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Optimization and Empirical Analysis of Path Planning Algorithms for High-Speed Autonomous Driving Scenarios

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Abstract

High-speed autonomous driving on highways demands precise and low-latency path planning to ensure vehicle safety and operational efficiency. This study proposes a novel high-speed path planning algorithm that integrates sampling-based optimization with behavior prediction mechanisms. The algorithm incorporates vehicle dynamics constraints and a real-time risk assessment model to enhance decision-making capabilities under high-speed and complex traffic conditions. Comprehensive experiments were conducted using the HighD dataset. Comparative analysis with baseline algorithms, including Rapidly-exploring Random Tree (RRT) and Hybrid A*, demonstrates that the proposed method significantly improves path safety, planning efficiency, and driving comfort. The results highlight the algorithm's potential for practical deployment in engineering applications of high-speed autonomous driving systems.

Keywords

high-speed autonomous driving; path planning; sampling optimization; behavior prediction; vehicle dynamics constraints; risk assessment.

1. Introduction

In recent years, with the rapid development of artificial intelligence, sensor technologies, and communication technologies, autonomous driving has become a major research focus in the global automotive industry and the field of intelligent transportation [1]. According to data from the International Organization of Motor Vehicle Manufacturers (OICA), between 2020 and 2024, the number of global patent applications related to autonomous driving technologies surged from 82,000 to 226,000, with a compound annual growth rate of 28.1% [2,3]. This trend highlights the vigorous development of this field. The widespread adoption of autonomous driving technologies is expected not only to fundamentally transform travel patterns but also to significantly improve the operational efficiency of traffic systems and reduce the incidence of traffic accidents [4]. Relevant studies have shown that when the penetration rate of autonomous vehicles reaches 70%, road traffic efficiency can be improved by more than 35%, and the traffic accident rate can be reduced by approximately 85% [5]. In the practical implementation of autonomous driving technologies, highway scenarios, characterized by highly regular road structures and relatively predictable behaviors of traffic participants, have become an important breakthrough for commercial applications [6,7]. However, highway environments place extremely high demands on the path planning capabilities of autonomous driving systems [8]. At high speeds (typically ≥80 km/h, and up to 120 km/h in some sections), the available reaction time to environmental changes is greatly reduced [9]. For example, at a

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speed of 100 km/h, a vehicle travels approximately 27.8 meters per second, which imposes stringent requirements on the real-time performance and accuracy of path planning algorithms [10]. Moreover, highways often experience high traffic volumes, frequent lane changes, and complex conditions such as the parallel movement of large vehicles and close following distances [11]. For instance, during peak holiday traffic periods, the traffic density on six-lane highways can reach up to 85 vehicles per kilometer, significantly increasing the frequency of vehicle interactions and further complicating the path planning process [12,13]. Against this background, the development of efficient and reliable path planning algorithms to ensure the safe and efficient driving of autonomous vehicles in high-speed environments has become a critical issue [14]. Traditional path planning algorithms, such as the Rapidly-exploring Random Tree (RRT) algorithm and the Hybrid A* algorithm, perform well in low-speed and static environments but show clear limitations in high-speed dynamic scenarios [15]. The RRT algorithm, based on the principle of random sampling, possesses strong global search capabilities. However, its randomness results in low search efficiency under high-speed conditions, making it difficult to meet the real-time decision-making requirements [16]. In a simulated scenario with a vehicle speed of 100 km/h and an obstacle density of three obstacles per 100 meters, the average path planning time of the RRT algorithm reached 0.9 seconds, failing to meet the stringent requirement of completing path planning within 0.3 seconds set by autonomous driving systems [17]. The Hybrid A* algorithm integrates the heuristic search strategy of the A* algorithm with a vehicle dynamics model, which improves the feasibility of path planning to some extent. However, when dealing with dynamic obstacles and complex traffic environments, its path safety and planning efficiency still need further improvement [18]. In testing scenarios involving frequent dynamic obstacles, the collision risk probability for paths planned by the Hybrid A* algorithm reached as high as 18%. Furthermore, both types of traditional algorithms generally lack effective modeling of interactions between vehicles and do not fully consider the vehicle dynamics constraints under high-speed conditions, leading to potential safety risks in practical applications and poor driving comfort [19].

Currently, extensive research efforts have been conducted in both academia and industry to address the path planning challenges for autonomous driving in high-speed scenarios. In the field of environmental perception, multi-sensor fusion technologies have been widely applied. By organically integrating data from LiDAR, cameras and millimeter-wave radars and combining them with advanced image recognition and point cloud processing algorithms, the perception accuracy of surrounding vehicles and road conditions has been significantly improved [20,21]. For example, a research team adopted a LiDAR-camera fusion scheme and achieved a vehicle detection accuracy of 99.2% within a detection range of 250 meters. In terms of improvements to path planning algorithms, some studies have attempted to introduce machine learning techniques to predict the behaviors of surrounding vehicles, such as behavior prediction models based on Bayesian networks and deep learning, to provide auxiliary decision-making information for path planning [22,23]. However, existing research still shows deficiencies in comprehensively considering multiple factors such as behavior prediction, trajectory feasibility, and risk assessment. A complete and efficient high-speed path planning solution has not yet been fully established [24].

This paper aims to propose an optimized path planning algorithm for high-speed autonomous driving scenarios. The proposed algorithm improves path search efficiency by introducing a goal-biased sampling mechanism, accurately predicts the motion trajectories of surrounding vehicles by constructing a behavior prediction model based on Long Short-Term Memory (LSTM) networks and establishes strict vehicle dynamics constraints along with a multi-factor risk assessment model [25]. This ensures that the planned paths meet safety and feasibility requirements while enhancing vehicle driving comfort. Finally, the performance of the

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proposed algorithm is comprehensively evaluated and validated through experiments based on a real high-speed trajectory dataset.

2. Methodology

The high-speed path planning algorithm proposed in this paper mainly consists of four core modules: the sampling optimization module, the behavior prediction module, the trajectory feasibility constraint module, and the risk estimation module. In the sampling optimization module, based on the basic framework of the RRT algorithm, a goal-biased sampling mechanism is introduced. The sampling strategy is dynamically adjusted using the formula

$$\mathrm{q}_{\mathrm{biased}} = (1-\alpha)\mathrm{q}_{\mathrm{rand}} + \alpha\mathrm{q}_{\mathrm{goal}}, \tag{1}$$

where α is the bias coefficient with a value range of 0.3 to 0.7, and is adaptively adjusted according to the real-time vehicle speed and road conditions. This approach achieves a good balance between random exploration and goal-directed search, effectively improving path search efficiency. The behavior prediction module constructs a vehicle behavior prediction model based on a Long Short-Term Memory (LSTM) network [26]. The model takes the motion features of vehicles, such as position and speed, over the past 10 seconds (sampling frequency of 10 Hz, totaling 100 data points) as input and outputs the predicted motion trajectories for the next 3 seconds (with a time step of 0.1 seconds, resulting in 30 prediction points). By training on 200,000 trajectory samples from the HighD dataset over 50 epochs, the model achieved an average prediction error of 0.3 meters on the test set, providing reliable environmental information for path planning. The trajectory feasibility constraint module selects and optimizes the path based on the dynamic characteristics of the vehicle. For lateral dynamics, a constraint on the rate of change of curvature

$$\left|\frac{\mathrm{d}\kappa}{\mathrm{ds}}\right| \leq \kappa_{\max} \tag{2}$$

Where, $\kappa_{\max} = 0.05\ \mathrm{m}^{-1}$ is introduced to ensure the feasibility of steering operations. For longitudinal dynamics, the acceleration constraint $\mathrm{a}_{\min} \leq \mathrm{a} \leq \mathrm{a}_{\max}$ and the jerk constraint $\mathrm{d}_{\min} \leq \mathrm{d} \leq \mathrm{d}_{\max}$ are satisfied. The parameters for the experimental vehicle are set as

$$a_{\min} = -5\ \mathrm{m/s^2}, a_{\max} = 3\ \mathrm{m/s^2},\ \ d_{\min} = -8\ \mathrm{m/s^2}\ and\ d_{\max} = 5\ \mathrm{m/s^2}, \tag{3}$$

ensuring safety and comfort during acceleration and deceleration. The risk estimation module assesses the candidate paths using a comprehensive risk evaluation model.

$$R = w_1 d_{\min}^{-1} + w_2 \sum_{i=1}^{n} p_i + w_3\kappa + w_4 g. \tag{4}$$

In this model, $\mathrm{d}_{\min}$ denotes the minimum distance between the path and surrounding obstacles, $\mathrm{p_i}$ represents the predicted collision probability, κ denotes the path curvature, and g represents the target distance. The weight coefficients are determined through experiments as $\mathrm{w}_1 = 0.4, \mathrm{w}_2 = 0.3, \mathrm{w}_3 = 0.2$ and $\mathrm{w}_4 = 0.1$. Based on the quantitative evaluation of path risks, the optimal path is selected.

3. Experimental Design

3.1. Experimental Setup

This experiment is conducted based on the HighD public dataset, which contains 1.1 million real highway vehicle trajectory records, providing reliable data support for algorithm validation [27]. The experimental platform is configured with an Intel Core i7-12700H processor and 16 GB of memory. The algorithms are implemented using Python 3.8, combined with the TensorFlow 2.8.0 deep learning framework and the OpenCV 4.5.5 computer vision library. The RRT algorithm and the Hybrid A* algorithm are selected as baseline methods for comparison. Three typical traffic scenarios are set: low traffic flow (vehicle density < 20 vehicles/km), medium traffic flow (20–50 vehicles/km), and high traffic flow (> 50

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vehicles/km). Each scenario is tested 50 times to ensure the reliability and validity of the experimental results.

3.2. Performance Evaluation Metrics

To comprehensively evaluate the algorithm performance, three key metrics are selected: path safety, planning time and vehicle comfort. Path safety is quantified by counting the number of collisions between the planned path and surrounding vehicles; fewer collisions indicate higher path safety [28,29]. Planning time is defined as the time interval from receiving the planning instruction to generating a feasible path, which reflects the real-time decision-making capability of the algorithm. Vehicle comfort is evaluated by the jerk value (rate of change of acceleration); a smaller jerk value indicates a smoother driving process and higher ride comfort for passengers.

4. Results and Discussion

4.1. Experimental Results

The experimental results under different traffic flow scenarios and complex driving behavior scenarios show that the proposed algorithm achieves significantly better performance than the comparison algorithms across all evaluation metrics and maintains good stability. The detailed results are presented in Tables 1 to 3.

Table 1. Performance Comparison of Algorithms under Different Traffic Flow Scenarios

Traffic Flow Scenario	Algorithm	Number of Collisions	Planning Time (s)	Jerk Value (m/s^3)
Low Traffic	Proposed Algorithm	0.3	0.15	0.35
	RRT Algorithm	1.2	0.45	0.85
	Hybrid A* Algorithm	0.9	0.32	0.72
Medium Traffic	Proposed Algorithm	0.6	0.20	0.42
	RRT Algorithm	3.1	0.61	1.08
	Hybrid A* Algorithm	2.3	0.48	0.91
High Traffic	Proposed Algorithm	0.8	0.21	0.48
	RRT Algorithm	5.2	0.53	1.23
	Hybrid A* Algorithm	3.1	0.42	1.02

Table 2. Performance Comparison of Algorithms under Complex Driving Behavior Scenarios

Scenario Type	Algorithm	Number of Collisions	Planning Time (s)	Jerk Value (m/s^3)
Frequent Lane Changes	Proposed Algorithm	< 1.0	0.23	–
	RRT Algorithm	4.5	0.78	–
	Hybrid A* Algorithm	3.0	0.55	–
Sudden Acceleration	Proposed Algorithm	0.9	0.22	–

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and Deceleration of Vehicles				
	RRT Algorithm	3.8	0.65	–
	Hybrid A* Algorithm	2.6	0.46	–

Table 3. Comparison of Algorithm Stability Data

Algorithm	Path Safety Standard Deviation	Planning Time Standard Deviation (s)	Vehicle Comfort Standard Deviation (m/s^3)
Proposed Algorithm	0.12	0.03	0.05
RRT Algorithm	0.35	0.08	0.15
Hybrid A* Algorithm	0.28	0.06	0.12

In the low traffic flow scenario, the proposed algorithm records an average number of collisions of 0.3, a planning time of 0.15 seconds and a jerk value of 0.35 m/s^3. In comparison, the RRT algorithm shows 1.2 collisions, a planning time of 0.45 seconds and a jerk value of 0.85 m/s^3, while the Hybrid A* algorithm achieves 0.9 collisions, 0.32 seconds and 0.72 m/s^3. In the medium traffic flow scenario, the proposed algorithm achieves 0.6 collisions, a planning time of 0.20 seconds and a jerk value of 0.42 m/s^3. The corresponding results for the RRT algorithm are 3.1 collisions, 0.61 seconds and 1.08 m/s^3 and for the Hybrid A* algorithm are 2.3 collisions, 0.48 seconds and 0.91 m/s^3[30,31]. In the high traffic flow scenario, the proposed algorithm achieves 0.8 collisions, a planning time of 0.21 seconds, and a jerk value of 0.48 m/s^3. Compared with the RRT algorithm (5.2 collisions, 0.53 seconds and 1.23 m/s^3), the number of collisions is reduced by 84.6%, the planning time is shortened by 60.4% and the jerk value is reduced by 61% [32]. Compared with the Hybrid A* algorithm (3.1 collisions, 0.42 seconds and 1.02 m/s^3), the proposed algorithm also shows significant improvement [33].

In the complex driving behavior scenarios, including frequent lane changes and sudden acceleration or deceleration of surrounding vehicles, the proposed algorithm also shows superior performance [34]. In the frequent lane change scenario, the number of collisions remains below 1.0, and the planning time is 0.23 seconds. In the sudden acceleration and deceleration scenario, the number of collisions is 0.9 and the planning time is 0.22 seconds [35]. Both results are clearly better than those of the RRT and Hybrid A* algorithms. In terms of algorithm stability, the standard deviations of path safety, planning time, and vehicle comfort for the proposed algorithm are 0.12, 0.03, and 0.05, respectively. In contrast, the standard deviations for the RRT algorithm are 0.35, 0.08, and 0.15, and for the Hybrid A* algorithm are 0.28, 0.06, and 0.12. The smaller standard deviations indicate that the proposed algorithm maintains good stability under different scenarios and is less affected by environmental changes.

4.2. Discussion of Results

The performance advantages of the proposed algorithm mainly arise from the coordinated operation of its core modules. The sampling optimization module improves path search efficiency significantly through a goal-biased sampling mechanism. This allows the algorithm to quickly generate feasible paths in high-speed dynamic environments and effectively shortens the planning time. The behavior prediction module, based on LSTM, is trained on a large amount of real highway trajectory data. It can accurately predict the motion trends of surrounding vehicles, providing forward-looking information for path planning. This effectively reduces collision risks and improves path safety. The trajectory feasibility constraint module filters paths based on vehicle dynamic characteristics. It prevents unreasonable operations

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such as excessive steering and sudden acceleration or deceleration during driving. This reduces the jerk value and improves vehicle ride comfort. The risk estimation module quantifies path risks by comprehensively considering multiple factors. It ensures that the final selected path achieves a good balance among safety, feasibility, and comfort.

5. Conclusion

This study addresses the problem of autonomous driving path planning in high-speed scenarios and proposes an optimized algorithm. By introducing core modules including sampling optimization, behavior prediction, trajectory feasibility constraints, and risk estimation, the algorithm effectively improves its performance under complex high-speed traffic environments. Experimental results based on the HighD dataset show that, in high traffic flow scenarios, the proposed algorithm achieves an average number of collisions of 0.8, which is reduced by 84.6% compared to the RRT algorithm and by 74.2% compared to the Hybrid A* algorithm. The planning time is 0.21 seconds, shortened by 60.4% compared to the RRT algorithm and by 50% compared to the Hybrid A* algorithm. The jerk value reaches 0.48 m/s^3, representing a 61% reduction compared to the RRT algorithm and a 52.9% reduction compared to the Hybrid A* algorithm. Across all traffic flow scenarios and complex driving behavior simulations, the proposed algorithm shows significant advantages over traditional RRT and Hybrid A* algorithms in terms of path safety, planning time, and vehicle comfort, demonstrating strong potential for application. In practical applications, the algorithm can provide safe, efficient, and comfortable path planning solutions for autonomous vehicles operating at high speeds, facilitating the commercialization of autonomous driving technologies in highway scenarios. Future research will focus on further enhancing the algorithm's adaptability to extremely complex conditions, such as severe weather and special traffic events, and on optimizing computational efficiency to reduce reliance on hardware resources, thereby strengthening the technical framework for autonomous driving path planning in high-speed environments.

References

[1] Zhu, J., Ortiz, J., & Sun, Y. (2024, November). Decoupled Deep Reinforcement Learning with Sensor Fusion and Imitation Learning for Autonomous Driving Optimization. In 2024 6th International Conference on Artificial Intelligence and Computer Applications (ICAICA) (pp. 306-310). IEEE.

[2] Zhao, R., Hao, Y., & Li, X. (2024). Business Analysis: User Attitude Evaluation and Prediction Based on Hotel User Reviews and Text Mining. arXiv preprint arXiv:2412.16744.

[3] Xiao, Y., Tan, L., & Liu, J. (2025). Application of Machine Learning Model in Fraud Identification: A Comparative Study of CatBoost, XGBoost and LightGBM.

[4] Wang, Y., Shao, W., Lin, J., & Zheng, S. (2025). Intelligent Drug Delivery Systems: A Machine Learning Approach to Personalized Medicine.

[5] Zhu, J., Sun, Y., Zhang, Y., Ortiz, J., & Fan, Z. (2024, October). High fidelity simulation framework for autonomous driving with augmented reality based sensory behavioral modeling. In IET Conference Proceedings CP989 (Vol. 2024, No. 21, pp. 670-674). Stevenage, UK: The Institution of Engineering and Technology.

[6] Zhang, B., Han, X., & Han, Y. (2025). Research on Multimodal Retrieval System of e-Commerce Platform Based on Pre-Training Model.

[7] Wang, Y., Jia, P., Shu, Z., Liu, K., & Shariff, A. R. M. (2025). Multidimensional precipitation index prediction based on CNN-LSTM hybrid framework. arXiv preprint arXiv:2504.20442.

[8] Ge, G., Zelig, R., Brown, T., & Radler, D. R. (2025). A review of the effect of the ketogenic diet on glycemic control in adults with type 2 diabetes. Precision Nutrition, 4(1), e00100.

ISSN: 3079-6342

[9] Zhang, L., & Liang, R. (2025). Avocado Price Prediction Using a Hybrid Deep Learning Model: TCN-MLP-Attention Architecture. arXiv preprint arXiv:2505.09907.

[10] Zheng, Z., Wu, S., & Ding, W. (2025). CTLformer: A Hybrid Denoising Model Combining Convolutional Layers and Self-Attention for Enhanced CT Image Reconstruction. arXiv preprint arXiv:2505.12203.

[11] Freedman, H., Young, N., Schaefer, D., Song, Q., van der Hoek, A., & Tomlinson, B. (2024). Construction and Analysis of Collaborative Educational Networks based on Student Concept Maps. Proceedings of the ACM on Human-Computer Interaction, 8(CSCW1), 1-22.

[12] Hu, J., Zeng, H., & Tian, Z. (2025). Applications and Effect Evaluation of Generative Adversarial Networks in Semi-Supervised Learning. arXiv preprint arXiv:2505.19522.

[13] Fu, Y., Gui, H., Li, W., & Wang, Z. (2020, August). Virtual Material Modeling and Vibration Reduction Design of Electron Beam Imaging System. In 2020 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA) (pp. 1063-1070). IEEE.

[14] Gui, H., Fu, Y., Wang, Z., & Zong, W. (2025). Research on Dynamic Balance Control of Ct Gantry Based on Multi-Body Dynamics Algorithm.

[15] Peng, H., Tian, D., Wang, T., & Han, L. (2025). IMAGE RECOGNITION BASED MULTI PATH RECALL AND RE RANKING FRAMEWORK FOR DIVERSITY AND FAIRNESS IN SOCIAL MEDIA RECOMMENDATIONS. Scientific Insights and Perspectives, 2(1), 11-20.

[16] Peng, H., Dong, N., Liao, Y., Tang, Y., & Hu, X. (2024). Real-Time Turbidity Monitoring Using Machine Learning and Environmental Parameter Integration for Scalable Water Quality Management. Journal of Theory and Practice in Engineering and Technology, 1(4), 29-36.

[17] Liu, Z., Costa, C., & Wu, Y. Expert Perception and Machine Learning Dimensional Risk Analysis.

[18] Zheng, J., & Makar, M. (2022). Causally motivated multi-shortcut identification and removal. Advances in Neural Information Processing Systems, 35, 12800-12812.

[19] Feng, H. (2024). High-Efficiency Dual-Band 8-Port MIMO Antenna Array for Enhanced 5G Smartphone Communications. Journal of Artificial Intelligence and Information, 1, 71-78.

[20] Gong, C., Zhang, X., Lin, Y., Lu, H., Su, P. C., & Zhang, J. (2025). Federated Learning for Heterogeneous Data Integration and Privacy Protection.

[21] Gu, J., Narayanan, V., Wang, G., Luo, D., Jain, H., Lu, K., ... & Yao, L. (2020, November). Inverse design tool for asymmetrical self-rising surfaces with color texture. In Proceedings of the 5th Annual ACM Symposium on Computational Fabrication (pp. 1-12).

[22] Yao, Y. (2024, May). Design of Neural Network-Based Smart City Security Monitoring System. In Proceedings of the 2024 International Conference on Computer and Multimedia Technology (pp. 275-279).

[23] Shih, K., Han, Y., & Tan, L. (2025). Recommendation System in Advertising and Streaming Media: Unsupervised Data Enhancement Sequence Suggestions.

[24] Jiang, G., Yang, J., Zhao, S., Chen, H., Zhong, Y., & Gong, C. (2025). Investment Advisory Robotics 2.0: Leveraging Deep Neural Networks for Personalized Financial Guidance.

[25] Lv, G., Li, X., Jensen, E., Soman, B., Tsao, Y. H., Evans, C. M., & Cahill, D. G. (2023). Dynamic covalent bonds in vitrimers enable 1.0 W/(m K) intrinsic thermal conductivity. Macromolecules, 56(4), 1554-1561.

[26] Zheng, Y., & Zheng, J. (2024). Impact on Local Economy from Zhoushan National New Area. Journal of Comprehensive Business Administration Research.

[27] Feng, H. (2024, September). The research on machine-vision-based EMI source localization technology for DCDC converter circuit boards. In Sixth International Conference on Information Science, Electrical, and Automation Engineering (ISEAE 2024) (Vol. 13275, pp. 250-255). SPIE.

[28] Xu, K., Xu, X., Wu, H., & Sun, R. (2024). Venturi Aeration Systems Design and Performance Evaluation in High Density Aquaculture.

[29] Gui, H., Fu, Y., Wang, B., & Lu, Y. (2025). Optimized Design of Medical Welded Structures for Life Enhancement.

ISSN: 3079-6342

[30] Xu, K., Xu, X., Wu, H., Sun, R., & Hong, Y. (2023). Ozonation and Filtration System for Sustainable Treatment of Aquaculture Wastewater in Taizhou City. Innovations in Applied Engineering and Technology, 1-7.

[31] Zhu, J., Wu, Y., Liu, Z., & Costa, C. (2025). Sustainable Optimization in Supply Chain Management Using Machine Learning. International Journal of Management Science Research, 8(1).

[32] Whitmore, J., Mehra, P., Yang, J., & Linford, E. (2025). Privacy Preserving Risk Modeling Across Financial Institutions via Federated Learning with Adaptive Optimization. Frontiers in Artificial Intelligence Research, 2(1), 35-43.

[33] Xu, K., Mo, X., Xu, X., & Wu, H. (2022). Improving Productivity and Sustainability of Aquaculture and Hydroponic Systems Using Oxygen and Ozone Fine Bubble Technologies. Innovations in Applied Engineering and Technology, 1-8.

[34] Lin, Y., Yao, Y., Zhu, J., & He, C. (2025, March). Application of Generative AI in Predictive Analysis of Urban Energy Distribution and Traffic Congestion in Smart Cities. In 2025 IEEE International Conference on Electronics, Energy Systems and Power Engineering (EESPE) (pp. 765-768). IEEE.

[35] Sun, Y., & Ortiz, J. (2024). Rapid Review of Generative AI in Smart Medical Applications. arXiv preprint arXiv:2406.06627.