Prediction of Urban Traffic Accidents and Designer-Friendly Optimization Strategies

Xinning He[1*], Yinan Wu[1*], Hao Zheng[2]

Abstract: Predicting traffic accidents plays an important role in improving transportation efficiency and urban safety. Among other things, the built environment and road network design of a city can affect the incidence of traffic accidents. Existing studies tend to focus on abstract theories, posing challenges for urban designers to apply intuitively. This study proposes a workflow to analyze and predict urban traffic accidents by integrating urban road networks, land use, and building profiles. We extracted data on traffic accident occurrences in San Francisco in 2016-2023 and mapped the coordinates to the city's land use and road network maps, and developed a graph-born graph prediction model for urban traffic accidents using GAN neural networks. The model was able to produce fairly accurate predictions of traffic accidents in the city of San Francisco. We used the model to analyze the corresponding road safety situations under common urban prototypes and road network patterns from the perspective of urban design (road modeling), and summarized the impacts of common road and land use patterns on traffic safety in the city of San Francisco, as well as the possible ways to improve them. In addition, the model is applied to other cities in the U.S. to validate the model's migration capability.

Keywords: traffic safety; GAN; urban design; traffic accidents prediction

1 Introduction

Traffic safety is a critical component of public health and urban planning. The World Health Organization (WHO) reports that around 1.19 million people die annually due to road traffic crashes. Understanding the factors that contribute to traffic accidents is essential for improving urban transportation safety and efficiency. Traditionally, the focus has been on road networks and traffic flow, but the broader built environment—encompassing building layout, street width, intersection design, and land use—also plays a significant role. The road network not only facilitates city transportation but also shapes the interactions between various sites, making it crucial to view it through the lens of urban design [5]. Existing research often approaches the issue abstractly, either summarizing causes of accidents [17] or developing predictive models based on various factors [43]. While these methods offer insights, they frequently lack direct applicability for urban designers, who require intuitive guidance on how specific design choices influence traffic safety.

Studies have shown that built environment variables significantly impact traffic accidents, with land use mix (14.29%), freeway and arterial road density (12.43%), and secondary and local road density (11.54%) being the top contributors [20]. However, the lack of dynamic visualization tools to represent the relationships among these factors remains a challenge. Addressing this gap is essential for providing urban designers with clearer, more intuitive guidance that integrates architectural knowledge with traffic studies, ultimately leading to informed decisions that promote safer urban spaces.

2 Related Work

2.1 Built Environment and Traffic Accidents

Traffic safety is vital for sustainable urban development, yet the causes of traffic accidents are complex and multifaceted. Haddon identified three decisive factors influencing road traffic safety: human factors, environment, and vehicle [12]. Insufficient oversight and enforcement of traffic regulations frequently contribute to road accidents[10]. In addition to human factors and immutable conditions like weather [4] and time[33], the

[1]Tsinghua University, School of Architecture, e-mail: he-xn20, wuyn20@mails.tsinghua.edu.cn
[2]City University of Hong Kong, Department of Architecture and Civil Engineering, email: hazheng@cityu.edu.hk
[3]These authors contributed equally to this manuscript.

built environment—including human-made structures, public infrastructure, and land use—substantially affects traffic accident occurrences of a city also has a substantial impact on the occurrence of traffic accidents[24].

The layout and design of the built environment directly influence traffic flow and safety. Road design, including considerations for all road users, significantly impacts road safety [3]. Research indicates that road density affects safety, with traditional views suggesting that wider, lower-density networks enhance safety [40]. Conversely, evidence suggests that in dense urban areas, "less forgiving" designs—such as narrow lanes and traffic-calming measures—may improve safety [9]. Land use also significantly impacts traffic accidents, with mixed-use developments correlating with higher pedestrian collision risks [36]. Multi-factorial cross-analysis is crucial for a comprehensive understanding of traffic accidents.

2.2 Prediction Models for Traffic Accidents

Traffic accidents have been a longstanding focus of road safety research. With advances in data acquisition and analysis, research has shifted from traditional statistics to large-scale, data-driven predictive models. Accident data encompasses various factors, such as urban road geography, traffic volume, weather conditions, and driver behavior, forming the basis for analysis. Data sources include government agencies, public databases, embedded road infrastructure devices, in-vehicle sensors, and social media platforms [6, 11].

Accurately identifying and predicting future accidents holds significant practical value. Current mainstream analytical methods include Bayesian networks, genetic algorithms, artificial neural networks, deep learning algorithms and others[6, 11, 7]. Traditional probabilistic methods like Decision Tree algorithms are notable for their ability to predict traffic accident severity without requiring prior probabilistic knowledge of the studied phenomena[2, 27, 37]. However, their reliance on binary classification makes it difficult to incorporate visualized information as input or output. Increasing research attention has shifted toward deep neural networks, including LSTM, CNN and GAN models, which have been successfully applied to analyze traffic speed and accident data across both spatial and temporal dimensions[39, 38, 42]. Recent advancements in large language models (LLMs) have facilitated the development of agent-based models for accident analysis and prediction, incorporating effectors, sensors, communication, intention, motivation, and cognition. These methods are primarily applied in complex systems[15], like autonomous driving[34, 29, 1] and traffic control[32]. As this study focuses on built environment factors and excludes dynamic variables, their use is less relevant here.

2.3 Applications of GAN Models in Urban Studies

Generative Adversarial Networks (GANs), as advanced deep learning models, have shown significant potential in urban studies. GANs consist of a generator and a discriminator, which undergo adversarial training to produce data resembling real datasets. Various studies have employed GAN models for urban and transportation-related predictions. These models, such as TrafficGAN for traffic flow prediction[41], Curb-gan for spatiotemporal data analysis[42], and other GAN-based approaches for urban planning changes[31] and traffic accident prediction[28, 8, 21], have shown great value in their respective applications. Pix2Pix[18], a model suited for image translation tasks requiring paired data, has been widely applied in scenarios such as architectural plan generation[16, 22] and crime prediction[13]. More importantly, this method, which leverages real-world urban morphology image data for training and visualization, enables designers and the public to easily comprehend and apply the relationships between various factors and data.

However, existing research lacks a focus on understanding the relationship between the built environment and traffic accidents, instead prioritizing model architecture optimization. There is a notable gap in the application-level analysis, particularly in interpreting the "black box" of artificial neural networks (ANNs) from urban and architectural perspectives. Previous studies, such as the Urban-GAN model proposed by Quan et al.[30], have created multi-dimensional urban design computation systems that offer valuable insights for public participation in urban design. Our research aims to integrate expertise in architecture and urban planning, focusing on how urban-scale elements contribute to traffic safety. By using land use types and road network characteristics as key input variables, we seek to understand their influence on accident occurrences, ultimately providing designer-friendly guidance for urban traffic planning, fostering informed decision-making.

3 Methodology

3.1 Data Processing

We selected San Francisco, California, as the data source due to its rich urban environmental data, high level of urban development, and frequent traffic safety incidents. We used the open-source geographic information system QGIS to visualize the data.

The research concluded that a consecutive period of 5-10 years is the preferred time period for road accident prediction[25]. We collected two datasets of traffic accident records spanning from 2016 to 2023 from Kaggle [26]and the San Francisco government website, resulting in a total of 39,000 de-duplicated accident records. The dataset includes precise coordinates (latitude and longitude), date and time of the incidents, severity of the accidents, and the types of vehicles involved (automobile, bicycle, or pedestrian). To clearly identify the locations of the accidents, we visualized each accident as a black dot with 20% transparency and a diameter of 5 pixels. The image was then color-inverted to produce a black background with white dots, which served as the output image for training the GAN model.

We integrated road network data from OpenStreetMap and 2020 land use data from DataSF to be used as input for the GAN model. To improve the model's accuracy, we adjusted the RGB values, setting the R, G, and B dimensions to 0, 125, and 255, respectively. This adjustment maximizes the contrast between different color layers, thereby enhancing the model's performance and robustness (specific values are illustrated in the figure 1).

	Land Type	R	G	B
1	CIE = Cultural.institutional. Educational	125	255	0
2	MED = Medical	125	0	125
3	MIPS = Office (Management, Information, Professional Services)	125	125	0
4	MIXED = Mixed Uses (Without Residential)	0	125	0
5	MIXRES = Mixed Uses (With Residential)	125	0	255
6	PDR = Industrial (Production, Distribution, Repair)	255	125	0
7	RETAIL/ENT = Retail.Entertainment	255	0	0
8	RESIDENT = Residential	0	0	255
9	VISITOR = Hotels/Motels	125	125	255
10	VACANT = Vacant	0	125	125
11	ROW = Right-of-Way	0	255	255
12	OPENSPACE = Open Space	0	255	0
13	Missing data	255	0	255
14	Others	255	255	125
15	building	255	255	255
16	road	255	255	0

Fig. 1 The RGB values of different land use

3.2 Dataset Preparation

In determining the dimensions of the training images, we considered that traffic accidents often extend beyond a single intersection and may be influenced by the surrounding built environment across several blocks. Therefore, we selected an area coverage of approximately 600m x 600m per image. To ensure image clarity and to retain the maximum amount of useful information, we specified each image to be 512 x 512 pixels. Consequently, we selected a usual architect's scale at 1:50, and each final image represents 677.5m x 677.5m. In order to ensure the accuracy of the model's understanding of road widths and densities, it is essential to keep the scale of the input images consistent.

We used Python Image Library (PIL) for the automated cropping of input and output images. To mitigate the potential impact of image boundaries on data analysis, we employed an overlapping strategy for adjacent images to ensure full coverage of the map area. Specifically, each subsequent image was shifted by 256 pixels either in the X or Y direction from the previous image, covering the entire area(4). Additionally, a filtering mechanism was implemented to exclude blank images lacking data information, thereby enhancing the efficiency of model training.

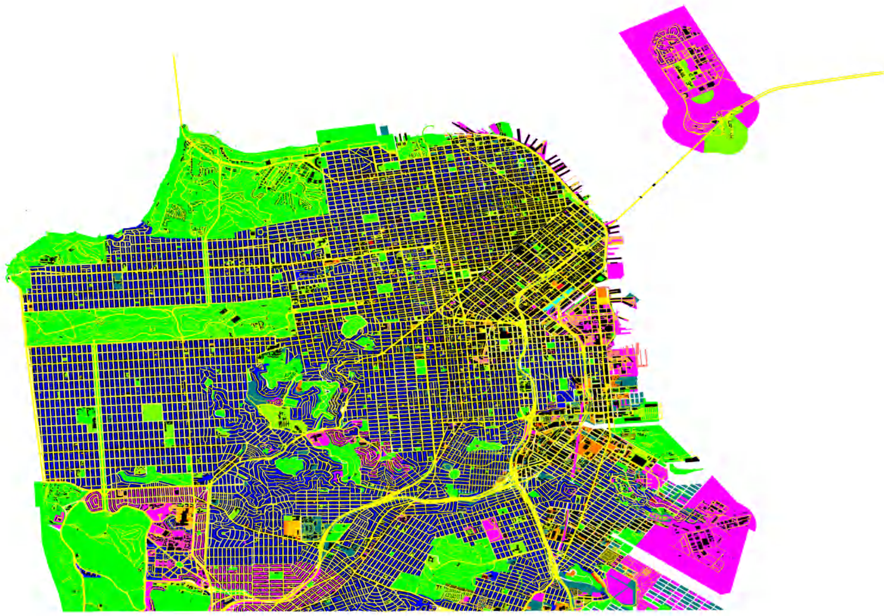

Fig. 2 The processed map of San Francisco

Fig. 3 The map of traffic accidents recorded between 2016 and 2023 in San Francisco

After processing, a total of 1,212 image sets were obtained. We randomly selected 1,100 image sets for the training dataset and reserved 112 image sets for the test dataset to evaluate the training results.

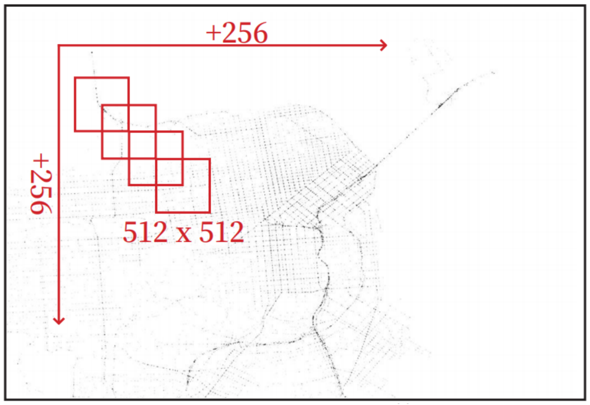

Fig. 4 The generation of dataset from a single large-scale map

3.3 Training

In this paper, the model training utilized the NVIDIA open-source pix2pixHD code[35], which incorporates a novel adversarial loss function along with a multi-scale generator and discriminator architecture. This setup enables the generation of high-resolution, realistic images with dimensions of 2048 x 1024 pixels. We believe this model effectively meets the image learning requirements of this study. Various hyperparameters, including learning rates, were fine-tuned multiple times to enhance training optimization. The neural network architecture of the model is illustrated in Figure 5.

To achieve an optimal model, we conducted multiple rounds of hyperparameter tuning, focusing primarily on comparing learning rate, number of epochs and batch size. We ultimately determined the locally optimal learning rate to be 0.00002, conducted a total of 300 epochs of training, setting the niter value to 210.

4 Result Analysis

4.1 Training Results

The results showed a significant reduction in both D_Loss and G_Loss after training, indicating that the model achieved satisfactory performance (Figure 6). As shown in Figure 7, with the increase in training time and epochs for the generative adversarial network (GAN) model, the simulated traffic accident data points generated by the model progressively approximated the real images. After completing the final training, we evaluated the reserved 112 test images (Figure 8).

To assess the practical predictive accuracy of the trained model, we utilize the Fréchet Inception Distance (FID) score, which measures the diversity and quality of the generated images[14]. A lower FID score indicates that the generated images are more similar to the real ones, reflecting better model validity. Our FID value is 20.01, illustrating a positive simulation.

4.2 Traffic Accident Patterns

We began by analyzing and understanding the impact of the built environment on the number of traffic accidents using existing real-world data. We classify the patterns of road and land use relationships into the following categories: Roads (Grid Network, Curved Roads, Multiple Road Intersections, Sparsely Built Area) and Land Use Types (Residential Dominant, Commercial/Entertainment Dominant, Mixed Land Uses)(see Figure 9). In this study, sparsely built area are not observed in residential-dominant areas, but in greenplace-dominant.

Our comparative analysis reveals that, for road patterns, areas with multiple road intersections have a significantly higher number of accidents surpassing grid networks, curved roads, and sparsely built area. Regardless of the land use type, areas with multiple road intersections experience the overall highest number of accidents,

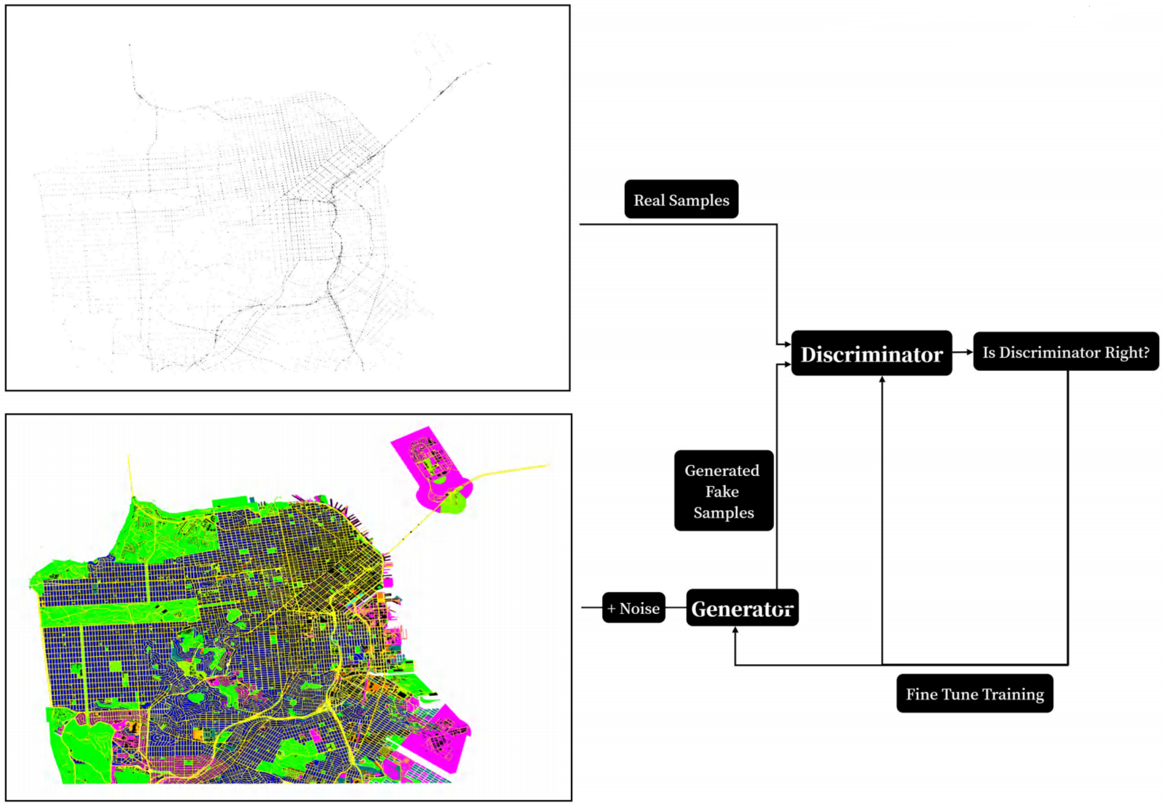

Fig. 5 The workflow of our model training

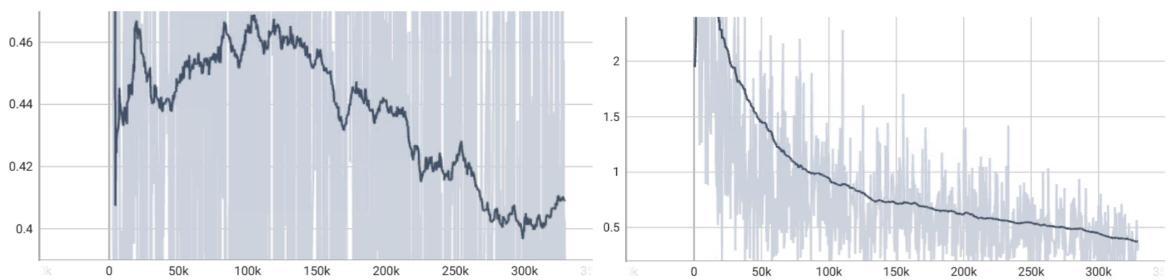

Fig. 6 The D_Loss and G_Loss in the training process

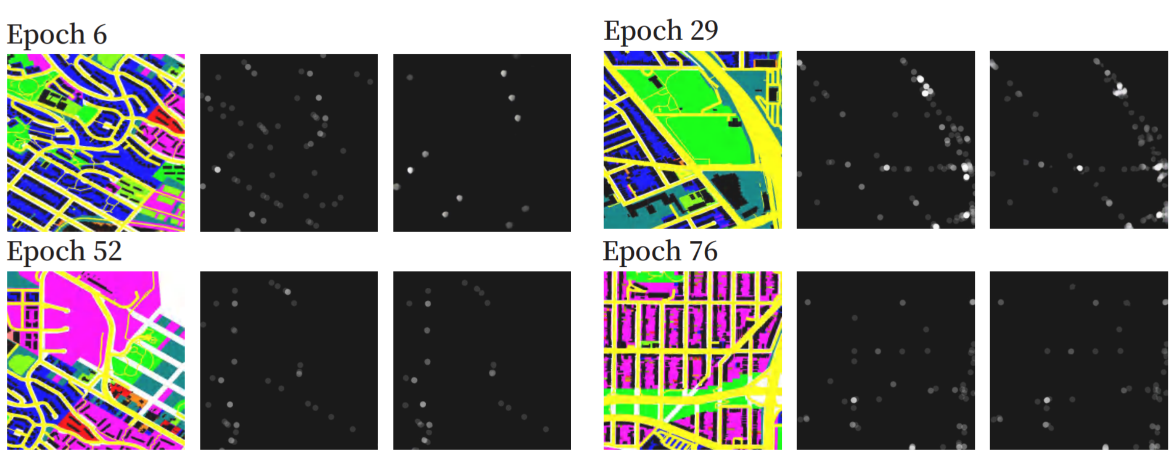

Fig. 7 Predicted results for each training epochs. left: input map; middle: real accidents map; right: generated accidents map

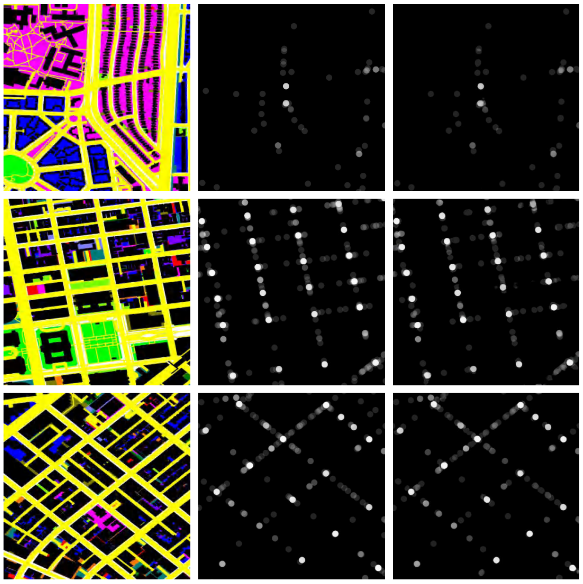

Fig. 8 Predicted results for test. left: input map; middle: real accidents map; right: generated accidents map

with incidents primarily concentrated at the intersections. Mixed land use areas, often characterized by higher road density, also report more accidents than single-use areas.

Overall, the layout with multiple road intersections is most prone to accidents. For grid networks, road density has a greater impact on accident numbers than land use type. Curved roads and sparsely built area generally show fewer accidents. Such analysis corresponds to the Marks' study [23] that the distribution of crash-es was fairly uniform across the gridirons and crash frequencies were dramatically higher for four-way than three-way intersections.

4.3 Urban Design Optimization

While theoretical research on the relationship between traffic accidents and urban road planning often remains abstract, our study aims to utilize big data and deep learning to offer urban planners more dynamic and actionable insights for design optimization.

We selected a district with high traffic accident density and complex land use patterns. Using Photoshop, we modified the input base map colors by incorporating various forms of green spaces or other land use types into the existing site (see Figure 10). These modified maps were then used as test inputs for the GAN model to predict traffic accidents, allowing us to assess whether different urban design strategies can effectively enhance traffic safety in the environment.

We conducted a multifaceted exploration of the relationship between built environment factors and traffic accidents from the perspective of designers:

(Steps 1-4) Impact of Green Space Placement on Reducing Traffic Accidents: We added green spaces along the road on different sides and found that positioning green spaces on both sides is more effective in reducing traffic accidents. Given the practical constraints in urban planning that often prevent large-scale changes, we also explored the impact of reshaping green spaces into elongated forms. This adjustment proved more effective in reducing traffic accidents, indicating a larger green space does not necessarily lead to a greater reduction in the probability of traffic accidents. The effectiveness of green spaces in reducing traffic accidents is dependent on various factors, like the size, placement and shape.

(Steps 5-6) Influence of Land Use Types on Traffic Accidents: We further investigated the effects of different land use types on traffic accident rates. Introducing narrow retail/entertainment areas or residential areas on both sides of the road impacts traffic accident reduction, but not significant among comparisons.

(Steps 7-9) Effect of Spatial Segmentation on Reducing Traffic Accidents: We examined the effect of spatial segmentation by dividing elongated green spaces. The results show that segmenting spaces can further reduce the occurrence of accidents, aligning with general urban design practices and highlighting the importance of segmentation in spatial planning.

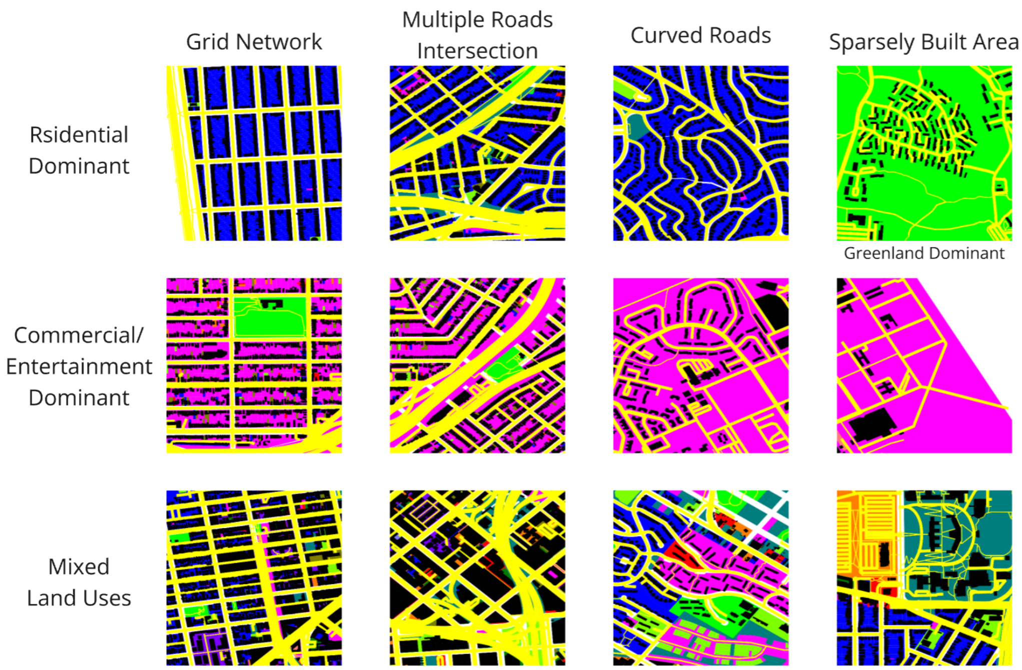

Fig. 9 The classification of the city plan

4.4 Urban Design Theory Validation

Previous urban designs focus mostly on the pedestrians, but as transportation increasingly become part of people's life, there's a raising for need attention on traffic and perspective from drivers and passengers. Those theories raised by researches yesterday may not apply to the cities today. We want to find the city plans suitable for living while ensuring traffic safety as well. Architects have concluded various city grids with unique characteristics, which raises the doubt that if these grids applicable for some cities will apply to another one. Therefore, we chose five diverse cities (Barcelona, Paris, Manhattan, Sandiego and Suzhou) to test on the model specific trained for San Francisco. Among the five cities, Barcelona, Manhattan and Sandiego have obvious grids. Paris has a center with roads radially spread out. Suzhou seems more random, with little buildings share a common block, and roads surround outside.

As shown in Figure 11, it turns out that city with gridions share a similar trend. Traffic accidents are more likely to happen on the wider roads. By contrast, the slim roads friendly to pedestrians and civilians according to Jane Jocabs[19], are welcoming to transportation as well. Though the practical urban design involves far more consideration than simply traffic accident rate, but this brand-new trial will open up mind for city designers to utilize the GAN model and experiment their imagined program on specific sites.

4.5 Test on the Migration Capability of the Model

After the validation of the model in San Francisco, we dig deeper into the question: can the model be migrated to another city in America? Considering the climate and cultural similarities, we chose another two cities in western America-San Diego and Seattle. Both of the cities have gridions but with different density and land-use distribution. However, the model shows a low quality on the prediction of both cities' traffic accidents (see Figure 12). While the model recognized the intersections and predicted a number of accidents, the dots are fewer than reality. Besides, the model fails to recognize the curved roads (especially highways) and presents no dots alongside these roads. In the future, we will further investigate on the prediction ability of our model and find its boundaries.

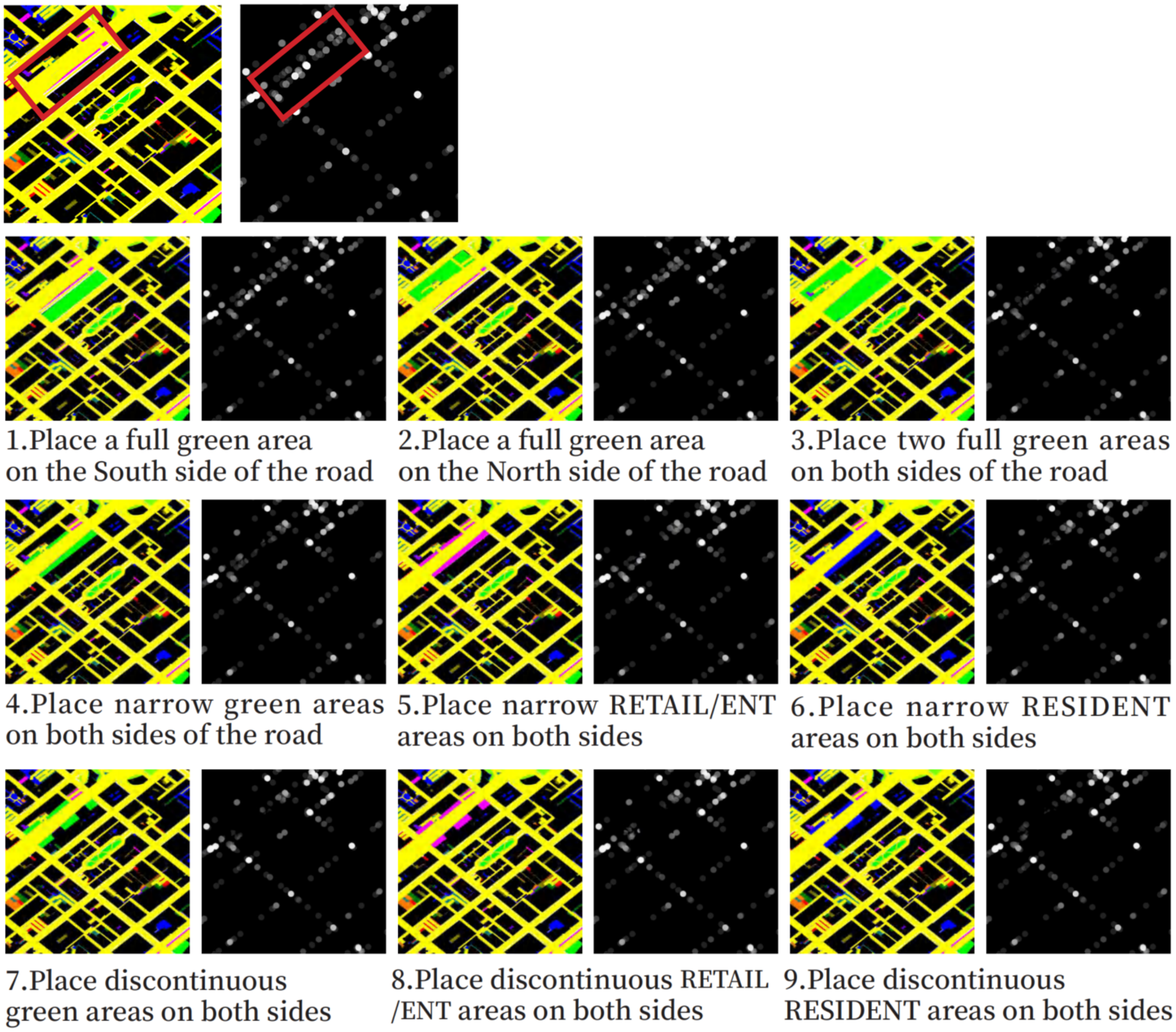

Fig. 10 Effects of different adjustments to the site

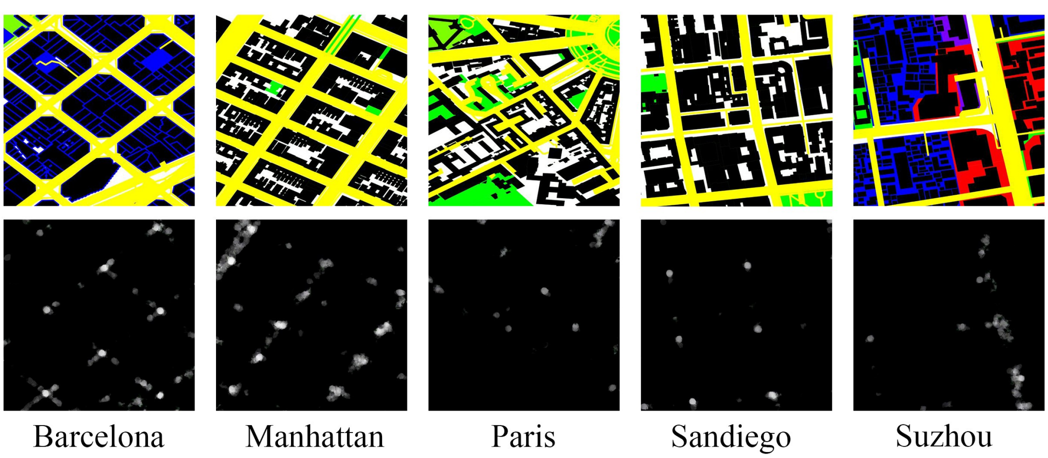

Fig. 11 The prediction of traffic accidents based on different city plans

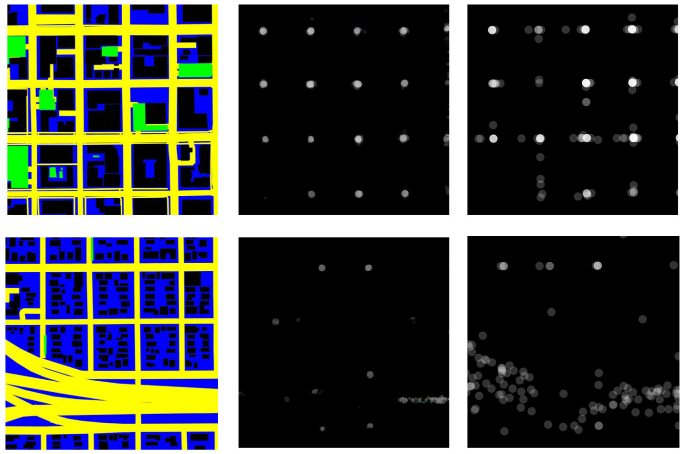

Fig. 12 The comparison between prediction and reality of traffic accidents in San Diego

5 Conclusion

5.1 Insights

Our study uses San Francisco as a case study to visualize urban built environment and traffic accident data through GIS and train a GAN model for traffic accident prediction.

Model Prediction: Our model has demonstrated high accuracy in predicting traffic accidents across various environments, including complex dense road networks, sparse road layouts dominated by green spaces, and areas with diverse land use types. This indicates that our model is capable of adapting to different urban layouts and traffic conditions.

Validation of Urban Planning Theories: By analyzing and categorizing data based on road infrastructure and land use types, and comparing accident data, we have validated urban planning theories specific to the San Francisco region. Our simulation of different design scenarios further verifies and extends existing urban planning theories, providing a more scientific and reliable basis for urban planning decisions.

Designer-Friendly Urban Planning Visualization Method: We have introduced a dynamic prediction model to explore the impact of modifications to the built environment on traffic accidents. This approach offers a visualization tool tailored for designers, facilitating a better understanding of the implications of design changes. By applying neural network and big data advancements to urban planning, we provide a reference for interdisciplinary knowledge collaboration.

5.2 Limitations and Future Work

Due to limitations in accessing urban traffic accident data, this model currently demonstrates good predictive accuracy only for San Francisco. However, this also suggests that traffic conditions may have unique characteristics across different cities, raising the question of whether to train a general model for urban prediction or to develop city-specific or region-specific models. This remains an area for further exploration. Besides, the present research focuses only on the urban form. Considering the complex causes of traffic accidents, our future research will incorporate additional factors to analyze the causes of these differences beyond the built environment.

We plan to develop a web platform based on our GAN model, tailored to provide an intuitive interface for urban planners. This platform will enable designers to easily modify the built environment and receive real-time traffic accident prediction feedback, aligning with their design logic and reducing technical barriers.

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