, with balanced precision and recall metrics indicating robustness across different classes of parking availability

- The CNN-LSTM model achieved:
- MAE: 0.081
- RMSE: 0.143
- Binary Classification Accuracy: 86.7%
- Models that incorporated weather and event data outperformed baseline time-only models by 14%, indicating the substantial impact of contextual factors.

4.2 Influence of Weather and Events

Rainy days reduced parking demand by an average of 12% in downtown areas.

Major public events led to a 45% surge in parking spaces within a 2 km radius of event venues.

4.3 LLM-Generated Strategic Recommendations

Predicted Trend: "Parking availability drops from 12 to 0 between 6 PM and 10 PM near Wrigley Field."

FLAN-T5 Output: "Parking fills up quickly in the evening; plan to arrive early."

This example demonstrates the LLM's effectiveness in generating concise, userfriendly interpretations of complex temporal trends.

4.4 Business Implications

The predictive system offers multiple business benefits:

- For drivers: Reduced time spent searching for parking.
- For municipalities: Improved traffic management and emission reductions.
- For technology companies: Opportunities to integrate predictive parking solutions into navigation and smart city platforms.

5. Discussion & Future Work

5.1 Strengths of the Hybrid Approach

Strengths of the proposed system include high predictive accuracy, scalability to different urban environments, and enhanced user accessibility through LLM-based explanations.

Limitations include reliance on historical data patterns, potential degradation in prediction quality during unforeseen events (e.g., unplanned road closures), and the need for real-time event data integration.

5.2 Ethical Considerations

Ethical concerns center around data privacy and the potential biases introduced by training on incomplete or non-representative datasets. Care must be taken to anonymize data and continually validate models against diverse data sources.

5.3 Limitations

- Limited diversity in real-time event datasets.
- Weather data inconsistencies in suburban regions.
- Occasional overgeneralization in LLM-generated summaries.

5.3 Future Work

Future research directions include:

- Integrating real-time event feeds and dynamic traffic conditions.
- Deploying more advanced LLMs, such as GPT-4, for even richer natural language explanations.
- Building a mobile application to deliver real-time parking forecasts and navigation assistance.
- Applying reinforcement learning techniques for adaptive model retraining based on live user feedback.

6.Conclusion

This study demonstrates the effectiveness of a hybrid CNN-LSTM-LLM framework in addressing urban parking challenges. By dynamically forecasting spot availability and providing actionable insights, the proposed model can significantly improve urban mobility planning and reduce environmental impact.

The integration of LLMs with traditional deep learning approaches bridges the gap between complex model outputs and practical, understandable strategies. Future work promises even broader applications in the context of smart cities and autonomous urban systems.

7.References

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