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Prediction of crime rate in urban neighborhoods based on machine learning

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ABSTRACT

As the impact of crime on the lives of residents has increased, there are a number of methods for predicting where crime will occur. They tend to explore only the association established between a single factor and the distribution of crime. In order to more accurately and quickly visualize and predict crime distribution in different neighborhoods, and to provide a basis for security planning and design by planning designers, this paper uses GAN neural networks to build a prediction model of city floor plans and corresponding crime distribution maps. We take Philadelphia as the research sample, use more than 2 million crime information of Philadelphia from 2006 to 2018 to draw the crime hotspot distribution map, and collect the corresponding map of Philadelphia, and train the model for predicting the crime rate of the city with more than two thousand sets of one-to-one corresponding images as the training set. When the training is complete, a floor plan can be fed directly to the model, and the model will immediately feed back a hotspot map reflecting the crime distribution. Using the untrained Philadelphia data as the test set, the model can accurately predict crime concentration areas and the predicted crime concentration areas are similar to the concentration areas considered in previous studies. With the feedback from the model, the city layout can be adjusted and the crime rate can be greatly reduced when the simulated city planner tunes into the city plan. In addition the ideas in this paper can be applied as a set of methodologies to predict other relevant urban characteristic parameters and visualize them.

1. Introduction

1.1. Research background

The presence of crime affects people's quality of life, which leads to various social problems (Mohler, 2014), and crime and criminality can impose costs on the public and private sectors (Iriberri and Leroy, 2007), which is one of the important factors to consider when choosing areas to relocate and visit. Improving safety within the design area is also one of the tasks of the planner in planning and design. In the distribution of urban crimes, the crime rate is often affected by an extensive list of factors, such as politics and economics, culture and education, employment, feudal consciousness, legal concepts, etc. (Paulsen, 2004).

Early criminological studies attempted to use demonstrate the relationship between crime and various influencing factors, for example, the authors examine the relationship between economic status and different rates of violence by means of fold trends (Lauritsen et al., 2014). The correlation with crime data is discussed by discussing data on unemployment rates, urban diversity, etc. (Hojman, 2004). Plain methods such as more disaggregated panel date approaches, natural experiments, international data, and individual-level analysis were used to explore the association between unemployment and the occurrence of crime events (Levitt, 2001). In addition to traditional statistical methods, there are spatial statistics used to obtain characteristics of crime distributions. There are a large number of studies focused mainly on predictive models of future crime location and time (Davies and Bishop, 2013). For example, kernel density estimation was used, a method that relies heavily on GIS and the use of crime hotspot displays, which can simply assumes past crime patterns, and predicts future crime patterns (Eck et al., 2005). The kernel density method was also used to demonstrate that the environment close to a crime event is prone to recidivism in terms of time or spatial distance (Mohler et al., 2011).

Deep learning is widely used for crime prediction with its advantage of abstract representation of data features (Kang and Kang, 2017). There are some traditional machine learning-based methods (Almanie et al., 2015). Using multiple regression and careful selection of indicator variables can lead to better results (Gorr and Olligschlaeger, 2002; Gorr et al., 2000). For example, cab traffic was used to simulate social interactions between disjoint areas, which may spread crime or resources and information used for criminal control (Wang et al., 2016). Multiple regression results for the period 1985-1997 for the greater Buenos Aires area show that inequality helps explain crime, but unemployment does not (Gerber, 2014). Moreover, unemployment

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does not explain inequality. A spatial auto-regression model-based spatio-temporal crime prediction method was proposed to automatically predict urban high-risk crime areas and crime trends (Catlett et al., 2018). They used crime data from Chicago for the period 2014-2016 and obtained a maximum mean absolute prediction error (MAPE) of 8.7%-11.9%. Five different machine learning algorithms were used to predict which types of crimes are most likely to occur at specific times and spaces in Chicago (Yuki et al., 2019). The decision tree model provided the best performance, achieving an accuracy of 99.88%.The crime events were analyzed in YD County from 2012 to 2015 and applied different prediction models such as Bayesian networks, random trees, and neural networks (Wu et al., 2018). The work showed that random trees gave the best results with an accuracy of 97.4%. A computational framework was proposed for application using SVM with kmeans clustering in Columbus, Ohio and St. Louis, Missouri (Rock et al., 2008). The small sets were labeled as hot or non-hot classes based on their respective crime rates. In addition, SVM was used to predict recidivism of crime (Wang et al., 2010). SVM and multilayer neural networks showed similar performance, but they both outperformed logistic regression methods. Deep neural networks were applied to integrate them with demographic, weather, and crime incidence information to improve the prediction of crime hotspots (Kang and Kang, 2017). The deep neural network consists of the following four layers: a spatial layer, a temporal layer, an environmental context layer, and a joint feature representation layer. The crime trends and crime types of individuals in different years were predicted based on their crime charge history using a similar neural network (Chun et al., 2019).

Novel neural network models have been proposed due to new approaches to machine learning in the deep learning subfield, taking into account spatial and temporal correlations. Typical deep learning models include Long Short-Term Memory (LSTM) and the Convolutional Neural Network (CNN). 12,000 satellite images were used to query crime rates from data and reports collected by police departments (Najjar et al., 2018). The findings predicted 79% accuracy by using deep learning concepts to perform CNN. LSTM was used to predict daily crime events in Atlanta, with a stable correlation coefficient R value of around 0.8 between predicted and observed records (Wang and Yuan, 2019). CNN and LSTM were used to predict the presence of crime events in Baltimore City (Esquivel et al., 2020). A matrix of past crime events is used as input to predict the presence of at least one event in the coming days. Feedforward Neural Networks (FNN), Recurrent Neural Networks (RNN), CNN, and a mixture of RNN and CNN were implemented based on data using the city of Chicago (Stec and Klabjan, 2018). The results show that the machine learning model can obtain 75.6% and 65.3% accuracy in Chicago and Portland, respectively. The prediction accuracy was discussed based on various algorithms and measures the model performance through the temporal order analysis of LSTM, and finally the ARIMA model was used for prediction (Safat et al., 2021).

1.2. Problem statement

The traditional approach is often used for prediction on long time scales, but it is not a suitable predictor even when considered on a monthly basis (Adams, 2001; Jefferis, 1999). This is because it only considers crime data and does not consider environmental factors, the importance of considering environmental factors stems from the broken window theory (Wilson and Kelling, 1982) and crime prevention through the environment (Casteel and Peek-Asa, 2000; Cozens et al., 2005). Slightly more advanced techniques, such as multiple regression, do improve predictive power, but still rely only on historical crime data. And the success of these methods relies heavily on the correct selection of indicator variables. And considering additional data sets leads to a significant increase in valid features (Stec and Klabjan, 2018). These methods have problems in crime incidence prediction, such as difficulties in detecting highly nonlinear relationships, redundancy, and dependencies among multiple data sets. The LSTM is inadequate for the analysis of environmental factors and has poor prediction for sparse crime distribution (Esquivel et al., 2020). In addition, for the aid given to the designer, the architect is concerned with the environmental security as the security in the planning area over a long period of time rather than the crime rate at a specific time in the future; therefore, the RNN and CNN approaches are not suitable for the purpose of this study.

1.3. Technical discussions

Generative adversarial networks (GANs) have been extensively studied in recent years (Goodfellow et al., 2014). It can produce surprisingly plausible images (Radford et al., 2015; Larsen et al., 2016; Karras et al., 2017; Arjovsky et al., 2017). Many convolutional neural nets use only content loss core model weights, but because GAN uses both content loss and adversarial loss, it has more unique image simulation and representation capabilities than traditional algorithms (Yangjie et al., 2018). And GAN does not have complex variance lower bounds, which can greatly reduce the difficulty of training and improve training efficiency (Gonog and Zhou, 2019). Recent studies on image-to-image translation have shown that such GAN are very effective in learning statistically dependent mappings between source and target domain images (Isola et al., 2017). Therefore it is necessary to use GAN as the main algorithm in order to help planners design safer neighborhoods, which can facilitate planners to directly access the planning map and obtain the corresponding crime distribution with clearer images.

In this paper, a machine learning approach will be used to predict the crime rate. Machine learning models are used to find relationships in pattern recognition and classification problems where there is no representation between inputs and outputs, as well as in data mining and prediction problems (Voyant et al., 2017). Machine learning's ability to handle nonlinear rational data has been demonstrated in many fields, allowing it to process very high-dimensional data at faster training rates and to extract data features (Zhang et al., 2020).

For example, machine learning methods which linear regression and Gaussian process regression models are used to estimate the solar radiation on daily data set taken from the wind central in Zonguldak province in Turkey (Karasu et al., 2017). A new forecasting model was developed based on support vector regression (SVR) with a wrapper-based feature selection approaching multi-objective optimization technique to forecasting the future price of crude oil (Karasu et al., 2020). A financial time series forecasting model is identified by support vector machine (SVM), for estimating the closing price of currency exchange rates (Altan and Karasu, 2019).

Similarly, architects have made many attempts to use machine learning. For instance, machine learning can perform the following tasks: predicting short-term traffic conditions between cities (Dougherty and Cobbett, 1997), predicting urban grounds subsidence (Kim et al., 2009), forecasting urban water demand (Campisi-Pinto et al., 2012), deducting urban structure types (Hecht et al., 2013), assessing the urban environmental qualities (Liu et al., 2017), exploring the relationship between urban visual factors and human perceptions (Zhang et al., 2018), generating 3D building models (Zhang, 2019), generating rebar design in concrete exterior walls (Liu et al., 2019), generating structural design solutions (Zheng et al., 2020), generating architectural drawings (Huang and Zheng, 2018), and generating urban design plans (Shen et al., 2020). The examples above illustrate that machine learning has been widely used in the field of architecture and urban design. A similar transition to analyzing the distribution of crimes in cities with prediction models generated by machine learning drastically improves the persuasiveness and credibility of the theory. Additionally, the disclosure of crime statistics paves the way for applying machine learning in the field of city planning and architecture design (Chan and Bennett Moses, 2016).

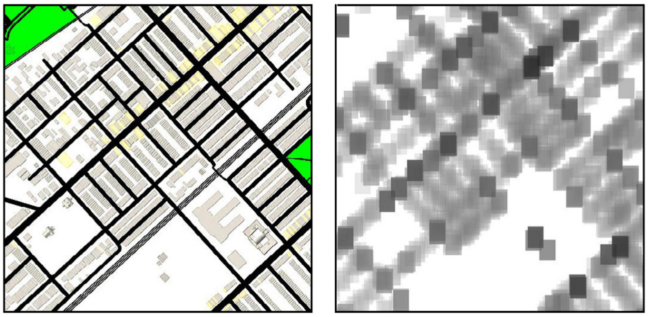

Fig. 1. Left: input map; right: output crime rate heat map.

1.4. Objectives

We construct a generative model for predicting the city's crime hotspot map. The method is outlined as follows: first, stylize a city map of Philadelphia. Then, the crime latitude and longitude data displayed on the official website of Philadelphia government is collected and visualized. After that, the big data of crime information is combined with the city map to train and generate a GAN model. In this way, both general users and planners can visualize and predict the crime rate of a given city neighborhood by computer.

The ultimate goal of this research is to use a computer to visually analyze the urban crime rates of a given map, which inputs block distributional information into the program. Subsequently, the crime heat map within the area can be served as an output (Fig. 1), which is a basis for adjusting city planning and building design. Eventually, the neural-network model is reused to verify the adjusted map by determining whether the revision of the building design achieves the purpose of reducing the urban crime rate.

Although crime transfer is also a common research object in criminology, avoiding crime transfer is not the goal of this research. In this research, the model can predict the crime rate in an area that the architect specifies and visually display it. Thus, the architect can change the plan according to the crime-rate prediction and ultimately design a plan with the lowest possible crime rate. Therefore, this study focuses more on the crime situation in pre-designed areas to provide suggestions to improve the design. Furthermore, crime always exists in human society (Carroll and Payne, 1977), thus the goal of this research is not to completely eliminate crime but to improve the design of specific areas to reduce local crime.

This method is beneficial to help urban planners design safer neighborhoods not only because of the superiority of the GAN algorithm and the ability to generate images more clearly, but most importantly by applying GAN to the evaluation of urban security, it is possible to quantitatively and immediately visualize the distribution of crime in the current planning design. In addition, the field of architecture and urban planning is not experimental, and when designers consider design security, they cannot quantitatively determine the crime situation in the planned area, and it is unrealistic to spend years to build an experimental building (Badland et al., 2010). Therefore, if the visual distribution of crime rates in a planned area is immediately available, designers can immediately adjust the design based on the predictions, thus greatly improving the safety of the designed urban area. The training of the crime hotspot map in connection with the map is more beneficial for direct application in the designer's use process.

2. Methodology

2.1. Generative adversarial network

An adversarial neural network consists of two neural networks that are trained alternately and compete with each other. The goal of the two neural networks is to reach the Nash equilibrium defined in game theory (Goodfellow et al., 2014). One of the neural networks is a generator (G), which mimics the real data distribution as much as possible to generate fake training sample P data (Fig. 2) based on the noise Z that obeys a certain distribution. The other neural network is the discriminator (D), which attempts to correctly determine whether the input data comes from real data or data created by the generator (Radford et al., 2015).

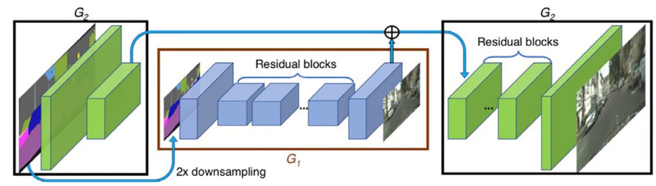

Fig. 2. The basic principles of GAN (Wang et al., 2018).

During the adversarial training process, the real data x and the generated data G(Z) are input into the discriminator simultaneously. The discriminator outputs probability values that rate the authenticity of the two sets of data. The discriminator minimizes the cross-entropy of the actual output result and the expected output result while the generator maximizes the probability that the generated data is true by adjusting the parameters based on the feedback from the discriminator. During the above process, the accuracy of the generator and the discriminator is improved. When the discriminator eventually cannot distinguish between the real data x and the generated data G(Z), the generator is considered to be optimal. The training goal of the generator is adjusting the values of D(X) and D(G(Z)) to be equal while the discriminator wants D(X) to be as large as possible and D(G(Z)) to be as small as possible. Training is optimal when D(X) and D(G(Z)) are equal.

Furthermore, GAN is a neural network based on inputting graphics and outputting images. Accordingly, for the purpose of helping architects optimize the planning and design of specific areas, this study does not input digitally represented crime coordinates and output digital neural networks. Moreover, each map may contain hundreds of data points on criminal activity, and outputting a large number of coordinates is unintuitive. Rather, images are used to represent criminal information. In this research, the GAN takes city maps as input and crime-rate heat maps as output and trains the network to recognize the relationship between two sets of images. The trained network model can give a crime-rate prediction based on a given map of the city area.

2.2. The generation of crime heat map

This research selects Philadelphia as the main research object. Philadelphia, as a representative of cities in the eastern United States, has a small, comprehensive environmental gap with other eastern coastal cities. Therefore, the model trained on Philadelphia has certain reference value for other eastern coastal cities in the United States. In addition, Philadelphia crime data is easy to obtain, and the latitude and longitude information of crimes can be directly obtained on the official website of the city government and saved in the form of a CSV file (PhiladelphiaPoliceDepartment, 2020). Because access to more data can ensure that the training model predicts more accurate results, we use all the crime data available on the city government's website. Therefore, the latitude and longitude information of more than two million crimes in Philadelphia from 2006 to 2018 was selected as the data for machine learning. The CSV file provided by the official website does not explain the specific meaning of the coordinates associated with crimes, but a large number of studies have shown that the probability of reporting to the police in the place where the crime occurred is very high (Hull, 1969), thus the coordinates of the crime can be roughly understood as the place where the crime occurred. The city website

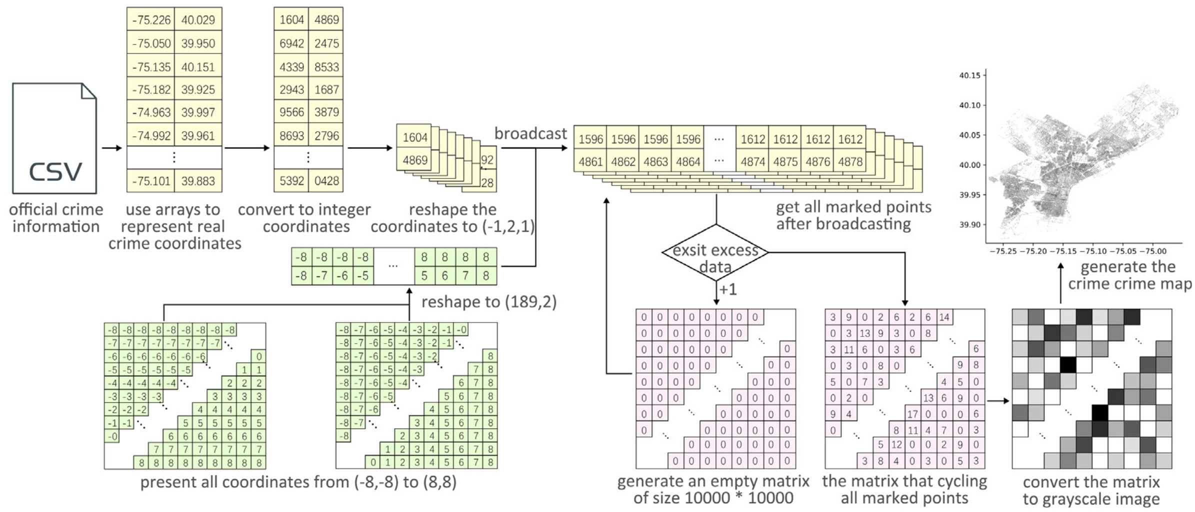

Fig. 3. The principle of generating the crime heat map.

did not provide any explanation on the relationship between criminal data and the addresses of criminal incidents. However, according to the generated crime heat map, all coordinate points are marked on the road. Thus, it can be reasonably assumed that the coordinates represent the projection point from the crime location or the crime-alarm location to the nearest street. The above speculation will not affect the accuracy of the model. According to the output image of the model, crime-prone areas can be ascertained because the model's output on the location of crime incidents is in the same form as the crime data provided by the government. That is to say all crimes are marked on the road, and since the government and police can conduct crime analysis based on existing data, they can also use the crime data output by the model. Although it is impossible to determine whether criminal records are wrong or omitted, these possibilities are not significant because the number of crime coordinates involved in training is large enough that individual information errors have a negligible effect on the overall calculation results.

The types of crimes are not considered in this research; only the latitudes and longitudes of all crimes are extracted from the official crime information. Although from a sociological perspective, different crime types correspond to different spatial characteristics, the spatial characteristics of different crime types do not fall into the area of interest for this research. The goal of this research is to reduce the overall crime rate within the design range, that is, to ensure all crime types corresponding to a specific space type are as low as possible.

In terms of data processing, we use Python scripts to convert the latitude and longitude information into a heat map of crime distribution (Ghosh and Guha, 2010). The related extension packages are Numpy (NumPy, 2020), Pandas (Pandas, 2020), and Matplotlib (Matplotlib, 2020). To summarize the process of generating the crime heat map, the operation begins with marking the point where the crime occurred and the points around it in the matrix, which show the frequency of crime with numbers corresponding to the map. According to the marked times, which determine the depth of the corresponding area in the picture, eventually a heat map that indicates the frequency of crime can be generated (Gerber, 2014) (Fig. 3). The darker gray a pixel appears in the picture, the more crimes have occurred, and the higher the crime rate is.

To describe the process in detail, we use Pandas to import the CSV file containing the crime coordinates into Python, simultaneously defining an empty matrix M with the size of $10000pixels * 10000pixels$, which represents the square area containing Philadelphia. In addition, corresponding coordinate points of each crime location are marked in this matrix M through proportional scaling, so that the coordinates originally expressed by latitude and longitude are converted into coordinates expressed by integers of 0 to 10000. Then we use $expand\_dim$ of NumPy to convert the two-dimensional array representing coordinates to a three-dimensional array and transform its shape into $(-1, 2, 1)$ (McKinney, 2012). The converted array is named as new_array. Since it is not noticeable to mark a single point on the extensive heat map, we take this point as a center point and mark all the points in the $17pixels * 17pixels$ range around it, forming an obvious square that indicates the location of the crime. This square indicates that the official crime incident occurred in the center of the square, and the size of the square does not indicate the size of the actual space. The side length of the crime marker is 17 pixels because when it is less than 17 pixels, the recognition of the heat map by the neural network is insufficient, which is not conducive to the training. This is because neural networks produce more accurate training results when provided with obvious data features. When the square is larger than 17 pixels, an overflow occurs during ordinary computer operations. After the crime coordinates have been marked, we use mgrid to generate a two-dimensional array representing the coordinates in the range $[-8 : 9 : 1, -8 : 9 : 1]$ and name the array as $around$. Subsequently, we broadcast the new_array and $around$ and capture an array that represents all the points that need to be marked in the heat map; its shape is $(-1, 2, 289)$ (Van der Walt et al., 2014).

Finally, using the loop command to mark each point in the matrix M with the size of $10000 * 10000$, and for each marked point, we add 1 to the number corresponding to the matrix. Each loop marks 289 points, and the number of loops equates with the number of the actual crime information coordinate point. Each number of the matrix M after the loop represents the number of times it is marked. At this time, by drawing with the imshow command and presenting the color of grey, it is possible to output a crime heat map with a resolution of 6000dpi. In the heat map, unmarked points appear white, while the points marked the most times appear black; the color values of other points correspond to the marked times (Gerber, 2014).

In addition to the above methods, some other methods have been tried, such as the Seaborn function (Seaborn, 2020). This function is based on the principle of drawing a histogram and directly depicts the position of the point. Nonetheless, the performance in the areas with lower crime rates in the generated graph is not ideal, and the overall color is very light, which is not conducive to machine learning (Ibrahim et al., 2019). The hist function (Pylab, 2020) uses the histogram as the basic principle of operation, assessing the density of the points around a certain point to determine the point's color depth. Although the conclusion of the generated image is better than that of Seaborn, there is no parameter to control the range of the reference points

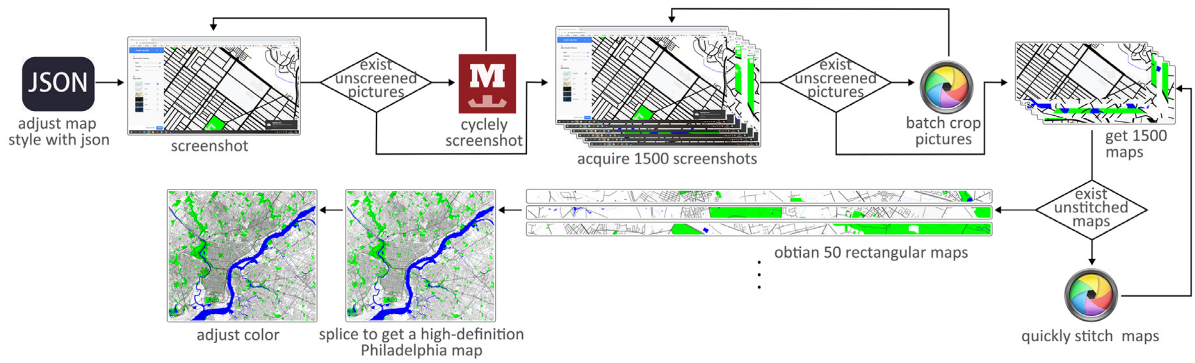

Fig. 4. Map collection process.

that determine the color of a certain point, and the definition of the generated image is far from sufficient. *Sklearn_kde* (Sklearn, 2020) and *Gaussian_kde* (SciPy, 2020) are based on a specific algorithm, considering all scatter plots to produce the density value of each point in a heat map; the color style is often consistent with a smooth and excessive gradient over a large area, and there are parameters to adjust the subdivision of colors. In the results produced with these methods, the colors of several blocks are very similar, so these algorithms are more suitable for describing the crime-prone areas of the city overall than for researching the layout of a specific building complex as in this discussion (Yoo and Wheeler, 2019).

2.3. The collection of city maps

In addition to producing the crime-rate heat map, it is necessary to collect the actual map of Philadelphia, which is used as the input of training the neural network in the next step (Fig. 4). In order to obtain a high-definition map containing Philadelphia's architecture and streets, we attempted to collect maps in Mapbox (Mapbox, 2020), which allows customization of the colors of buildings, grass, and streets on the map (Cadenas, 2014). However, the building information on Mapbox is incomplete, requiring reliance on other methods to collect maps of Philadelphia. On the contrary, the editor of Google map (Google, 2020) not only contains complete and specific building information but also can customize the color to a certain extent. Although Google Maps cannot distinguish specific building functions, such as residential buildings, schools, factories, etc., Google Maps can distinguish residential buildings from municipal buildings. As a result, we adjust all roads to black, grass to green, water to blue, and background to white. After the adjustment, the JSON code is exported for later use (Tagoe and Mantey, 2011). In fact, any form of map can be used as a training set for machine learning. The neural network does not fit the actual map to the crime heat map as a human would but instead uses the crime heat map to fit the relationship between the law of crime occurrence and the plan. Therefore, the characteristics of each pixel in the actual map and in the crime heat map, such as the color, location, and the relationship with surrounding pixels, become features of machine learning. The purpose of the processing of the map in this research is to improve the neural network's ability to distinguish the positions of different spaces, and to enhance the accuracy and legibility of the results that the model generates.

A screenshot is taken to obtain an image of the map, but the map displays the smallest level of buildings only at a high magnification, making the map too large to be captured manually. To accommodate this, we use mouse recorder software Mouserecorder (Mouserecorder, 2020) to record the movement of the mouse panning the map and taking a screenshot, and then the recording is repeated 50 times. The contents of each loop are divided into four parts, and only the first step is to take a screenshot. The purpose of the remaining three parts is to wrap the screenshot sequence, which allows the computer to take screenshots to obtain all the maps of Philadelphia automatically. After the screenshot is completed, 1500 mini maps are obtained.

In order to stitch the maps more conveniently, we use NeoImaging (Neoimaging, 2020) to batch crop excess parts of web pages for all graphs. In this software, after importing 30 horizontally connected maps at the same time and automatically stitching and saving, 50 long maps that have been stitched for the first time are acquired. If we were to use this software to stitch the 50 long maps vertically, we would not be able to obtain a clear map because the image would be too large. Therefore, we stitch the map manually in Photoshop and eventually produce a large map with a resolution of 300dpi. Because the building color in the map is too light, the color of the map is adjusted with Camera Raw in Photoshop (Fraser and Schewe, 2010). The exposure is adjusted to -1 and the contrast to 1, and a curve-adjustment layer is added to increase the brightness of the darkest area, producing a map of Philadelphia with greater color discrimination. The color is not adjusted to make the color value reach a specific value, but to increase the color difference between different regions as much as possible to make the color as saturated as possible, because the increase in color difference allows the neural network to distinguish different regions more easily and thus achieve more accurate learning. As a consequence, the Philadelphia map and the Philadelphia crime heat map are adjusted to coincide. Further, the unit-longitude and unit-latitude length in the hot map are the same, while the unit-longitude and unit-latitude length in the flat map are different. This problem is resolved by aligning the two maps and performing a single-axis zoom operation on the crime-rate heat map. Afterward, the two images almost coincide. It has been observed in this article that in all official government documents, crimes are marked on roads, and the straight lines connecting the crime-intensive areas correspond to the streets. Therefore, the two pictures can be aligned according to the principle that the straight lines connecting the crime markers are aligned with the street. While there is no guarantee that, after manual alignment, the marked crime location is exactly the same as the official crime location, this does not affect the accuracy of the model because the actual error is less than half the width of a non-arterial road.

After aligning the two images and removing the extra parts, we divide the two large images into 1:1 corresponding small images with sizes of 512 pixels by 512 pixels. Since there is no criminal information from outside of Philadelphia, we further delete the map areas outside of Philadelphia. That is, we use the Python script to determine whether there are gray or black parts in a given area of the heat map and delete from the data any areas without crime markers, as well as the corresponding areas of the actual map. At this point, 2,291 sets of actual maps and crime heat maps corresponding to each other are obtained.

Fifteen sets of pictures are randomly removed from the 2,291 sets of pictures to serve as the test set; they are not included in the training of the model. Because the model did not learn the characteristics of these 15 sets of data, the test set can be used to verify the accuracy of the

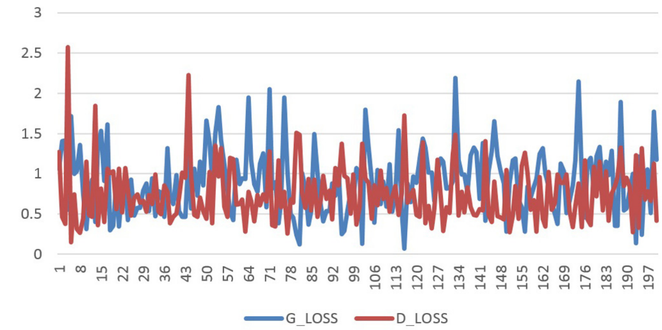

Fig. 5. Generator loss (G_LOSS) and Discriminator loss (D_LOSS) during training.

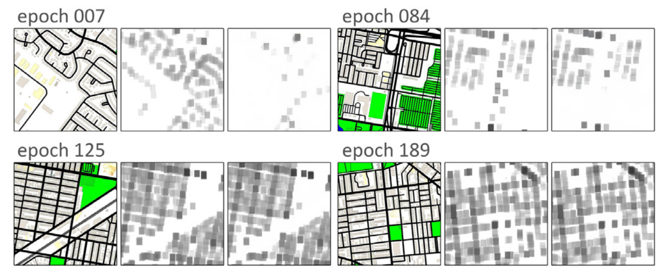

Fig. 6. Predicted results for each training epochs. For each group of images: Left: input map; Middle: real crime heat map; Right: generated crime heat map.

model. The remaining 2,276 sets of pictures are used as training sets. These pictures are used to train the neural network to fit the connection between the crime heat map and the actual map.

2.4. Neural network training

According to the principle of GAN, we choose Pix2pixHD (Wang et al., 2018) as the main algorithm. Fig. 5 shows the loss values of the generator and the discriminator. GAN is an adversarial network, and the sign of confrontation is that the loss values of the generator and the discriminator constantly fluctuate and compete. There is no situation in which one party completely suppresses the other; the continuous confrontation between the two parties is characteristic of successful and accurate GAN training. The training process is also successful when, on repeated occasions, the generator's loss value is low and the discriminator's loss value is comparatively high. In the end, the relationship between the crime heat map and the actual map was successfully ascertained through the continuous-optimization model.

For better convergence, we use the constant training gradient in the first 140 epochs of training, and the gradient decreases in the next 60 epochs, which is conducive to more precise fitting of data when the training is nearly finished. Since the loss value cannot illustrate whether the model has converged, we generate a monitoring website while training, which temporarily saves the model after each round of training and outputs the predicted result (Fig. 6). When the model is not fully trained, the accuracy of the predicted crime distribution in the generated image is low. It can be observed that the crime rate at a large intersection is relatively high, but the accuracy rate is not the same as the real result, and the generated image is blurred. Later, at about 80 training epochs, the accuracy of generated images is improved to a certain extent, but some concentrated crimes around large grassy areas cannot be predicted by the neural network. We still can draw the conclusion that corners of urban parks and the surroundings of public or large buildings are more likely to create higher crime rates. However, the prediction of the crime rate of roads within a large area of lawn and near dense neighborhoods is not accurate. After 200 epochs of training, the synthesized image performs accurately, with the crime heat map showing a clear pattern corresponding with different types of functional areas. Therefore, we decided to stop training after 200 epochs and store the prediction model at this point as the final model.

3. Results

3.1. Accuracy of the training set

After completing the GAN model training, we first regenerate the data in the training set to determine the degree of completion of the model's learning of the Philadelphia area data. The specific areas selected are used to highlight the criminal characteristics of certain road networks and land uses. The model is obtained through 10 years of training on crime information from the official statistics of all of Philadelphia. Therefore, the total amount and stability of the data can represent the crime distribution of the whole of Philadelphia. As with the input data, the pixel size of the output images are $512pixels * 512pixels$. The image style will also be the same as the crime hotspot map style used for training.

Given a sample with a list of municipal buildings and grassy areas (Fig. 7-a), the model accurately predicts the different impacts of municipal-building distribution and planning of roads within grassy areas on crime rates, achieving the same level of accuracy it has with main roads in non-residential areas. This indicates the model comprehensively considers the factors that lead to crime and forms an accurate and complex prediction model. Even though, in the mid-training period (Fig. 7-b), the model's prediction of areas with low crime rates is lower than the real value, it accurately predicts the high crime-rate points caused by municipal buildings and green park spaces. For other areas that include both municipal buildings and residential buildings, the model also makes accurate judgments. Therefore, it can be concluded that artificial intelligence quickly and accurately learns some factors that are likely to cause high crime rates.

Figs. 7-c, d, and e are related to neatly arranged townhouses, loosely distributed residential buildings, and ordered villas. For these residential areas with obvious distribution rules, the predicted crime rate images generated by artificial intelligence are often uniform and accurate. Even if there are small lawns on the blocks or large buildings occupying entire blocks, the high crime-rate points at the corners of blocks can be predicted and displayed. However, as the building density decreases, the prediction of the crime distribution in the relatively empty villa areas becomes inaccurate. In addition, there are some exceptions in the layouts that the model can accurately predict. Although Fig. 7-f contains neat townhouses, due to the emergence of municipal buildings in the area, the artificial intelligence erroneously predicts the distribution and intensity of high crime rates. This may be in light of special architectural functions and geopolitical conditions, or even non-architectural reasons; alternatively, it may be caused by the lack of comparable data for learning neural networks.

Figs. 7-g and h are samples containing large grassy areas and suburbs with relatively isolated roads. The high crime rate near the grass and roads in the figure is not predicted, which may be explained by the fact that there are few specified elements in this type of map, such as the number of intersections and the number of buildings around the road. This kind of road has too little reference information for an artificial intelligence to learn from, leading it to misjudge the crime rate.

When the traffic conditions are complicated, the model's prediction of crime distribution also becomes less accurate. For instance, Fig. 7-i is a sample with main roads and complex traffic. Fig. 7-j is a sample with highly complicated roads within the residential blocks. Fig. 7-k is an irregularly shaped block with dead-end streets. In traffic-intensive areas, not least the main roads around empty spaces, the accuracy of the generated image is relatively low. Even in the middle and late training periods, there are still cases of the model misjudging high crime-rate

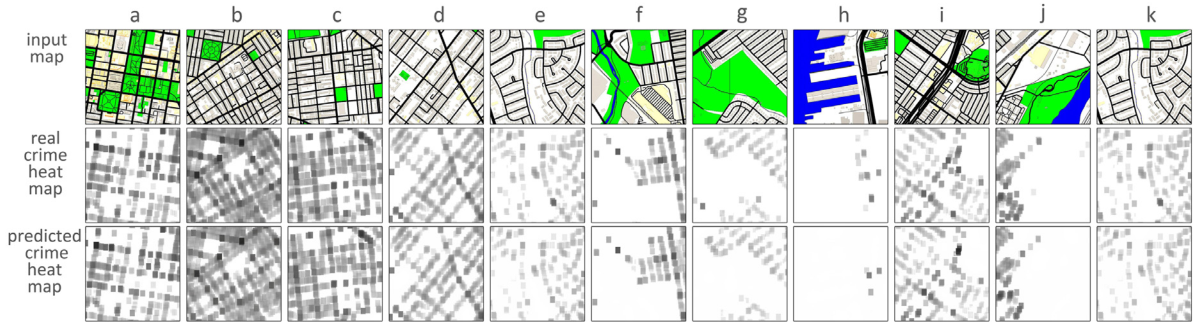

Fig. 7. Predicted results for the training images. For each group of images: Top: input map; Middle: real crime heat map; Bottom: generated crime heat map.

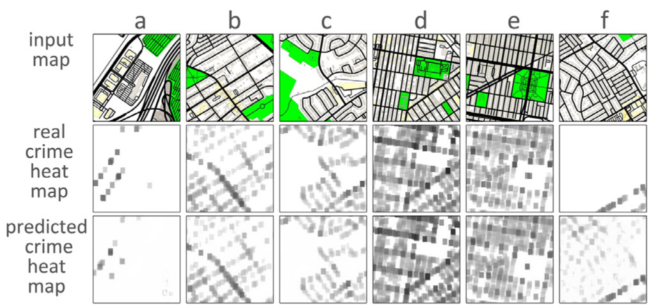

Fig. 8. Predicted results for the test images. For each group of images: Left: input map; Middle: real crime heat map; Right: generated crime heat map.

points and neglecting some low crime-rate points. This may be caused by the jumping randomness and the more complicated distribution of crimes as the traffic complexity increases. The presence of the dead-end streets and irregular blocks leads the model to generate inaccurate crime predictions because these two situations do not appear often in the training data, and there is a limited number of these sorts of learning samples. When more related city samples are learned, the accuracy of this type of street judgment will improve.

Generally speaking, for areas in the training set with high building density and moderate traffic density, the model can generate more accurate crime heat maps. As the building density decreases, the accuracy of the model prediction decreases. Road with too high or too low a density, as well as unconventional blocks and road types, are less likely to result in accurate predictions from the model. However, the overall accuracy of the GAN model is satisfactory, indicating a high degree of training completion.

3.2. Accuracy of the test set

However, the images generated from the test set can reveal the training results of the neural network more accurately than those of the training set. Because the test set is not included in model training, the model does not directly learn the data features of the test set. In order to output the heat map corresponding to the actual map in the test set, the model needs to apply the features learned from the training set. Because the heat maps output by the model based on the test set are extremely similar to the actual crime heat maps, and the test set has similar inaccuracy to the training set, it is believed that the model successfully learned the characteristics of the training set. In short, because the test set is randomly selected before training, the test accuracy of the test set shows that the crime characteristics learned by the model can be completely and very accurately applied to the crime distribution in Philadelphia.

Fig. 8-a is a sample of dense paths. Similar to the training set, the prediction result is different from the actual crime rate. Although the model makes a less accurate judgment on the distribution of crime, it can still predict part of the crime concentration area. After learning more relevant data, the model will improve its prediction accuracy for this type of street layout.

Figs. 8-b and c are samples containing small, loosely distributed residential buildings and irregularly shaped blocks. The model can provide accurate predictions for these types of blocks. However, while the judgment of the overall crime distribution may be correct, there is a phenomenon in which the prediction result of the crime intensity is lower than the actual result. At the same time, according to Fig. 8-c, the model accurately forecasts the high crime rate points caused by factors such as municipal buildings and main roads; both the test set and the training set result in accurate predictions of the crime rate for this type of area. Therefore, although accurate predictions are not made for some areas where crimes are concentrated, the overall prediction result is sufficient to conclude that the model is a trusted model, which can be further applied to generate predictions for other cities.

In the case of Figs. 8-d and e, which contain neatly arranged townhouses, the model accurately locates the points where the crime rate is higher, displaying better performance in predicting the crime rate in these types of arrangements. At the same time, there are some cases in which the predicted crime rate in areas with low crime rates is lower than the true value. Conversely, there are other cases in which the predicted rate at points with high crime rates is higher than the real value, causing the distribution of crime predicted by the neural network to be more concentrated for closely arranged blocks. At this point, the artificial intelligence has been trained as a trusted model and can provide architects with guidance.

In addition, as shown in Fig. 8-f, the real crime distribution is different from the predicted crime distribution. This is because the blank space in the real crime heat map is an area outside Philadelphia where no crime data has been collected and the generated heat map still makes predictions in this area. Given these facts, it is normal for the two heat maps to have a large difference.

In general, by analyzing the results of the test set and the training set, it can be concluded that the model is a credible crime-prediction model based on machine learning (Pirajan et al., 2019). Although the test set and the training set have similar accuracy problems, that is, the accuracy of the model tends to decrease as the building density decreases and the street distribution becomes more extreme, these problems will be solved by enriching the learning data with examples of similar arrangements. Therefore, in the case of non-extreme blocks, the model can accurately predict the most crime-prone areas, a capability that can be further applied in the prediction of other cities' crime rates, and ultimately in guiding architects to design urban-planning schemes with lower crime rates.

3.3. AI-assisted urban design

In order to verify the universality of the model, we generate crime-rate predictions for Princeton, Seattle, and New York, representatives of small, medium, and large cities, respectively, in the United States (Hipp

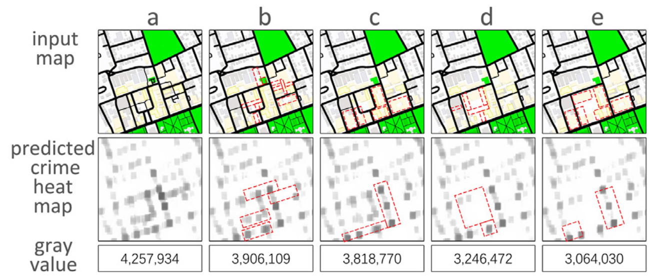

Fig. 9. Top: the input map of Princeton; Bottom: the predicted crime heat map of Princeton.

Fig. 10. Left: the actual sample of Princeton; Right: the final modified sample of Princeton.

et al., 2017). In Princeton, we choose areas with densely distributed roads and a large number of dead ends. In Seattle, we select regions with lawns and large public buildings. Finally, in New York, we select a central area of the city that contains a large number of municipal buildings and townhouses. After these maps are collected and processed by the same method as described above, the model is used to predict the crime rate on these maps. We generated statistics on all pixels in the predicted crime-rate heat map and added up their gray values to represent the crime index. Thus, by comparing the values, the change in crime rate before and after the map modification can be visually displayed.

In addition, the clarity of other city crime heat maps generated is quite different from that of Philadelphia's, which is approximately equivalent to the clarity of the images generated during the middle training period. This may be due to the different typical street scales and the varying complexity of the road network in different cities. The clarity of the crime markers in the experimental Seattle crime heat map is similar to that of the other two cities' maps. This result shows that the similarity between Seattle and Philadelphia is comparable to that between New York and Princeton, and that the training model has a degree of credibility when applied in Seattle. In order to further improve the accuracy of the model in predicting the distribution of crime in these cities, a large amount of crime data in these cities can be collected and a new model can be trained according to the method described in this research.

3.3.1. *Small-scale city*

Fig. 9-a is a sample from Princeton that contains many complexly arranged paths. It can be observed that there are some areas with a high crime rate in these densely distributed roads. Large areas of grass, municipal buildings and main roads next to grass also increase the possibility of crime to a certain extent.

In the Philadelphia maps used for machine learning, it was observed that simplifying the paths and buildings can reduce the crime rate near these parts. Therefore, we delete several paths at the crime center (O'Brien, 2019) (Fig. 9-b). Subsequently, the crime rates at the intersections corresponding to small roads are reduced, but this reduction is not passed on to other crime-prone locations, thereby achieving the goal of reducing overall crime rates. On this basis, under the premise that the building function and area are roughly unchanged, the densely arranged small buildings are replaced with larger, single buildings (Fig. 9-c). Although this has little effect on the high crime rate points in the sample, it is useful to eliminate low crime-rate points and eventually make crime events more concentrated in space and, therefore, more easily managed.

Similar to the above process, the roads forming irregular blocks are deleted and replaced with open space (Fig. 9-d). In addition, large buildings replace densely distributed small buildings (Fig. 9-e). The result is similar in some ways to that of the above process, eliminating some areas with a high crime rate without increasing the crime rate in the vicinity (Adel et al., 2016). Additionally, using larger buildings is shown to reduce low crime-rate points. At this point, compared with the real map sample before modification (Fig. 10), the crime rate of the modified sample dropped to 72% of the original, and the large reductions in crime are mainly concentrated in the high crime-rate regions. Therefore, on the basis of the analysis of Princeton's dense road network, in order to decrease the crime rate and strengthen public security management, the city plans need to avoid dense road arrangements as well as appropriately consolidating building volume.

3.3.2. *Medium-scale city*

Seattle is chosen as the representative of medium-sized cities. Because Seattle is a western city, the difference between it and Philadelphia is larger than the difference between Philadelphia and New York or Princeton. However, it is impossible to know how much the difference between them affects the accuracy of the model. Therefore, for experimental purposes, this research tries to input the map of Seattle into the model to verify whether the training model is applicable to Seattle.

In Seattle's urban areas with larger lawns and public buildings (Fig. 11-a), the crime rate is higher at the intersections of main roads and the corners of parks. Furthermore, scattered grassy areas, dead-end streets, densely distributed residential buildings and paths in groups may all give rise to higher crime rates.

The main workflow is as follows: (1) applying Philadelphia's crime-distribution laws relating to grassy areas to the sample of Seattle (Boessen and Hipp, 2018); (2) removing more small urban lawns and streets to make the distribution of grassy areas more concentrated; (3) adjusting intersections with higher crime rates around grassy areas to T-junctions; (4) downgrading streets and reducing road complexity on the long sides of green spaces (Sadeek et al., 2019). Simultaneously, in order to minimize changes to the original road conditions, a secondary road away from the green space and municipal buildings is changed to the main road. After these adjustments, the crime rate of the generated images is reduced, especially around the lawns (Fig. 11-b). In fact, according to the laws of crime distribution in Philadelphia, high crime-rate points consistently appear around urban parks, and main roads often have higher crime rates than surrounding secondary roads. When the main road is beside a park, and as the flow of people increases, the crime rate will generally increase significantly. This result suggests that integrating green space and T-junctions, as well as avoiding contact between grassy areas and main roads, can be used as an effective method to reduce the crime rate in other urban planning.

The difference between Fig. 11-c and the previous one is that the east-west main road is downgraded. Although Fig. 11-b has undergone a similar change, with the road in the north-south direction being downgraded, the effects of the changes to the two roads vary. Downgrading the east-west road has little effect on decreasing the crime rate. This is because more than one factor influences the crime rate and the model is complicated. Therefore, it is not guaranteed that the same factor will have the same impact in different street conditions. For the purposes of this test, the training model needs to be treated as a predictor to assist architects, and the prediction result is fed back in real time.

In order to further reduce the crime rate between blocks, a building was converted into a small, loosely distributed building with less floor

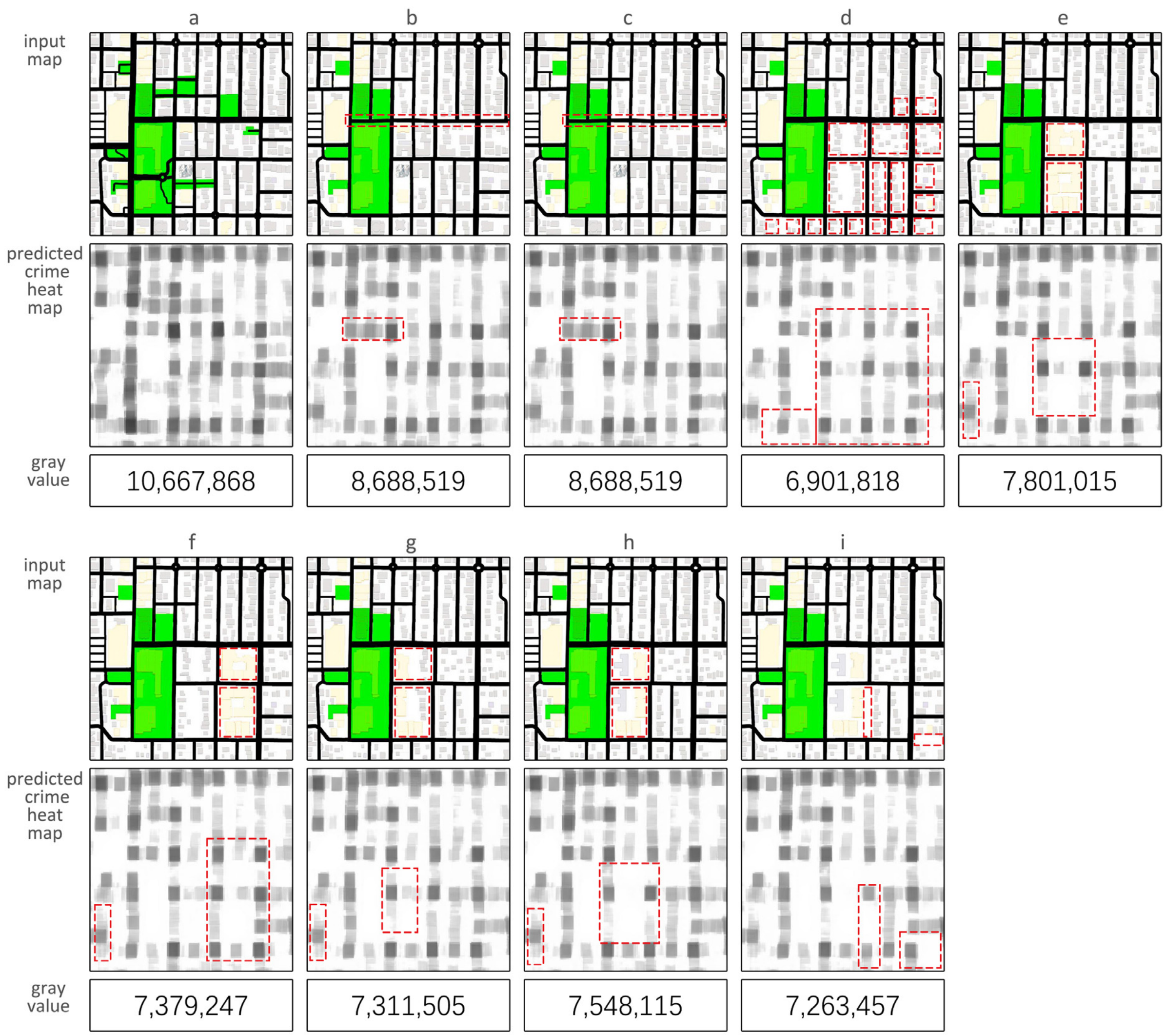

Fig. 11. Top: the input map of Seattle; Bottom: the predicted crime heat map of Seattle.

space (Fig. 11-d). This distribution is one of the most obvious forms of crime reduction in the samples of Philadelphia, and it also has a relatively stable effect of reducing the crime rate in Philadelphia and other cities (Browning et al., 2010).

Since the impact of municipal buildings on the crime rate is not absolute and stable, and in order to minimize alterations to the original distribution of municipal building area, we test the degree of impact of different forms of municipal buildings on the crime rate: 1) we replace the loosely distributed residential buildings with large municipal buildings (Figs. 11-e and f); 2) we insert smaller and loosely distributed municipal buildings instead of residential buildings (Figs. 11-g and h). In the prediction results, except for the places where the large municipal buildings are connected to the park (Fig. 11-e), the crime rate has increased distinctly. In other cases, municipal buildings and large-scale residential buildings have little effect on the crime rate. Therefore, the arrangement of municipal buildings can vary more without significantly increasing the crime rate. In the above test process, the impact model of municipal buildings on the crime rate is more complicated and is greatly affected by other factors in the sample. As a result, the artificial intelligence is required to directly act as a predictor and feed back the results in real time.

On the basis of the above, an intersection with a secondary road in the figure is converted to a T-junction at a place with a high crime rate (Fig. 11-i). The crime rate in the feedback is further reduced in the place where the crime is concentrated, an effect that is further demonstrated in the crime distribution in Philadelphia. Therefore, it can be concluded that arranging T-junctions is a stable way to reduce the crime rate. At this time, relative to the crime rate of the real map (Fig. 12), the crime rate of this sample was reduced to 68%, which achieves the goal of using the feedback of the artificial-intelligence model to adjust the urban layout plan and reduce the crime rate in this area.

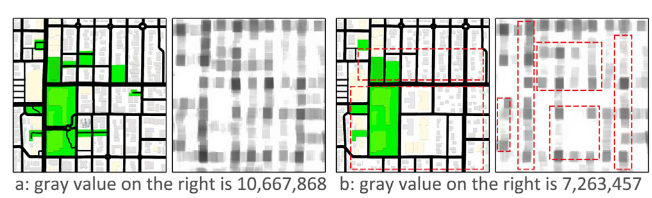

Fig. 12. Left: the actual sample of Seattle; Right: the final modified sample of Seattle.

3.3.3. Large-scale city

Fig. 13-a is a sample of a block containing many municipal buildings in New York. It can be observed that the crime rate at intersections is high and often higher than that of other parts of the street. At the same time, the arrangement of municipal buildings near the corner may also increase the crime rate.

In order to minimize the crime rate, we follow these steps: (1) deleting roads within the blocks in the sample as much as possible;

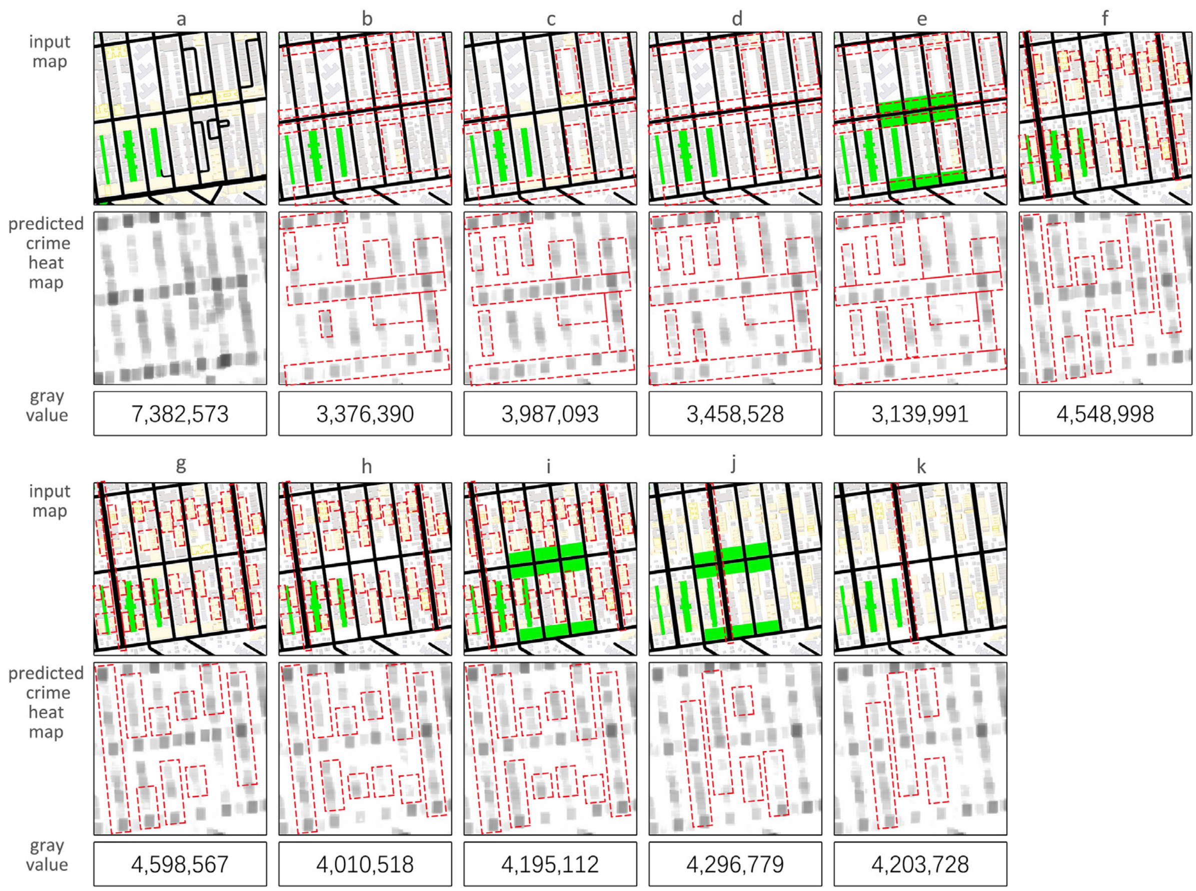

Fig. 13. Top: the input map of New York; Bottom: the predicted crime heat map of New York.

(2) downgrading the two main roads; (3) replacing the large municipal buildings with small, loosely distributed residential buildings (Fig. 13-b). On the basis of the prediction results fed back by the model, it can be observed that these operations have a visible effect on decreasing the crime rate of a certain place. Deleting roads within blocks, downgrading roads, and applying loosely distributed houses to reduce the flow of people has a more stable effect of lowering crime rates in Philadelphia and other cities.

In order to explore in greater depth the impact on crime rates of different building types at the ends of the blocks, as shown in Figs. 13-c, d, and e, we separately adjust the small, loosely distributed residential buildings at the ends of the blocks to the original municipal buildings, vacant land and parks. According to the previous experience of adjusting the block arrangement, these three situations increase the incidence of crime. On the contrary, on the basis of the feedback results, only setting municipal buildings at the end of the neat townhouse area increases the crime rate at the corner of the block, while the impact on crime distribution of adding small public activity spaces, such as squares or parks, is completely different from the general situation. Even though, under normal circumstances, the corners of urban parks tend to become areas where crime is concentrated, the limited size of the public activity spaces in the samples may reduce the crime rate (Taylor et al., 2019). From these results, it can be observed that the influencing factors of crime rate are complicated and that the specific impact of parks of different sizes and placements on different planning types still needs real-time feedback from the model generated by the neural network.

Although the above operations are enough to reduce the crime rate of this sample, the main roads and building functions of the city have changed too much. In order to restore the city function as much as possible, we make four more adjustments corresponding to the original. This entails replacing the east–west main roads in the original sample with two north–south main roads, replacing the municipal buildings at the ends of the blocks with the municipal buildings on the long sides of the blocks. The above changes correspond to Figs. 13-f, g, h, and i. The prediction results show that adding municipal buildings in the middle of the block still increases the overall crime rate, but compared with the actual sample Fig. 13-a, the crime rate is significantly reduced. What is more, the establishment of public space at the ends of blocks is still the most effective way to reduce the crime rate (Anderson et al., 2013). In addition, even if two main roads are added in the maps, the increase in the crime rate of the modified sample is limited, and the crime rate is no higher than that of the original sample in this circumstance. In conclusion, when it is necessary to maintain the traffic conditions and building functions of a certain sample, the real-time feedback of artificial intelligence and manual adjustment can also fulfill the purpose of reducing the crime rate. If the sample function can be adjusted, the crime rate of the sample can consistently be dropped to a greater extent.

In order to further verify the stability of the city sample, a north–south main road adjacent to the public space is added to the real maps in Figs. 13-j and k. Although the combination of the trunk road and the public space raises the probability of bringing greater traffic and elevating the crime rate, the results of the feedback, after these adjustments, do not display a high crime rate (Valente, 2019). At this point, compared with the unmodified New York sample (Fig. 14), the crime rate is reduced to 57% of the real situation. Once again, the process shows that the factors affecting the occurrence of crime are very complex. Humans can only approximately point out factors that affect the crime rate, while the intensity of the factor's effect from block to block varies enormously.

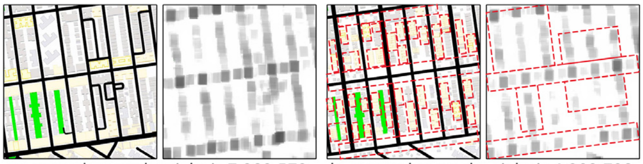

Fig. 14. Left: the actual sample of New York; Right: the Final modified sample of New York.

4. Conclusion

In the past, in environmental criminology, Newman's theory of defensible space states that the openness, landmark, privacy, detectability, and accessibility of a house may affect the occurrence of crimes (Newman, 1972). The mutual communication between neighbors, the unity and equality of the community, and other factors can reduce the crime rate to a certain extent. During the experiment of 3.3, a number of similar methods were used to reduce crime rates, such as avoiding more internal roads in neighborhoods, fewer road switchbacks, using a certain number of thru-ways, cul-de-sacs, and applying scattered small residences would reduce crime rates. All of these measures reduce the connectivity of the streets to some extent. Extensive research suggests that the street network affects people's mobility, thereby affecting the mobility of potential criminals. An increase in the mobility of criminals makes it more likely that potential criminals and criminal opportunities will meet, ultimately increasing the crime rate (Beavon et al., 1994). This idea is supported by the article (Merry, 1981), which argues that neighborhoods with more turning points increase the likelihood of escape for offenders, and therefore these areas are more likely to be exploited by offenders.

Although crime centers are often concentrated on main roads, not all main roads have high crime rates (Beavon et al., 1994). In contrast, in the vicinity of parks and elementary schools, the crime rate is lower due to the presence of neighborhood surveillance (Kim and Shin, 2014). Due to naturally occurring surveillance mechanisms in these areas, more strangers or passersby on well-traveled, highly visible streets can benefit as a crime prevention strategy (Shu, 2009). Because the extents of the effects of these factors change, the degree of impact on output tends to vary in combination with different urban layouts. Thus it is not the case that a particular urban layout has a certain effect on crime rates.

The goal of this paper is not to qualitatively or quantitatively study street placement and crime rates, but to obtain a predictive model of urban crime rates using GAN training. the adjustment process for streets and buildings in the experiments in Section 3.3 is equivalent to simulating an urban planner using our training model to obtain feedback on crime rate predictions and adjusting design solutions to ultimately achieve a reduction in urban crime rates. The adjustment methods in question only achieved crime rate reduction in the experiment, and some of them are consistent with previous research on crime rate reduction. This study does not demonstrate the generalizability of these crime reduction methods or what urban planning features are more likely to reduce urban crime rates.

5. Discussion

In order to more accurately visualize and predict the crime distribution in different neighborhoods, and to provide a basis for security planning and design for planning designers, this paper uses GAN neural network to build a prediction model of city plan and corresponding crime distribution map based on years of crime data in Philadelphia. It enables GAN to fit the connection between the pattern of crime occurrence and the planar map through the crime hotspot map, where the connection GAN fits can be understood as the sum of comprehensive environmental features. Thus there is no need to artificially verify the accuracy of a feature by using it as a reference target, as in traditional mathematical models.

Through the above discussion, we simulate the process of using this model by urban planners. By inputting the city plan into the GAN model, the model can immediately predict the crime distribution map of the area, and the designer can then further adjust the plan according to the feedback, and finally quantitatively achieve the purpose of reducing the crime rate within the design. In the process of adjusting the city plan map, previous research results related to crime rate can be applied, such as avoiding too many internal streets in the neighborhood.

This model can help architects optimize urban planning and design. When architects examine the crime rates associated with different design schemes, the model can immediately feed back the corresponding crime distributions. By verifying the crime distribution of different schemes, the architect can find the most satisfactory layout. As a result, the architect does not need to actually construct the design plan and conduct long-term experiments to determine the crime distribution of this plan. Once the neural-network model is trained, it can generate prediction images very quickly, taking roughly a few milliseconds.

This model is also helpful to the police. For existing neighborhoods, the police can refer to the previous crime-prone areas to centrally deploy police forces. However, for newly built areas, there is no historical data that can be used as a direct reference to determine the distribution of crimes. In such a case, the model can predict the crime distribution in the new environment based on the crime distribution law in the existing environment. Furthermore, the model's high accuracy can provide police with a reference for useful crime information in unfamiliar areas.

This study has several future development goals. First of all, by learning different types of street and building layouts in various cities, we can further raise the universality and accuracy of the neural-network model. Additionally, taking advantage of genetic algorithms, we can use the artificial-intelligence model as a feedback agent to find the solution with the lowest overall crime rate instead of manually adjusting the map to minimize the crime rate (Sofronova et al., 2019). In addition, although the GAN model is generally regarded as a method to improve accuracy, this study does not define a formula for testing the accuracy of a GAN. Defining the accuracy of the GAN can provide a more accurate prediction of the distribution of crimes (Dey and Bhattacharjee, 2020). Last, other factors that affect the living standard of residents can be comprehensively considered, averting situations in which the local residents' lives are affected by factors not considered in the model.

In the future, with the disclosure of information and the improvement of technology in various professional fields, we can acquire more data available for the study of artificial intelligence. The most important point is that the research approach of this paper can be used as a workflow to evaluate other urban features and immediately visualize and quantitatively display them. It suggests a workflow for designers to optimize their designs, and for citizens in general to evaluate and choose their living environment.

CRediT authorship contribution statement

Jingyi He: Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Hao Zheng:** Conceptualization, Methodology, Software, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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