Ann. For. Res. 66(1): 64-80, 2023
ISSN: 18448135, 20652445

ANNALS OF FOREST RESEARCH
www.e-afr.org

FORESTRY COMMERCIAL SIGNBOARD DESIGN AND MANAGEMENT STRATEGY BASED ON INTELLIGENT RECOGNITION OF STREET VIEW IMAGES

Wei Gan1 , Lan Qiu1, Ziwei Zhang1*, Ying Lin1, Zongyu Hong1, Yuchen Lei1
1.School of Architecture and Urban Planning, Huazhong University of Science and Technology, Wuhan 430074, China
Correspondence Email:m202173997@hust.edu.cn

Abstract

With the development of computer technology and the popularization of various imaging devices, a large amount of landmark and street view image data has been accumulated on the Internet. Given a query image, how to efficiently and accurately retrieve images with similar content from these large-scale image sets has become an urgent need in many applications. Driven by the industrial revolution, the contemporary forestry industry has undergone tremendous changes in terms of scale, environment, and management methods. The visual design of the forestry industry has evolved from a monotonous signboard or signage to a brand image design with a unique personality. At the same time, there are various forms of media, such as digital media, print media, advertising media, etc. The fusion of various concepts and technologies makes the ancient art of visual design glow with new vitality. A forestry scene semantic segmentation model based on DeepalBV3+ is proposed, and an image enhancement algorithm based on generative confrontation network is designed to improve the semantic segmentation accuracy of forestry scenes under different lighting environments. The experimental results show that the OA, MA and MIoU evaluation indexes of the model are 0.9420, 0.7799 and 0.6925 respectively, which are significantly improved compared with the original model and can meet the requirements of forestry semantic segmentation.

Key words: Intelligent recognition of street scenes; Forestry Commercial signboard design; Deep learningt

1 Introduction

With the development of computer technology and the popularization of various imaging equipment, various industries have accumulated a large amount of image data. According to conservative estimates, 1.2 trillion images were generated in 2017, and mankind has entered the era of image big data [1]. The forestry industry is an important part of urbanization infrastructure, and the understanding of urban street scenes is an important basis for realizing emerging applications of smart cities such as autonomous driving, intelligent navigation, and intelligent monitoring [2]. The rapid economic development has led to a high degree of prosperity in commerce, absorbed the accumulation of people and logistics, and promoted the continuous development and growth of the city [3]. As an ancient civilization, China has prospered in the world with its developed economy and commerce since the Han and Tang Dynasties, and there have been prosperous cities such as Luoyang, Chang'an, Bianjing, and Lin'an that the world yearns for. Since the reform and opening up, China's economy has shown a momentum of rapid development. With the international standards, business areas continue to expand, more frequent trade activities. People's clothing, food, housing, and transportation are all involved in the wave of commerce [4]. The development of China's modern industry has only a few decades of history, and there is still a big gap compared with the industrial foundation of Western countries for nearly a century [5].

At present, China's urban construction has entered the historical stage of transformation and development, which means that the future urban construction can't just focus on incremental mode, but must pay attention to the planning and utilization of stock resources[6]. A beautiful city must emphasize the existence and needs of people, pay attention to the experience of every citizen in the urban space, and make people living there feel safe, convenient and comfortable [7]. As an open place for citizens to conduct public exchanges and hold various activities, urban public space is an important area to show the image of the city and create a high-quality and dynamic urban space. It has become the consensus in the industry to actively guide people-oriented urban construction and create high-quality, vibrant and charming urban public space [8]. With the continuous improvement of business philosophy, traditional commercial streets have gradually moved towards the road of brand, and brand image is an important means to enhance the appeal of commercial streets [9]. The establishment of the brand image of the commercial street includes marketing, marketing, literature, design and other disciplines, and integrates regional culture, regional traditions and other customs. As the carrier of transmitting information, expounding views and expressing emotions, images are the bridge of communication between people and play an important role in people's daily life [10].

Street view images contain a wealth of urban infrastructure information, in which traffic signs provide key information for driverless and intelligent navigation technology. Through intelligent recognition of road condition changes, speed restrictions, driving behavior restrictions and other information in these signs, vehicles or drivers can respond, so as to avoid accidents. In addition, street view images provide important data sources for data collection of urban infrastructure management system, such as electronic map production, urban component census, road information management, road sign information maintenance and update, etc. Extracting these information manually will consume a lot of time and human resources, so it will be of great practical significance to realize the intelligent recognition and classification extraction of interest targets in street view images. To ensure the uniformity of image quality, the collected streetscape image data should be preprocessed. Traditional semantic segmentation methods are mainly achieved by extracting image features. However, due to the extremely complex visual relationships of urban streets in the real world, the types of target objects are complex, the spatial location distribution is uneven, and the imaging results are very vulnerable to light interference, which makes the semantic segmentation task in the urban street scene a complex problem, which restricts the accuracy and efficiency of urban street semantic segmentation, It cannot meet the needs of autonomous driving and smart city for semantic segmentation applications, and key data cannot be fully utilized.

Deep learning is the fastest-growing branch of machine learning in recent years. Compared with traditional machine learning, the essence of deep learning is a learning method with multiple levels, which can complete the extraction of shallow, middle and deep image features through the combination of levels. Its innovation lies in:

(1) This paper studies the semantic segmentation method of urban street scene image based on deep learning, and focuses on the reasoning of feature extraction principle and network training method.

(2) In order to improve the spatial resolution of the image and enhance its edge details, an image enhancement algorithm combining edge detection operator and dense residual network is proposed.

(3) In order to eliminate the influence of illumination and other factors on the accuracy of street scene semantic segmentation, a street scene semantic segmentation algorithm combining deep lab v3+ and dark channel prior theory is proposed.

In this paper, the design of commercial signboards along the street with intelligent recognition of streetscape images is studied, and the framework is as follows:

The first chapter is the introduction. This part mainly expounds the research background and significance of commercial signboards along the street, and puts forward the research purpose, methods and innovations of this paper. The second chapter is a summary of relevant literature, summarizing its advantages and disadvantages, and putting forward the research ideas of this paper. The third chapter is the method part, focusing on the design method of commercial signboards along the street, which combines convolutional neural network algorithm and deep learning street image intelligent recognition. The fourth chapter is the experimental analysis. In this part, experiments are carried out on data sets to analyze the performance of the model. Chapter five, conclusion and prospect. This part mainly reviews the main contents and results of this research, summarizes the research conclusions and points out the direction of further research.

2 Related Work

Street view target recognition has the characteristics of diversity and complexity. Street scene recognition based on deep learning is a very hot research direction in recent years. This chapter analyzes the advantages and disadvantages of traditional algorithms through literature, and develops from r-cnn to candidate box +cnn+svm. Because of its slow running time and low efficiency, fastrcnn and fasterrcnn are derived. Later, Yolo of cnn+nms takes classification and regression problems together as a loss function to calculate, which can reduce the difficulty of training and identify them in real time. It has certain advantages in recognition efficiency and recognition speed. However, the performance of the algorithm is different in different street view data sets. Especially for some small targets, their recognition performance is not ideal.

By combining edge features with maximum entropy detection algorithm, Deng Z improves the detection accuracy of unstructured roads and other scenes, and solves the problem of poor detection accuracy caused by light intensity, road shadows and other interference factors [11]. Zeng Z proposed a real-time segmentation algorithm of driving video by combining edge information and regional information. Experimental results show that the segmentation result of this algorithm is more uniform and smooth than previous algorithms and has high robustness [12]. Pal s has developed an unstructured road cutting algorithm that combines entropy information and image edge features. First, the road area is distinguished by the threshold detection of RGB entropy and the minimum difference of RGB entropy histogram is obtained. Secondly, the grid is converted into a gray-scale image by calculating its pixel ratio. Finally, the grid near the edge is found by the edge to edge method to accurately segment the road area [13]. Jiang s and other traffic sign recognition algorithms based on mathematical morphology are the most representative. They study the use of morphological skeleton function to build a template based on the characteristics of traffic signs, and then match the image with the template, so as to realize the automatic recognition of traffic signs. This method has good recognition robustness, but the construction of the template is more complex, and can only recognize specific traffic signs, The automatic recognition of traffic signs in natural scenes will be difficult to achieve a good recognition effect [14]. Chen Z et al. Proposed an intelligent detection method of triangle traffic signs, which uses his color space for color segmentation, and then uses neural network to detect the vertices of triangles, so as to realize the automatic detection of triangle signs [15]. Matthews a proposed an image segmentation method based on graph theory algorithm and multi-order relationship, and introduced image nonlocal relationship, high-order relationship based on image block and super pixel and image global relationship based on similarity transfer into the traditional graph theory model. Combined with numerical analysis, pattern classification, information theory, etc.many links such as the construction and optimization of energy function based on graph theory segmentation framework were designed [16]. The core advantage of the full convolution neural network proposed by Sethi m is that the network can obtain the relationship mapping from pixel to pixel without classifying specific blocks. After adjusting the structure of the traditional convolutional neural network, a full convolutional network can be obtained, which can learn the characteristics of images with different resolutions [17]. Satoh I trained a semantic segmentation model based on full convolution neural network to extract pedestrian information on the street, so as to reduce the noise interference in the background. Compared with other algorithm results on the OTB data set, it can be found that the accuracy and success rate of this method in the case of occlusion are significantly improved [18]. Ting Wu proposed pspnet and used spatial pyramid pooling to fuse features at different levels[19]. Cheng Z et al. Fused multi-level features on the basis of mobilenetv2, retained the original real-time running speed while improving accuracy, and further verified it on the cityscapes data set [20].

On the basis of summarizing the previous research results of deep learning technology in semantic segmentation of urban street scenes, aiming at practical problems such as light interference in different cities, this paper proposes a high-precision image semantic segmentation model based on deeplabv3+, and proposes an image enhancement algorithm combined with application scenes to improve image resolution, which provides a theoretical and technical method for obtaining high-precision urban semantic information through deep learning technology.

3 Methodology

3.1 Research summary and theoretical framework of Street commercial signboard design

With the development of science and technology and the wide application of various materials, the design of plaque is more flexible and diverse. To give full play to the function of signboards, we should not only pay attention to the choice of materials for making signboards, but also pay more attention to the word design of signboards and the naming of shops. Designers use their professional ability and experience in customer service to design signboards in different forms. Most signs are vertical and horizontal, some are hung above the door, some are hung under the eaves, and some are directly embedded in the buildings. Some shop operators, who know how to bring forth the new, design signs that are not only catchy but also memorable. Therefore, the signboards that can attract customers into the store must have a strong visual impact, and at the same time, the words have a high degree of generalization, thus having a certain impact on customers' psychology. The text design on the signboard should pay attention to the following aspects. (1) We should pay attention to the overall coordination, and the font, color feeling, position and so on should complement each other; (2) In terms of store naming, the text should be as concise as possible, simple but not simple, and the content should have a certain connotation. At the same time, it should be catchy, so that people can see it at a glance and don't bother to guess; Nowadays, young people like some personalized font designs, which can more easily attract consumers, but we should pay attention to the deformation of these words to be easy to identify, and do not blindly pursue personality and ignore the most basic purpose of the text design on the signboard. Of course, this is not to say that other aspects can be ignored. We should also work hard on the decoration and rendering of signs. The operators of some commercial stores are creative and innovative, and use some mascots and symbols designed by themselves to attract the attention of consumers, which is vivid and interesting, so as to attract consumers more and increase the probability of consumers entering the store. In order to achieve the best communication effect, we should pay more attention to the size of the words on the signboard. Not only should we consider the effect of close viewing, but we should also consider whether the size of the text is appropriate in the middle and long distance.

For an excellent commercial store signboard design, the novel, unique and elegant design will have considerable advantages in the same industry. (1) Guide consumer groups. The signs of commercial stores identify the scope of goods, service items, business hours, business scope, etc. sold by the stores, such as catering stores, 3C digital stores, book shopping centers, etc. (2) Reflecting the business characteristics and service tradition of commercial shops, some shops selling medicine, calligraphy, calligraphy and painting, and traditional snacks have a long history and good commercial nature, such as some well-known brands daoxiangcun, Tongrentang, etc. When designers or copywriters do planning work, they should comprehensively analyze and consider the situation of commercial street from the whole market environment. When the commercial street promotes its image, it must consider the relevant enterprise strategies. Therefore, it is necessary to draw corresponding communication strategies and put forward the core creative concepts from three aspects: consumers, characteristics and competitors faced by commercial streets. As shown in Figure 1.

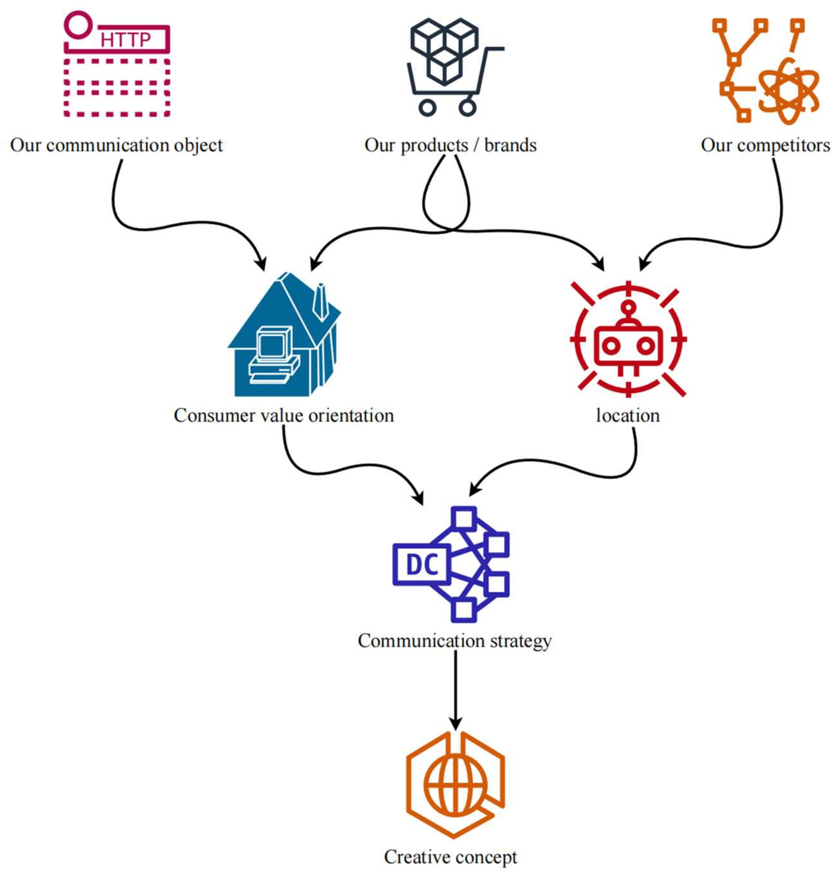


Figure 1 Derivation of creative concept

Consumers who shop in traditional commercial streets will be involved in almost all levels of needs, but the emphasis of different levels of consumer needs is different. We can make a reasonable analysis of consumers' needs according to their social class, income level, education level and age.

3.2 Semantic Segmentation and Feature Extraction of Urban Street Scenes

With the rapid development of artificial intelligence technology and deep learning technology, semantic segmentation algorithm based on deep learning is greatly ahead of traditional methods in both segmentation results and debugging time. Therefore, semantic segmentation technology of urban street scenes based on deep learning has become one of the hot research directions of many researchers.

In Figure 2, a 5 is entered × For a 5-size random pixel image, the range of pixel values is specified between 0 and 255, and the number of channels of the convolution kernel is consistent with the input matrix, that is, in the process of convolution, the convolution kernel adds products according to the rules from left to right and from top to bottom, and the size of the characteristic image of the to is also 3 when the step size is 1 × 3。

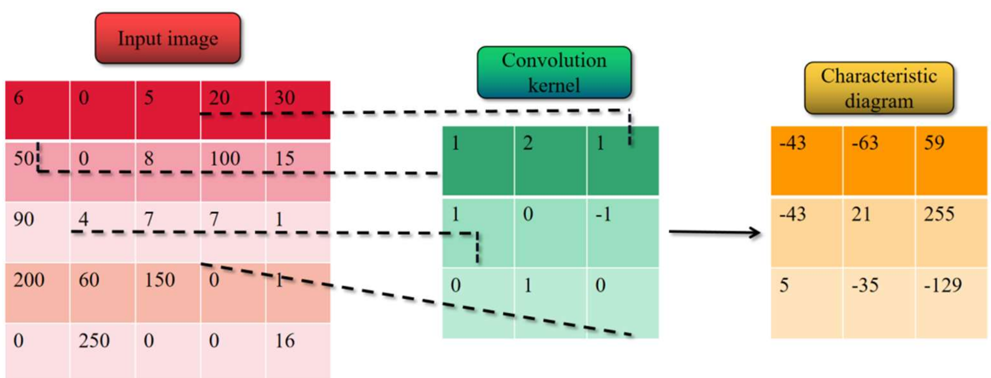


Figure 2 Single channel convolution operation

A single-channel image is called a grayscale image, while a color image has three channels of RGB3. When a color image is convolved, the depth of convolution kernel must be consistent with the number of channels in the image, that is, convolution kernel with depth of 3 is used. Add the results to get a single feature map, and then determine the final depth of the output feature map according to the number of convolution kernels.

Convolution layer is composed of a large number of convolution kernels, which is the core part of convolution neural network. Through convolution operation, the corresponding feature map of the image can be obtained. According to the definition, the eigenvalue obtained by convolution operation contains important structural information of the image. In essence, it is to discover the implicit information of the number through continuous multiplication. The mathematical definition of its continuous form is as follows:

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) g(t-\tau) d\tau \tag{1}$$

The discrete form is:

$$(f * g)[n] = \sum_{m=-\infty}^{\infty} f[m] g[n-m] \tag{2}$$

When the input source is a two-dimensional image I, set the two-dimensional kernel function as K, the coordinates of a point on the image I are recorded as (m,n), and the pixel value at (m,n) on a channel is recorded as $I(m,n)$. At this time, the clipping operation form is as follows:

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i-, j-n) K(m,n) \tag{3}$$

3.3 Improved deeplabv3+ algorithm

There are difficulties in semantic segmentation of street scenes, which mainly lie in the complex types of objects, uneven spatial distribution and the imaging results are easily disturbed by light. When the sun shines strongly, the RGB three-channel pixel values of the sky and the distant part are very large, resulting in too large a difference between the front and back scenery, which makes it impossible to correctly identify the foreground target. When the light is less than cloudy, there are more than one RGB channel with higher pixel values, which leads to the semantic segmentation model can't correctly distinguish the foreground from the background. In general, DeepalBV 3+is effective in extracting local features, but it lacks the ability to use global features. As shown in Figure 3.

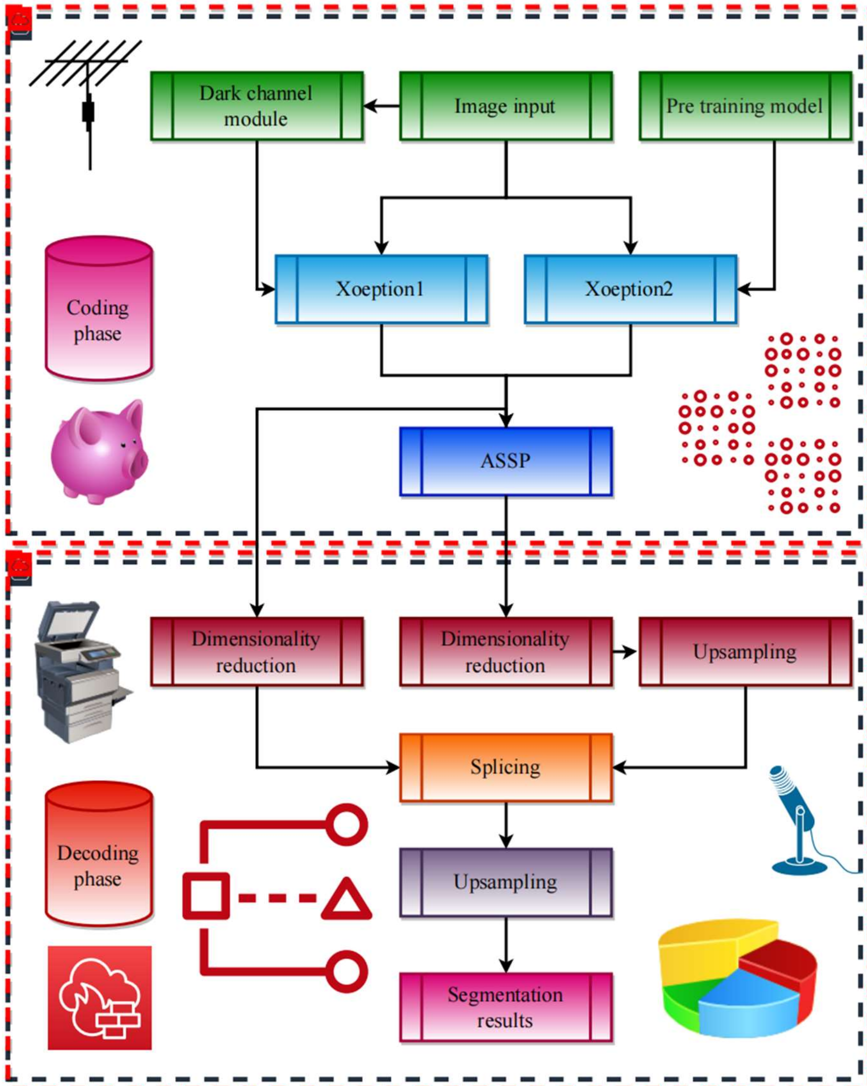


Figure 3 Flow chart of DeepalBV 3+model fusion method

The network structure of feature extraction network input layer is divided into two layers: main line and branch line. The input urban street view image is inverted on the branch road and passes through the dark channel prior module.

$$J^{dark}(x,y) = \min_{\omega \in \Omega(x,y)} \left[\min_{c \in (r,g,b)} J^{c}(\omega) \right] \tag{4}$$

The atmospheric scattering model describing foggy images is expressed as the following formula:

$$I(x) = J(x)t(x) + A(1 - t(x)) \tag{5}$$

$$t(x) = e^{-\beta d(x)} \tag{6}$$

The formula (4) is filtered by seeking the minimum value on both sides of the deformation, and the formula (5) is brought in to obtain the following formula:

$$t(x) = 1 - \varphi \min_{\omega \in \Omega(x,y)} (\min_c \frac{I^c(\omega)}{A^c}) \tag{7}$$

Considering that only areas outside the sky are expected to be enhanced, a coefficient of $P(x)$ is introduced:

$$P(x) = \begin{cases} 2t(x), 0 < t(x) < 0.5 \\ 1, \quad 0.5 < t(x) < 1 \end{cases} \tag{8}$$

The final reconstruction result formula (9) is obtained, where φ is the adaptive constant $(0 < \varphi \le 1)$.

$$J(x) = \frac{I(x) - A}{P(x)t(x)} + A \tag{9}$$

4 Result Analysis and Discussion

This section verifies the method proposed in this chapter on two street view image position recognition data sets: tokyo24/7 and SanFrancisco data sets. The tokyo24/7 data set contains 315 query images taken by mobile phones in three different time periods (day, evening and night) at the same location, as well as 75984 reference images intercepted from 6332 Google Street View panoramas. The panorama of each location generates 12 images. All pictures have geographical location tags, and the queried location tags are used to verify whether the retrieved reference image is correct. In the experiment, the commonly used evaluation indicators in street view image position recognition are used recall@N To evaluate the recognition performance of different methods. In this evaluation index, if there are correct results in the first n search results, it is considered that the query image can be correctly recognized. Before cityscapes dataset, many large datasets did not reach the complexity of scenes in real urban streets. This shows that integrating the dark channel prior theory and multi-channel weighted fusion structure into the deep lab v3+ model can effectively improve its semantic segmentation accuracy. As shown in Table 1.

Table 1 Segmentation accuracy of different categories under different feature extraction networks

Category	DeepLabV3+MobileNet	DeepLabV3+MobileNet50	DeepLabV3+MobileNet101	DeepLabV3+Xception	Our
Train	0.5642	0.5601	0.4682	0.7253	0.71235
Road	0.9774	0.9474	0.7812	0.7745	0.5253
Sidewalk	0.7223	0.7545	0.5913	0.7882	0.9842
Building	0.8812	0.8224	0.8921	0.6452	0.8953
Vegetation	0.9424	0.9214	0.9654	0.5545	0.8723

For the features of. NetVLAD, the code and depth model disclosed in reference [12] on its homepage are used to extract them in the experiment. The model with intra-whiten operation trained on TokyoTimeMachine data set is used to extract NetVLAD features from Tokyo24/7 data set. For the SanFrancisco data set, the NetVLAD feature trained on Pittsburgh250k data set is used in the experiment, because the reference images of the two data sets are similar. For each query image, the maximum resolution is 640×320 while maintaining its aspect ratio before entering the depth network.

In the process of gray-scale filtering, the only parameter that needs to be determined is the gray-scale threshold τ, which is used to distinguish images taken under different illumination. Based on the test results in the section of gray filtering, this section conducts experiments on Tokyo24/7 data set to select the best parameters, and uses different thresholds to filter the images with low gray values in the initial search results. The experimental results are shown in Figure 4.

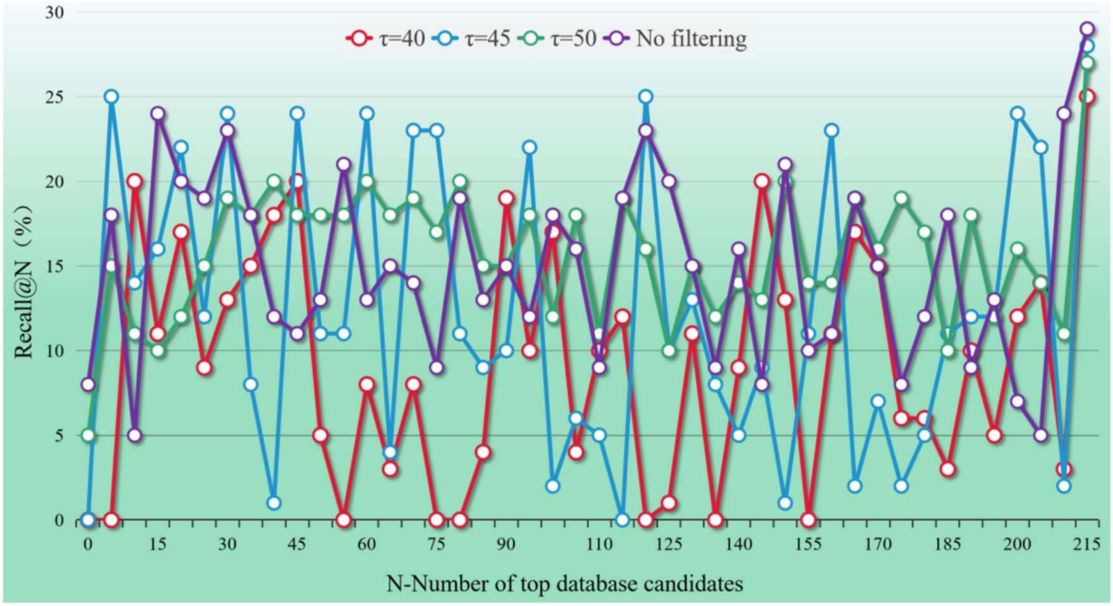
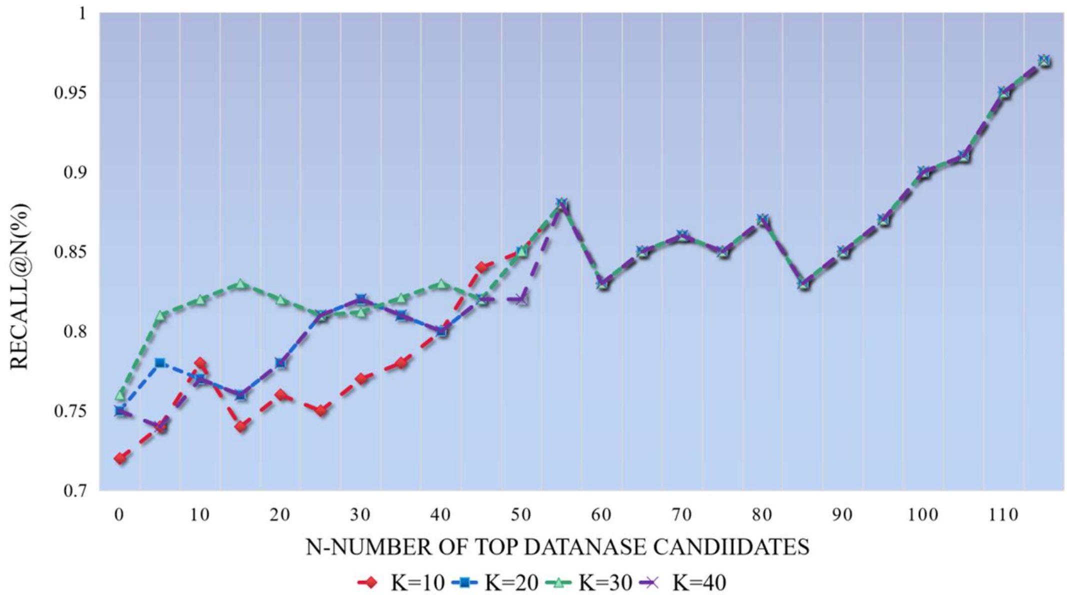


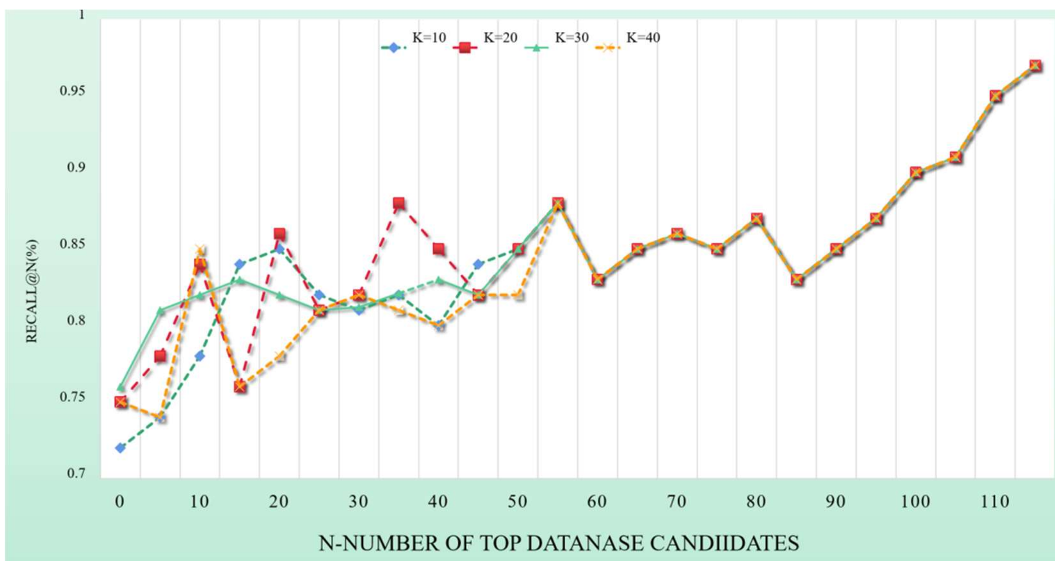
Figure 4 Selection results of gray filtering parameters on tokyo24/7 dataset

It can be seen that using gray filtering can improve the accuracy of recognition within a certain threshold range. In the subsequent experiments τ The value is set to 45. In the experimental results, the top-5 recall rate obtained by using the original netvlad method （ Recall@5 ） It is 81.9%, while the recall rate after gray filtering is 84.4%. Although gray filtering only slightly improves the recall rate on tokyo24/7, this operation is very useful for subsequent grouping fusion, because the dark background image in the initial result has been deleted from the result list, avoiding the impact on subsequent operations.

In packet fusion, it is necessary to determine the reordering size n and the nearest neighbor parameter k. The reordering size n represents that the packet fusion operation needs to act on the first n initial results. The nearest neighbor parameter k is used to determine the nearest neighbor relationship between each other. In order to avoid performance degradation, the limit n in the experiment is less than 50, which is consistent with the experimental setting in other position recognition. The influence of different N and K values on the final recognition accuracy was tested in the experiment, and the results are shown in Figure 5.



(a) Limit n less than 50

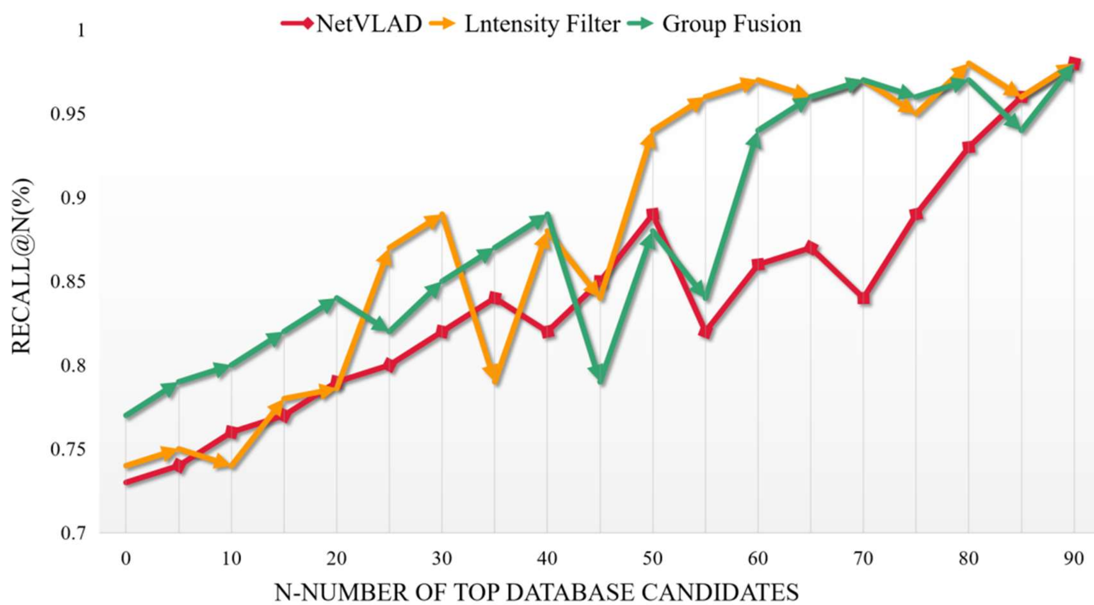


(b) N and K identification accuracy

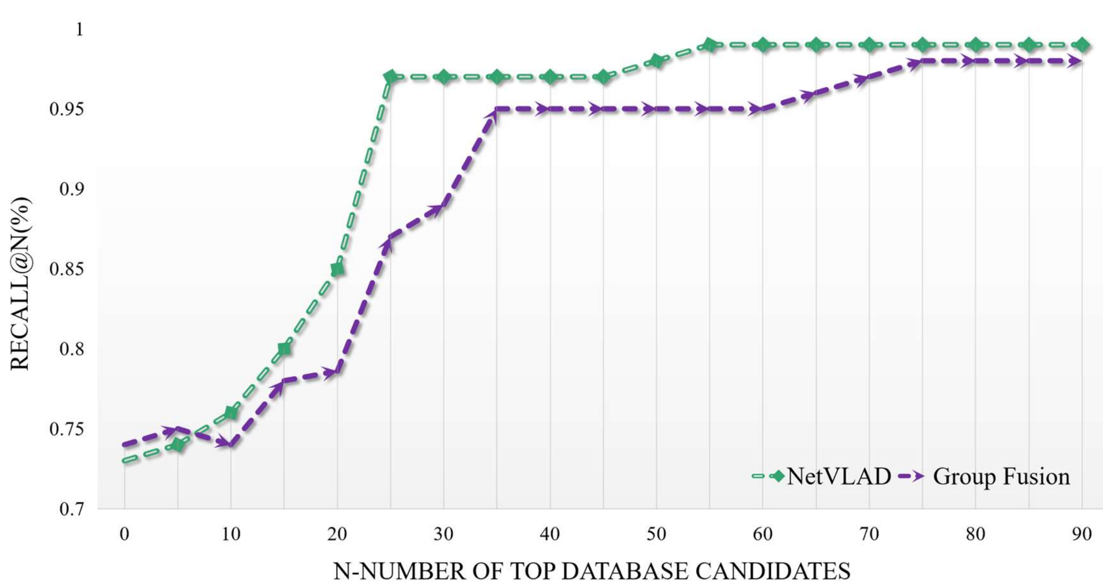
Figure 5 Selection results of grouping fusion parameters on tokyo24/7 dataset

Because only the most relevant results are ranked in the Top-1 position in grouping fusion, recall@N curves under different parameters will coincide when n increases. When n is 30 or 50, recall@1 will reach its peak value when k=30, which means that it is a relatively stable setting when it indicates that it is close to each other. In the subsequent experiments, both K and N are set to 30. For SanFranciscoLandmark data set, K and N are set to 30 based on a similar parameter selection method. Because this data set contains 1.06 million reference images, it is very timeconsuming to calculate the nearest neighbors for all reference images. In order to reduce the computation time, for each query, only the first 1000 initial results are considered as neighbors.

The gray filtering and grouping fusion methods proposed in this chapter are used to reorder the initial results. In the experiment, the method proposed in this chapter is compared with the best method based on NetVLAD features. Based on the experimental results of parameter selection, reordering is only carried out on the first 30 search results, and then the most similar results are ranked in front of the initial search list to avoid performance degradation. The recognition results on Tokyo24/7 data set are shown in Figure 6.



(a) All inquiries



(b) Daytime inquiries

Figure 6 End diagram of location recognition on tokyo24/7 dataset

It can be seen from the figure that the method proposed in this chapter can further improve the recognition results on the tokyo24/7 dataset compared with the best netvlad method at present, which shows that the correct results can be ranked ahead of the search list through the reordering operation. Specifically, the recall rate on top-1 results, i.e Recall@1 From 71.4% to 76.5%, and the overall recall rate has also increased. Recognition recall rate before top-5 （Recall@5） The improvement of the recognition recall rate can be attributed to the grouping fusion operation, and the subsequent improvement of the recognition recall rate comes from the grayscale filtering operation. The method proposed in this chapter mainly improves the recognition performance on the query taken at dusk and night. Gray filtering can effectively filter out irrelevant results, and location-based grouping fusion can improve the recall rate on top-1 for different types of query images.

5 Conclusions

In the forestry environment, DE hanging advertisements can attract customers, attract the attention of passers-by, let passers-by know what products are sold, etc., and the banners flying on the street attract people's attention. In the initial stage of forestry industry development, images and media were spontaneously formed according to commercial needs, lacking certain planning and system. With the input of modern business concepts, the brand image has completely changed the external visual form of the commercial street. Individualization and systematization are the characteristics of the visual image design of modern commercial streets. The research significance and development history of deep learning image semantic segmentation technology are expounded. This paper introduces the working mechanism of semantic segmentation based on deep learning technologies such as convolution, pooling, and nonlinear activation functions, and gives a basic introduction to the deep lab v3+ network, which is applied to the task of forestry industry signboard design. Finally, a brief introduction to the transfer learning of network models.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Funding Statement

This work is partly supported by the Planning Fund for Humanities and Social Sciences Research of Ministry of Education of China：Research on design and management strategy of commercial signboard along the street based on intelligent recognition of street view image (No. 21YJA760019) .

References

[1]Zhang L, Zhen-Qiang W U. Design of the characteristics of image intelligent recognition system based on OpenCV[J]. Electronic Design Engineering, 2015,47(37):1-7.

[2] Efendioglu H S, Yildirim T, Toker O. Advanced image processing and artificial intelligence based approaches to fiber optic statistical mode sensor design[J]. International Society for Optics and Photonics, 2011,458(84):2-8.

[3] Han L, Han L. Research on visual recognition intelligent system of city brand image based on fuzzy theory and regional culture[J]. Journal of Intelligent and Fuzzy Systems, 2021(APR.):1-9.

[4] Tsai T H, Cheng W H, You C W. Learning and Recognition of On-Premise Signs From Weakly Labeled Street View Images[J]. IEEE Transactions on Image Processing, 2014, 23(3):1047-1059.

[5] Yan W Y, Shaker A, Easa S. Potential Accuracy of Traffic Signs' Positions Extracted From Google Street View[J]. IEEE Transactions on Intelligent Transportation Systems, 2013, 14(2):1011-1016.

[6] Zhang C, Ding W, Peng G. Street View Text Recognition With Deep Learning for Urban Scene Understanding in Intelligent.pdf[J]. IEEE Transactions on Intelligent Transportation Systems, 2020, PP(99):3-20.

[7] Beverland M B. Managing the Design Innovation–Brand Marketing Interface: Resolving the Tension between Artistic Creation and Commercial Imperatives[J]. Journal of Product Innovation Management, 2010, 22(2):3-6.

[8] Xing Z, Li G. Research on Intelligent Recognition of Coast Image Features in Distributed System Based on Deep Learning[J]. Journal of Coastal Research, 2020, 108(sp1).

[9] Bachanek K H, Tundys B, Winiewski T. Intelligent Street Lighting in a Smart City Concepts—A Direction to Energy Saving in Cities: An Overview and Case Study[J]. Energies, 2021, 14(8):7-24.

[10] Li Y, Tong G, Chen H. Object Detection for Panoramic Images Based on MS-RPN Structure in Traffic Road Scenes[J]. IET Computer Vision, 2019, 13(5):4-19.

[11] Deng Z, Zhou L. Detection and Recognition of Traffic Planar Objects Using Colorized Laser Scan and Perspective Distortion Rectification[J]. IEEE Transactions on Intelligent Transportation Systems, 2017,2017(11):1-11.

[12] Zeng Z, Wu M, Zeng W. Deep Recognition of Vanishing-Point-Constrained Building Planes in Urban Street Views[J]. IEEE Transactions on Image Processing, 2020, 29:5912-5923.

[13] As I, Pal S, Basu P. Artificial intelligence in architecture: Generating conceptual design via deep learning[J]. International Journal of Architectural Computing, 2018, 16(4):306-327.

[14] Li P, Jiang S. Analysis of the characteristics of English part of speech based on unsupervised machine learning and image recognition model[J]. Journal of Intelligent and Fuzzy Systems, 2020, 39(99):1-11.

[15] Chen Z, Su Y, Liu Y. Key technologies of intelligent transportation based on image recognition:[J]. International Journal of Advanced Robotic Systems, 2020, 17(3):110-120.

[16] Li G, Matthews A. Color recognition of design object of manual decoration element based on convolution neural network under the impact of COVID-19[J]. Journal of Intelligent and Fuzzy Systems, 2020, 39(6):8739-8746.

[17] Sethi M, Lijding M, MD Francesco. Flexible Management of Cloud-Connected Digital Signage[J] IEEE International Conference on Ubiquitous Intelligence and Computing. IEEE, 2016,36(33):5-32.

[18] Satoh I. An Agent-Based Framework for Context-Aware Digital Signage[J]. advances in intelligent & soft computing, 2010,46(64):35-40.

[19] Ting W U, Zhu M Z. Research and implementation of image intelligence processing system[J]. Computer Engineering and Design, 2011,36(8):19-23.

[20] Cheng Z. A Brief Talk on Environmental Experience Graphic Design in the Construction of Characteristic Tourism From Signage Design[J]. Psychology Research, 2022, 12(6):7-10.