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The Analysis of Intelligent Urban Form Generation Design based on Deep Learning

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Abstract. In response to the growing demand for intelligent solutions in urban planning, this study constructs a deep learning-based framework for generating intelligent urban morphology, effectively addressing pressing real-world challenges. At the outset, the study explores the core concepts of green and ecological principles within the evolution of contemporary urban forms, establishing a robust theoretical foundation for subsequent investigations. The study provides a detailed explanation of the practical application paradigms of deep learning, encompassing meticulously selected technical methodologies, carefully designed algorithmic structures, and an optimized parameter configuration system. Together, these elements form a comprehensive technological application framework. An innovative application of convolutional neural networks is introduced for the in-depth analysis and processing of urban street imagery. This advancement enables critical urban planning functions, including road network design, detailed analysis of building distributions, optimization of public facility layouts, and dynamic traffic flow analysis. These capabilities address the key limitations of traditional planning methods by enhancing intelligent analysis and precise decision-making. To evaluate the model's performance quantitatively, a systematic testing scheme is developed and implemented, covering various scenarios, including daytime and nighttime conditions. This approach ensures a comprehensive assessment of the precision and effectiveness of each functionality. The core significance and contributions of this study are encapsulated in its empirical findings. The proposed model achieves accuracy and fit metrics exceeding 93% across all testing dimensions, representing a significant advancement that provides robust and targeted support for urban planning practices. By integrating deep learning technologies into the intelligent urban morphology generation framework, the study successfully implements critical functions such as efficient road network planning and scientific analysis of building distributions. Furthermore, the study introduces cutting-edge technological tools and innovative methodologies to the urban planning discipline, advancing the development of intelligent urban planning. Its contributions are of profound value in both theoretical innovation and practical application, offering transformative potential for the field.

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1. Introduction

With the rapid development of Artificial Intelligence (AI) technology, Deep Learning (DL) has made significant achievements in various fields, particularly in image recognition and natural language processing [1]. The acceleration of urbanization has brought increasingly complex challenges to urban planning and design. How to utilize advanced technologies to achieve more scientific, efficient, and sustainable urban development has become an important research topic. Against this backdrop, DL, with its exceptional capabilities in data analysis and pattern recognition, has gradually gained widespread attention in the field of urban planning. However, applying DL to the intelligent generation of urban forms remains a relatively novel and exploratory research direction. Although research in this area is still in its early stages globally, some noteworthy preliminary results have been achieved [2]. For example, several studies have used DL technology to process and analyze urban datasets, extract valuable features, and generate urban forms that adhere to specific design principles [3]. These exploratory studies provide valuable experience and a foundation for further applications of DL in the intelligent generation of urban forms.

Despite its potential in this field, DL faces many challenges and limitations in this field [4]. First, the acquisition and processing of urban data presents significant difficulties. Urban data spans multiple disciplines and fields, and its accuracy and completeness profoundly impact the quality of generated urban scenarios [5]. Additionally, the implementation of DL methods requires specialized knowledge and is highly dependent on high-performance computing resources [6]. Furthermore, the decision-making process of DL models often lacks transparency, making it difficult to interpret the generated urban forms [7]. Lastly, the intelligent generation of urban forms also involves ethical and privacy concerns, necessitating greater attention to data security and user privacy protection [8]. To address the challenges in intelligent urban form generation, this study explores the application of DL technology and analyzes its advantages, challenges, and future development prospects. A key feature of this study is the introduction of a new algorithm. Compared to existing advanced algorithms, this algorithm can not only process one-dimensional urban data analysis but also effectively tackle complex urban scenarios. Specifically, the proposed algorithm integrates various advanced technologies, showing stronger adaptability and accuracy when handling heterogeneous urban data, and performs excellently in dynamic urban environments. Through a comprehensive study of DL applications in urban form generation, this study aims to provide innovative tools and methods for urban planners and designers, thereby promoting the digital transformation and innovative development of urban planning.

Against the backdrop of accelerating urbanization and the increasingly complex and diverse demands of urban planning and design, this study is committed to addressing the key issue of how to effectively apply DL technology to achieve intelligent urban form generation. It analyzes the numerous advantages, primary challenges, and future development trends of DL in practical applications, aiming to provide valuable insights and contributions to the field. The specific objectives of this study are as follows:

(1) Comprehensive analysis of DL principles and application mechanisms: This study thoroughly analyzes the principles and application mechanisms of DL technology in urban form generation. It details the core algorithms and model architectures, laying a theoretical foundation for future research.

(2) Systematic summary of key insights and effective methods: Although the application of DL technology in urban planning is still in the exploratory phase, this study systematically reviews relevant application cases, and summarizes common patterns and effective methods for driving urban form generation using DL.

(3) Filling theoretical gaps: By integrating and analyzing existing research outcomes, this study aims to fill the theoretical gaps in the application of DL in urban planning and provide new research directions and theoretical support for the academic community.

(4) Empowering urban planning practices: The findings of this study not only make theoretical contributions but also provide urban planners with scientific evidence and innovative strategies, supporting the digital and sustainable transformation of urban development.

By achieving these objectives, this study aims to promote the deep integration of DL in urban form generation, foster innovation in urban planning practices, and enrich the theoretical and practical dimensions of the field. A major contribution of this research is the introduction of an innovative approach that has significant advantages over existing advanced algorithms. Current mainstream algorithms typically follow a single technical path, which struggles to handle the complexity of urban data and the variability of dynamic scenarios. For instance, some algorithms excel at processing structured data but perform poorly with unstructured data, while others excel in static scene analysis but struggle to adapt to rapidly changing urban environments. In contrast, the approach proposed integrates multi-source heterogeneous data processing techniques, dynamic adaptive learning strategies, and cross-domain knowledge fusion models. This enables it to break through data type barriers and uncover potential relationships between different data sources. Whether processing geographic spatial information, population mobility data, or cultural preference information extracted from social media, the proposed method effectively integrates and analyzes them, demonstrating strong adaptability. Additionally, the method performs exceptionally well in dynamic urban scenarios, such as the rapid expansion of newly developed areas or real-time fluctuations in traffic flow. By dynamically adjusting model parameters and optimizing generation strategies, it ensures that the generated urban form designs not only meet practical needs but also maintain high timeliness and accuracy.

This study also provides a detailed evaluation of the advantages and challenges of applying DL in urban form generation. As the demand for accuracy and efficiency in urban planning and design continues to grow, the limitations of traditional methods have become increasingly evident. By comparing DL technology with traditional urban design approaches, this study clarifies the applicability of DL and highlights its inherent limitations. The findings offer important references for optimizing urban planning processes, improving design quality, and driving technological innovation and progress in the urban planning field. By addressing these key challenges, this study further emphasizes the transformative potential of DL in the intelligent generation of urban form, laying a solid foundation for its widespread application in the field. To enhance the clarity and structure of the introduction, the research questions, methods, and contributions are listed and detailed as follows:

(1) Research Questions

This study focuses on how to effectively apply DL technology to achieve intelligent urban form generation and addresses the following key questions:

1) How can the complexity of urban data acquisition and processing be overcome?

2) How can the adaptability and accuracy of DL models in urban form generation be improved?

3) How can real-time demands and changes in dynamic urban environments be addressed?

4) How can the transparency and interpretability of DL model decision-making processes be solved?

5) How can data security and user privacy protection be ensured in urban form generation?

(2) Research Methods

This study employs the following methods to achieve the research objectives:

1) Proposing an innovative algorithm that integrates multi-source heterogeneous data processing, dynamic adaptive learning, and cross-domain knowledge fusion.

2) Verifying the superior performance of the new algorithm in complex urban scenarios through comparative experiments.

3) Systematically summarizing the application patterns and effective methods of DL in urban form generation through case studies.

4) Filling the theoretical gap in the application of DL in urban planning through theoretical analysis and practical validation.

(3) Research Contributions

The main contributions of this study include:

1) Proposing an innovative algorithm that significantly improves the adaptability and accuracy of urban form generation.

2) Systematically summarizing the key insights and effective methods of DL in urban form generation.

3) Filling the theoretical gap in the application of DL in urban planning and providing new research directions for the academic community.

4) Providing urban planners with scientific evidence and innovative strategies to support the digital and sustainable transformation of urban development.

Through these clear, specific, and structured descriptions, this study aims to provide theoretical support and practical guidance for the application of DL in intelligent urban form generation, promoting innovative development in the field of urban planning.

2. Literature Review

In recent years, the application of deep learning in urban planning has steadily increased, spanning various domains such as urban form generation, urban land classification, and urban traffic prediction. By processing and analyzing extensive urban data, deep learning technology can extract valuable features and provide more accurate and systematic decision support for urban planning. Consequently, numerous scholars have conducted in-depth research on technological advancements in this area.

Herath and Mittal (2022) highlighted various applications of AI and the Internet of Things in urban planning, including intelligent traffic management, energy management, environmental monitoring, public safety, and emergency response. These applications contribute to enhancing city efficiency, reducing resource waste, improving quality of life, and promoting sustainable development [9]. Gohar and Nencioni (2021) proposed a graph-based deep learning approach for building clustering. This method uses graph convolution and neural networks to design the learning model and analyze adjacent buildings represented as a graph, extracting intrinsic features that describe building clustering relationships. Compared to existing methods, this approach demonstrates superior performance, improving the accuracy and reliability of clustering results [10]. Fan et al. (2023) introduced a new method for urban planners and policymakers to estimate a city's socio-economic conditions, applicable for monitoring and assessing various aspects of urban sustainable development. Using computer vision models and street-view images, the researchers extracted crucial information hidden in urban landscapes to estimate diverse urban phenomena [11]. Zhao et al. (2022) investigated multiple factors influencing intelligent transportation in urban development. Through literature analysis and questionnaire surveys, they identified 20 key variables, including policy, technology, communication, resident perception, and talent. Additionally, they established a causal model with seven concepts and proposed a root cause analysis method based on fuzzy cognitive maps. The results indicated that the 20 variables could be categorized into six dimensions, all showing significant positive correlations with intelligent transportation development. These findings contribute to a more comprehensive understanding of the fundamental drivers of intelligent transportation construction, offering valuable recommendations for policymaking and improving construction efficiency [12]. Neupane et al. (2021) explored the application of deep learning in the semantic segmentation of urban remote sensing images. Through a review of recent research and meta-analysis, they found that deep learning surpassed traditional methods in image classification, improving accuracy and addressing several challenges. By employing complex models and algorithms, deep learning enables pixel-level classification and recognition of images, enhancing the interpretative accuracy and efficiency of remote sensing images. This advancement significantly supports urban planning, environmental monitoring, and disaster assessment. Future research directions include improving model architecture, optimizing training algorithms, and addressing challenges related to large-scale datasets [13].

In the field of urban remote sensing image semantic segmentation, recent research has demonstrated a clear development trend and pattern. Current studies primarily focus on the refinement and expansion of deep learning techniques. With the increasing availability of high-resolution remote sensing images and the continuous evolution of deep learning methods, more studies have emerged in this domain. Over the past three years, many researchers have concentrated on optimizing model architectures. Some studies have introduced novel convolutional neural network (CNN) structures, such as attention mechanism-based convolutional modules, to enhance the model's ability to focus on and extract key semantic information from images. Regarding the optimization of training algorithms, some studies have adopted adaptive learning rate adjustment strategies. These strategies dynamically adjust the learning rate based on gradient changes during the training process, thereby improving training efficiency and stability. To enhance the interpretative accuracy of remote sensing images, certain studies have incorporated multi-source data for auxiliary training, such as geographic information and meteorological data. This enriches the input information dimensions and improves the model’s ability to understand and segment complex urban scenes. However, several challenges have arisen during the progression of this study. When handling large-scale datasets, issues related to data storage, reading, and preprocessing have become bottlenecks. The massive volume of remote sensing image data places high demands on computational resources, leading to prolonged training times and, in some cases, exceeding the computational capacities of certain research institutions. Additionally, enhancing model generalization remains a challenge: while specific datasets may show satisfactory results, model performance often significantly degrades when applied to remote sensing images from different geographic regions or complex environments, making stable and efficient semantic segmentation difficult to achieve. In response to these issues, this study implemented a series of targeted solutions. To handle large-scale datasets, an efficient data management and preprocessing pipeline was constructed. Distributed storage and parallel computing technologies were employed to accelerate data reading and processing, effectively reducing the time required for data handling. Furthermore, data augmentation techniques were used to expand the dataset and increase its diversity, thereby improving the model's adaptability to various data distributions. To enhance the model's generalization capabilities, a multi-scale feature fusion module was designed. This module automatically captures image features at different resolutions and effectively merges them, allowing the model to better adapt to the complex and ever-changing urban environments. The proposed method offers significant advantages. In terms of model architecture, the innovative multi-scale feature fusion module provides a more comprehensive and in-depth semantic understanding of urban remote sensing images, significantly outperforming traditional methods in segmentation accuracy in complex scenarios. In terms of data processing, the efficient data management and preprocessing pipeline ensures effective use of large-scale datasets, thus enhancing research efficiency. However, the method also has certain limitations. For instance, the multi-scale feature fusion module increases the computational complexity of the model, imposing higher demands on hardware. In extremely complex urban environments, while the model's performance improves, some inaccuracies in semantic segmentation still occur, indicating that further optimization and refinement are required in future work.

3. Research Model

3.1. Deep Learning

With continuous technological advancements, the application of deep learning has become a crucial pathway for societal development [14]. As a branch of machine learning, deep learning encompasses multiple data processing centers and employs abstract computational models capable of batch iterative data processing. deep learning models consist of input layers, hidden layers, and output layers, with the hidden layers being the most complex and containing numerous computational centers [15]. In the field of image processing, the deep convolutional neural network (DCNN) is one of the earliest models used in deep learning. It demonstrates excellent performance in handling multi-dimensional data through local connections, weight sharing, pooling, and multi-layer structures [16]. In this context, the CNN algorithm is specifically employed to deeply analyze urban spatial structures. The design concept is based on the multi-dimensionality and complexity of urban spatial structure data. The local connection and weight-sharing characteristics of the CNN algorithm effectively capture spatial features and patterns within the data. By constructing multi-layer structures, deep-level features can be gradually extracted, leading to a more accurate understanding and analysis of urban spatial structures. Additionally, pooling operations are utilized to reduce data dimensionality, improve computational efficiency, and mitigate the risk of overfitting. This design concept aims to fully leverage the advantages of the CNN algorithm, providing an efficient and accurate method for analyzing urban spatial structures.

The CNN calculation equation is as follows:

$$f(\mathrm{X}) = \sum_{i=1}^{L} \mathrm{X}_j * W_i + b_j \quad (\mathbf{1})$$

In Equation (1), X represents the output values of each layer, i denotes the layer of the CNN, W represents the weight matrix of the CNN, and b represents the bias vector of the CNN. Equation (2) describes the objective function:

$$J(W,b) = -\frac{1}{m}\sum_{i=1}^{m}[y^{(i)} \times log\ h_{W,b}(X^m) + (1-y^{(i)}) \times log\ (1-h_{W,b}(X^m))] \quad (\mathbf{2})$$

In Equation (2), m represents the number of training samples, and y denotes the labels of the samples. This study primarily employs the DCNN algorithm to process images of contemporary urban spaces. By analyzing spatial features, the study explores intelligent design approaches for modern urban environments [17].

3.2. Urban Form Design Concepts under Green Ecology

In contemporary society, where environmental concerns are increasingly at the forefront, the concept of green ecology has become essential in urban planning and design. This approach not only prioritizes the appearance and functionality of urban areas but also emphasizes harmonious coexistence with the natural environment. The central goal of urban form design under green ecological principles is to create a sustainable, healthy, and livable urban environment [18-20].

At the core of this concept lies a deep respect for nature. Urban form design must account for local natural conditions, including topography, climate, and hydrology, to prevent irreversible environmental damage. By thoughtfully utilizing topographical features and protecting wetlands and ecologically sensitive areas, urban forms can integrate seamlessly with their surroundings [21-23]. Moreover, the principle of ecological priority requires the protection and restoration of ecosystems throughout urban development. This includes safeguarding biodiversity, reducing pollutant emissions, and increasing urban green coverage to maintain the ecological health of the environment [24]. Green spaces are integral to urban form design. Developing areas such as parks, green belts, and water systems provides citizens with spaces for leisure, recreation, and exercise. These spaces also contribute to regulating the urban climate, improving air quality, and fostering an ecologically friendly environment that enhances the overall livability of cities [25-27].

Energy utilization is another critical element of green ecological urban design. Prioritizing energy conservation, reducing emissions, and integrating renewable energy sources are fundamental to creating sustainable urban areas [28]. Implementing energy-efficient technologies and using sustainable building materials can significantly reduce energy consumption in buildings. Additionally, the adoption of renewable energy sources, such as solar and wind power, reduces dependence on fossil fuels, lowers carbon emissions, and supports long-term urban sustainability [29]. Finally, human well-being must remain a priority. Urban form design should address the needs and experiences of residents by creating convenient and comfortable living environments [30]. It should include diverse public spaces and facilities that cater to various demographic groups, fostering social interaction and enhancing community cohesion within urban areas [31-33].

3.3. CNN Model

This study analyzes contemporary urban spatial features using a CNN model. The CNN model processes images by extracting features through multiple layers and producing feature outputs via the final weight matrix [34]. The architecture of the CNN comprises convolutional, pooling, and activation layers, which collectively extract and produce image features at various levels of abstraction [35]. Figure 1 illustrates the fundamental computational principles of the CNN model.

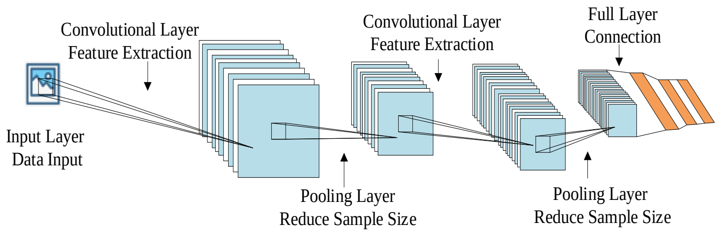

Fig. 1. Basic principles of the CNN model

Figure 1 demonstrates the core computational principles of the CNN model. The process begins with the convolutional layer, which synthesizes and extracts image features. Next, the pooling layer simplifies the extracted features, making their processing more efficient and rapid. The CNN model utilizes a backward computation method to identify errors in the feature extraction process. These errors are then used to adjust the parameters of the feature extraction model, thereby enhancing the accuracy of image analysis [36-38].

This study performs image feature analysis based on the principles of intelligence and green ecology, aiming to facilitate the intelligent technological transformation of cities while adhering to sustainable urban development strategies [39]. By analyzing green ecological aspects, specific features of contemporary urban spaces can be examined, enabling the design of intelligent urban forms in modern cities [40]. The typical structure of a CNN comprises input, convolutional, pooling, fully connected, and output layers. CNN processes input data by performing feature extraction. The feature extraction is described as Equation (3):

$$\mathrm{H}_i = f(\mathrm{W}_{i\otimes}\mathrm{H}_{i-1} + \mathrm{b}_i) \quad (\mathbf{3})$$

In Equation (3), i represents the network convolution layer, W is the computational weight, b refers to the offset vector in the computation process, and the activation function is applied to obtain the feature vector H_i [41]. The pooling process in a CNN is expressed by Equation (4):

$$\mathrm{H}_i = subsampling(\mathrm{H}_{i-1}) \tag{4}$$

After multiple pooling operations and the representation or classification of features transformed through a fully connected network, the final mapped result is expressed as Equation (5):

$$\mathrm{Y}(m) = P(\mathrm{L} = l_m \mid \mathrm{H}_0; (\mathrm{W}, \mathrm{b})) \tag{5}$$

```
import tensorflow as tf

# CNN model construction
def build_cnn_model():
    model = tf.keras.Sequential([
        # Input layer, assuming the input data shape is (batch_size, 64, 64, 1)
        tf.keras.layers.InputLayer(input_shape=(64, 64, 1)),
        # Convolutional layer 1
        tf.keras.layers.Conv2D(32, (3, 3), strides=1, padding='valid', activation='relu'),
        # Convolutional layer 2
        tf.keras.layers.Conv2D(64, (3, 3), strides=1, padding='valid', activation='relu'),
        # Pooling layer 1
        tf.keras.layers.MaxPooling2D((2, 2), strides=2),
        # Pooling layer 2
        tf.keras.layers.MaxPooling2D((2, 2), strides=2),
        # Flatten layer
        tf.keras.layers.Flatten(),
        # Fully connected layer
        tf.keras.layers.Dense(100, activation='relu'),
        # Output layer, assuming 5 categories for output
        tf.keras.layers.Dense(5)
    ])
    return model

# Instantiate the model
cnn_model = build_cnn_model()

# Define the loss function (e.g., sparse categorical cross-entropy loss)
loss_function = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)

# Define the optimizer (e.g., Adam optimizer)
optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)

# Training step function
@tf.function
def train_step(inputs, labels):
    with tf.GradientTape() as tape:
        # Forward propagation of the model
        predictions = cnn_model(inputs)
        # Calculate the loss
        loss = loss_function(labels, predictions)
    # Calculate the gradients
    gradients = tape.gradient(loss, cnn_model.trainable_variables)
    # Update the model parameters
    optimizer.apply_gradients(zip(gradients, cnn_model.trainable_variables))
    return loss

# Assume there are training data and labels here (need to be replaced according to the actual situation)
train_images = tf.random.normal((100, 64, 64, 1))  # Example training image data
train_labels = tf.random.uniform((100,), minval=0, maxval=5, dtype=tf.int32)  # Example training labels

# Training loop
for epoch in range(100):  # Assume training for 100 epochs
    total_loss = 0
    for i in range(0, len(train_images), 32):  # Assume batch size is 32
        batch_images = train_images[i:i + 32]
        batch_labels = train_labels[i:i + 32]
        loss = train_step(batch_images, batch_labels)
        total_loss += loss
    print(f"Epoch {epoch + 1}, Average Loss: {total_loss / (len(train_images) // 32)}")
```

Fig. 2. Algorithmic code and computational workflow

In Equation (5), m represents the index of the label category, L signifies the loss function, and P represents the mapping operation. The loss function is expressed as Equation (6). Alternatively, the mean squared error (MSE) loss function is given by Equation (7):

$$\mathrm{NLL}\ (\mathrm{W}, \mathrm{b}) = -\sum_{m=1}^{|\mathrm{Y}|} \log\ \mathrm{Y}(m) \tag{6}$$

$$\mathrm{MSE}\ (\mathrm{W}, \mathrm{b}) = \frac{1}{|\mathrm{Y}|} \sum_{m=1}^{|\mathrm{Y}|} (\mathrm{Y}(m) - \hat{\mathrm{Y}}(m))^2 \tag{7}$$

To mitigate overfitting of the network parameters, a second-norm regularization term is typically added to the final loss function. Its calculation is as Euqation (8), and the gradient descent optimization equations for updating the weights and biases are presented as Equations (9) and (10):

$$E(\mathrm{W},\mathrm{b}) = \mathrm{L}(\mathrm{W},\mathrm{b}) + \frac{\lambda}{2}\mathrm{W}^{\mathrm{T}}\mathrm{W} \tag{8}$$

$$\mathrm{W}_i = \mathrm{W}_i - \eta\frac{\partial E(\mathrm{W},\mathrm{b})}{\partial \mathrm{W}_i} \tag{9}$$

$$\mathrm{b}_i = \mathrm{b}_i - \eta\frac{\partial E(\mathrm{W},\mathrm{b})}{\partial \mathrm{b}_i} \tag{10}$$

Here, η represents the learning rate [42]. Based on these principles, this study employs CNN to explore intelligent generation technology for urban form, providing technical support for future smart city development. Figure 2 illustrates the algorithm's code and computational workflow.

4. Experimental Design and Performance Evaluation

4.1. Datasets Collection

This study utilizes the Cityscapes dataset for model evaluation [43]. Cityscapes is an open dataset specifically designed for computer vision applications, providing robust data support for the understanding and analysis of urban scenes. While primarily intended for semantic segmentation tasks, it also has significant applications in urban planning. The dataset consists of 3,257 high-resolution images captured from 50 cities in Germany, covering diverse street scenes under various lighting conditions, including morning, daytime, and nighttime. Each image has a resolution of 2048 × 1024 pixels and has been professionally annotated with labels such as buildings, roads, and pedestrians. In the context of urban planning, the Cityscapes dataset supports four primary functions: road network planning, analysis of building distribution, public facility layout optimization, and traffic flow analysis.

Another dataset employed in this study is the MIT Street Scenes dataset [44]. This dataset comprises approximately 10,000 high-resolution images captured from various urban streets, each with a resolution of about 1000 × 750 pixels. It includes a wide range of weather conditions, times of day, and diverse urban scenarios, such as city centers, suburban areas, and residential neighborhoods. Each image is meticulously annotated with elements like roads, buildings, vehicles, pedestrians, and traffic signs, providing precise and detailed labeling. The dataset's diversity and realistic depiction of urban street conditions make it invaluable for urban planning, traffic analysis, autonomous vehicle development, and advancements in image recognition algorithms.

For this study, both the Cityscapes and MIT Street Scenes datasets are utilized for model training and testing. During the training phase, 2,000 images are selected from the Cityscapes dataset, and 7,000 images are drawn from the MIT Street Scenes dataset. For the testing phase, 500 images from the Cityscapes dataset and 1,000 images from the MIT Street Scenes dataset are used. By effectively leveraging these two datasets, the model undergoes rigorous training and comprehensive testing to ensure its performance and accuracy.

4.2. Experimental Environment

In the experimental environment design of this study, precise parameter settings are crucial to ensuring the reliability of the research results. The Cityscapes dataset is chosen for training and testing due to its rich urban elements and diverse scenes, providing a solid foundation for the model to effectively learn city form-related features. The batch size is set to 32, which strikes a balance between computational efficiency and model learning performance, and ensures neither slow training speed nor instability in parameter updates. The number of iterations is set to 100, giving the model ample opportunity for optimization and enabling it to adapt to data patterns and iteratively refine parameters. The Adam optimization algorithm is selected for its ability to adaptively adjust the learning rate during training. The initial learning rate is set to 0.001. Tests have shown that this value ensures a stable learning process. Every 10 iterations, the learning rate decays by a factor of 0.1 to fine-tune parameters in the later stages of training. The model weights are randomly initialized with a Gaussian distribution to break symmetry and promote faster convergence. In terms of hardware, the Intel(R) Core(TM) i7-3520M CPU @ 2.90GHz provides powerful computational capabilities. The 8GB of memory supports data storage and model execution, ensuring smooth experimentation and improving the overall stability and efficiency of the training process.

This study clearly defines three key components in urban planning: road network planning, building distribution analysis, and public facility layout. Below is a detailed description of the input and output variables for each component, and a brief explanation of how the variables are processed to ensure the CNN model can effectively handle these data.

(1) Road Network Planning

Input Variables:

1) High-Resolution City Street Images

Definition: They provide visual information about road features, including road width, direction, number of lanes, and traffic signs.

Processing Method: These image data are processed by the CNN model to extract geometric features of the roads and spatial distribution information. Since CNN primarily handles two-dimensional image data, high-resolution street images can be directly used as input.

2) Geographic Information System (GIS) Data

Definition: They include terrain features such as elevation and slope, which influence the feasibility and constraints of road construction.

Processing Method: GIS data are typically input in a one-dimensional encoded format. Terrain features are converted into numerical vectors to facilitate topological analysis by the CNN model.

3) Traffic Flow Data

Definition: They reflect the congestion levels and traffic demand on different road segments.

Processing Method: Traffic flow data are encoded as a time series and transformed into a two-dimensional matrix using spatial interpolation methods for CNN processing. For instance, traffic flow data across different time periods are mapped onto a spatial grid, forming a two-dimensional input for the model.

Output Variables:

1) Road Type

Definition: The classification of roads into three types: main roads, secondary roads, and local streets.

Output Format: Class labels (such as 0 for main roads, 1 for secondary roads, and 2 for local streets) can help planners identify the hierarchy of roads within the network.

2) Road Connectivity

Definition: It describes the configuration of intersections and the directional relationships between roads.

Output Format: A graph structure that represents the topological connectivity of the road network. For instance, the adjacency matrix can be used to depict the connection relationships between road nodes.

3) Road Capacity Level

Definition: The classification of roads based on their capacity to handle traffic, divided into high, medium, and low levels.

Output Format: Classification results (such as 0 for high capacity, 1 for medium capacity, and 2 for low capacity) are used to assess the load-bearing capability of different roads in the network.

(2) Building Distribution Analysis

Input Variables:

1) Satellite Remote Sensing Images

Definition: They provide detailed information about building outlines, height, and land coverage.

Processing Method: These image data are processed by the CNN model to extract spatial distribution features of buildings. Since satellite images are two-dimensional, they can be directly used as input for the CNN.

2) Land Use Planning Data

Definition: They serve as a guideline for evaluating the rationality of building distribution.

Processing Method: The data are inputted in one-dimensional encoded form, such as converting different functional zones (such as residential, commercial, and industrial) into numeric labels, allowing the CNN model to recognize building distribution patterns.

3) Population Density Data

Definition: They impact the type and scale of buildings in an area.

Processing Method: Population density data are transformed into a two-dimensional matrix through spatial interpolation, such as mapping the data onto a spatial grid. This enables the analysis of population distribution in conjunction with remote sensing images.

Output Variables:

1) Building Function Type

Definition: It is divided into four categories: Residential Buildings, Commercial Buildings, Industrial Buildings, and Public Buildings.

Output Format: Classification labels (such as 0 for Residential Buildings, 1 for Commercial Buildings, 2 for Industrial Buildings, and 3 for Public Buildings) help planners identify buildings with different functions.

2) Height Classification

Definition: It is classified based on height ranges, such as Low-rise (1-3 floors), Mid-rise (4-10 floors), and High-rise (above 10 floors).

Output Format: Classification results (such as 0 for Low-rise, 1 for Mid-rise, and 2 for High-rise) are used to evaluate the vertical distribution of buildings.

3) Density Level

Definition: Based on the density of building distribution, the area is divided into three categories: Sparse, Moderate, and Dense.

Output Format: Classification labels (such as 0 for Sparse, 1 for Moderate, and 2 for Dense) are used to assess land use efficiency.

(3) Public Facility Layout

Input Variables:

1) Population Distribution Data

Definition: They determine the service coverage area of public facilities.

Processing Method: They are converted into a two-dimensional matrix using spatial interpolation methods, such as mapping population distribution data onto a spatial grid to form a two-dimensional input for analysis in combination with facility locations.

2) Resident Demand Survey Data

Definition: They provide information on residents' preferences and demand levels for different public facilities.

Processing Method: They are transformed into a one-dimensional vector through statistical encoding, such as converting residents’ demand ratings for different facilities into a numerical vector to assist the decision-making of facility sizing with the CNN model.

3) Urban Functional Zoning Data

Definition: They highlight the priority of facility layouts in specific areas.

Processing Method: They are input as a one-dimensional encoded form, such as converting different functional zones (such as residential areas and commercial areas) into numerical labels to identify the facility demands of different zones.

Output Variables:

1) Facility Type

Definition: It is divided into categories such as parks, schools, hospitals, and libraries.

Output Format: Classification labels (such as 0 for park, 1 for school, 2 for hospital, and 3 for library) help planners identify different types of facilities.

2) Facility Size

Definition: Recommends the size and capacity of the facility based on demand data.

Output Format: Numerical results (such as student capacity for schools, and number of beds for hospitals), used to guide the specific design of the facility.

3) Location Recommendation

Definition: Determines the optimal location for public facilities.

Output Format: Geographic coordinates (such as latitude and longitude) are used to determine the exact location of the facility.

(4) Model Performance Validation

To validate the model’s performance and reliability, this study uses accuracy and fit metrics. These metrics are calculated by evaluating the consistency between the model’s predicted output and actual observed data. By clearly defining input and output variables and fully utilizing the features of the CNN model, this study provides a clear analytical framework for road network planning, building distribution analysis, and public facility layout. This framework not only reduces the ambiguity of variable mapping but also offers scientific evidence and technical support for urban planning practice. In the future, as data quality and model performance improve, this method is expected to play a more significant role in urban planning.

(1) Accuracy Calculation:

The accuracy of the model is calculated using Equation (11):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{11}$$

In Equation (11), TP (True Positive) refers to the number of samples correctly predicted as positive by the model; *TN* (True Negative) refers to the number of samples correctly predicted as negative by the model; *FP* (False Positive) refers to the number of samples incorrectly predicted as positive by the model; *FN* (False Negative) refers to the number of samples incorrectly predicted as negative by the model.

(2) Fit Metric (Coefficient of Determination) Calculation:

In this study, the Coefficient of Determination (R^2) is used to assess the model's goodness of fit. The calculation formula is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{12}$$

In Equation (12), n signifies the number of samples, y_i denotes the actual value of the *i*-th sample, $\hat{y}_i$ is the predicted value of the i-th sample, $\overline{y}$ denotes the mean of the actual values. Here, despite the primary focus on classification issues, the introduction of the coefficient of determination, R^2, remains necessary. R^2, as a metric for assessing the goodness-of-fit between the model’s predicted values and actual values, enables a comprehensive evaluation of the model's performance and provides quantitative decision support for urban planning. By probabilistically processing the classification results and calculating R^2, this study not only evaluates the alignment between the model's predictions and actual data but also provides a scientific basis for optimizing urban planning. In the urban planning process, the application of R^2 is mainly reflected in the assessment of the relative merits of different planning schemes, optimizing planning decisions, improving the interpretability of the schemes, and supporting dynamic planning and adjustments. For example, in road network planning, by calculating the R^2 value of the predicted road type distribution against the actual distribution under different planning scenarios, planners can visually compare the advantages and disadvantages of each scheme and select the one with the highest R^2 value as the final implementation plan. This scheme’s road network distribution better aligns with the ideal distribution model derived from historical data and current analysis, which can better meet urban traffic flow demands and improve road connectivity. The application of R^2 in building distribution analysis is equally significant. By calculating the R^2 value of the building function distribution against the actual distribution under different planning scenarios, planners can choose the scheme that best aligns with the city’s functional layout. For instance, in the planning of a new district, the research team analyzes the building function distribution under different planning scenarios using the CNN model and calculates the R^2 value. They find that

Scheme X has an R^2 value of 0.90, significantly higher than the other schemes. As a result, planners select Scheme X as the final implementation plan, as its building function distribution better matches the actual needs of the city's functional layout. In the planning of public facility distribution, the application of R^2 helps evaluate the alignment between facility distribution and actual demand. Additionally, the introduction of R^2 makes urban planning decisions more scientific and rational. With quantitative evaluations, planners can more intuitively judge which planning schemes best meet the actual needs of urban development. Furthermore, as a straightforward evaluation metric, R^2 enhances the interpretability of planning schemes. By displaying the R^2 values of different planning schemes, planners can more clearly explain the rationality and advantages of the schemes to decision-makers and the public, thereby increasing the acceptability and effectiveness of the plans. In the dynamic process of urban development, planning schemes need to be adjusted based on actual conditions. By regularly calculating R^2, the implementation effects of the planning schemes can be assessed, and dynamic adjustments can be made based on the evaluation results. For example, in public facility layout, the R^2 value can be used to assess the alignment between facility distribution and actual demand, allowing for optimization of facility placement. In summary, although this study mainly focuses on classification issues, the introduction of R^2 provides important quantitative support for model performance evaluation and urban planning decisions. By probabilistically processing the classification results and calculating R^2, it is possible to comprehensively assess the alignment between model predictions and actual data. In urban planning, R^2 not only helps evaluate the relative merits of different planning schemes but also optimizes planning decisions, enhances the interpretability of schemes, and supports dynamic planning and adjustments.

4.3. Parameters Setting

This study aims to design an intelligent ecological model for urban form based on CNN technology. As a result, the model design includes parameter testing for CNN technology, using carefully selected model parameters. Table 1 presents the results of the design of the basic structure of the CNN model.

Table 1. Design of the basic structure of the CNN model

Layer Type	Input Shape	Output Shape	Parameters/Configuration
Input Layer	(32, 64, 64, 1)	(32, 64, 64, 1)	--
Convolutional Layer 1	(32, 64, 64, 1)	(32, 64, 64, 32)	Convolutional Kernel Size: (3, 3, 3), Stride = 1, Padding = 0
Convolutional Layer 2	(32, 64, 64, 32)	(32, 64, 64, 64)	Convolutional Kernel Size: (3, 3, 3), Stride = 1, Padding = 0
Pooling Layer 1	(32, 64, 64, 64)	(32, 64, 64, 64)	Window Size: (2, 2, 2), Stride = 2
Pooling Layer 2	(32, 64, 64, 64)	(32, 64, 64, 64)	Window Size: (2, 2, 2), Stride = 2
Fully Connected Layer	(32, 64, 64, 64)	(100, 5)	Activation Function: ReLU
Output Layer	(100, 5)	(100, 5)	--

In the construction of the CNN model for this study, the input layer serves as the entry point for the data flow, responsible for receiving 32 single-channel samples of a specific size (64×64). These samples contain raw information related to urban morphology and provide the foundational material for subsequent feature extraction processes. Convolutional Layer 1 uses a 3×3×3 convolution kernel with a stride of 1 and no padding. During the convolution operation, based on the principles of local connectivity and weight sharing, this layer performs detailed local feature extraction on the input single-channel features. By applying a sliding convolution operation with the kernel, the input single-channel features are transformed into 32 feature maps with distinct representations. These feature maps preliminarily capture key information such as spatial structures and texture variations in the input data, laying the groundwork for deeper feature extraction. Convolutional Layer 2 advances the feature extraction process by expanding the output channels to 64. In this step, more complex convolution operations are performed based on the feature maps from the previous layer, enabling the extraction of more abstract and deeper feature patterns. This greatly enriches the diversity and complexity of the feature representations, enhancing the model's ability to understand and express features. As a result, the model can capture subtle differences and underlying patterns within the urban morphology data more effectively. Both Pooling Layers 1 and 2 use a 2×2×2 window and downsample the feature maps with a stride of 2. This downsampling mechanism plays a crucial role in reducing both the dimensionality of the data and the computational load. By applying max or average pooling on local regions of the feature maps, key feature information is preserved while effectively reducing the data size, minimizing computational resource consumption, and mitigating the risk of overfitting. This ensures the stability and reliability of the model during both training and generalization. The features obtained from the convolution and pooling operations are then flattened and input into a fully connected layer with 100 neurons. In this layer, the Rectified Linear Unit (ReLU) activation function is introduced. The ReLU function performs a nonlinear transformation on the neuron outputs, overcoming the limitations of linear models in terms of expressive capacity. It sets input values less than 0 to 0 while retaining positive output values, introducing nonlinearity into the model. This enhances the model’s ability to learn complex relationships within the data, allowing it to better fit the intricate mapping between input and output and improving its classification performance.

The final output layer generates classification results for five categories based on 100 samples. In alignment with common classification paradigms in urban planning and urban morphology research, as well as the potential applications of this study, the following design is adopted. Firstly, road type classification includes categories such as highways, urban expressways, main roads, secondary roads, side streets, and pedestrian streets, among others. These categories represent various levels and functions of roadways. This classification assists in the precise identification of the distribution and connectivity of different types of roads in road network planning, providing valuable insights for optimizing traffic flow and improving road throughput efficiency. Secondly, building function classification encompasses residential buildings, commercial buildings, industrial buildings, public service buildings (such as schools, hospitals, and government offices), cultural and entertainment buildings, and religious buildings. Accurately classifying building functions enables a deeper understanding of the functional layout and spatial distribution of urban buildings, offering strong support for urban land use planning and functional zoning. Additionally, public facility category determination involves parks, squares, sports venues, libraries, museums, bus stations, metro stations, and other types of public facilities. Identifying the categories of public facilities is crucial for optimizing their layout, enhancing the accessibility and equity of public services, and better addressing the living needs of citizens. Furthermore, traffic flow level classification divides traffic into high, medium, and low levels. This classification provides an intuitive representation of traffic congestion in different urban areas and road segments, offering quantitative reference points for traffic flow analysis, traffic signal control, and road planning, thereby contributing to alleviating urban traffic congestion. Lastly, land use type identification includes categories such as construction land, agricultural land, green spaces, water bodies, wetlands, and others. Accurately identifying land use types is a fundamental task in urban planning and land resource management. It is essential for the rational planning of urban spatial layouts, the protection of ecological environments, and the achievement of sustainable urban development.

4.4. Performance Evaluation

Evaluations are conducted for both daytime and nighttime scenarios to assess the model's specific performance. These evaluations cover the model's capabilities in road network planning, building distribution analysis, public facility layout, and traffic flow analysis. Figure 3 illustrates the evaluation results for the model's road network planning performance.

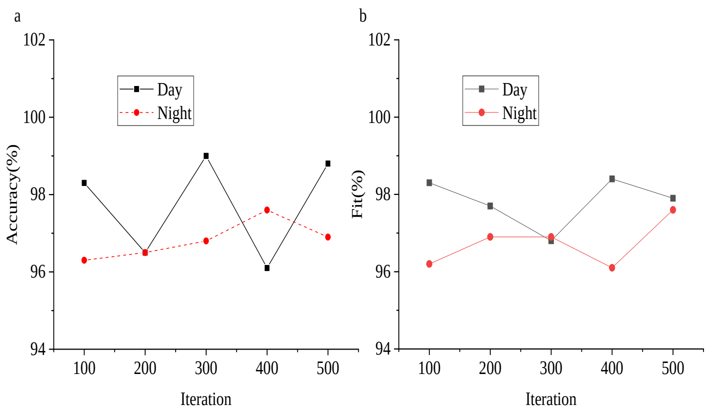

Fig. 3. Evaluation results of the model's road network planning ability (a: accuracy, b: fitting degree)

Figure 3 shows that during the evaluation, the accuracy of the CNN model designed for road network planning fluctuates as the number of iterations increases. The data points in the figure are displayed in increments of 100 iterations, resulting in a broad interval range during the statistical analysis of the data, which contributes to the observed instability in the results. Nonetheless, the model achieves an accuracy and fit exceeding 96% for road network planning in both daytime and nighttime scenarios. Figure 4 presents the evaluation results for the model's ability to analyze building distribution.

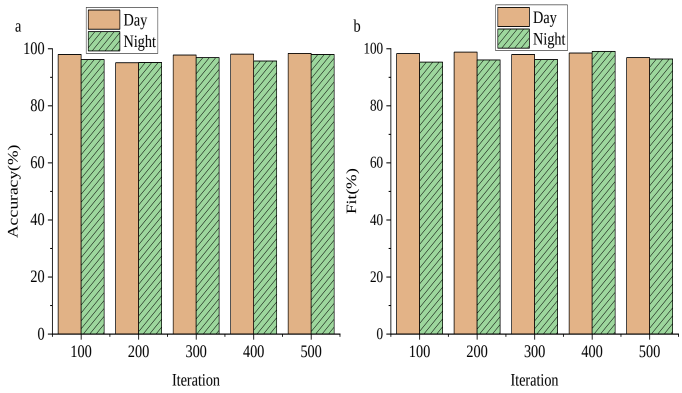

Fig. 4. Evaluation results of the model's building distribution analysis ability (a: accuracy, b: fitting degree)

Figure 4 indicates that the model achieves an accuracy exceeding 94%, with a fitting degree surpassing 95%. Figure 5 shows the evaluation results for the model's performance in analyzing the public facility layout.

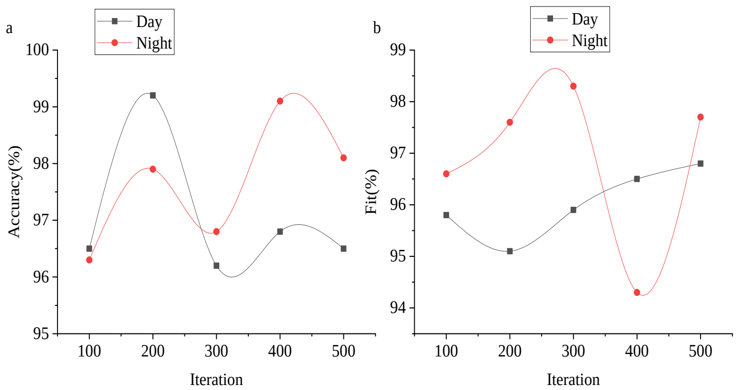

Fig. 5. Evaluation results of the model's public facility layout analysis ability (a: accuracy, b: fitting degree)

Figure 5 demonstrates that the model's accuracy in analyzing the public facility layout consistently exceeds 96%, with the fitting degree remaining above 94%. However, the accuracy does fluctuate with the number of iterations, as the data points in the figure are presented as average values over increments of 100 iterations. This approach may obscure some detailed information, leading to noticeable fluctuations among the data points. Despite this, the model's performance remains satisfactory. Figure 6 illustrates the evaluation results for the model's ability to analyze traffic flow.

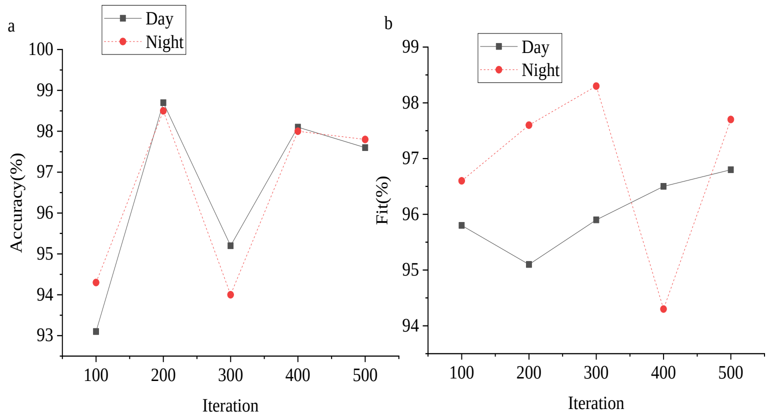

Fig. 6. Evaluation results of the model's traffic flow analysis ability (a: accuracy, b: fitting degree)

Figure 6 shows that the model achieves an accuracy exceeding 93% and a fitting degree greater than 94% in traffic flow analysis. However, the accuracy fluctuates with the number of iterations, as the data points in the figure are presented as average values over increments of 100 iterations, which may obscure some subtle variations in the data. Nonetheless, the model's overall performance remains optimal, demonstrating that the research design is both sound and feasible.

In model construction, the input layer receives preprocessed urban street view image data, which contains rich spatial information about the city. The convolutional layers utilize their local connectivity and weight-sharing properties to extract features from the image. For example, by employing convolutional kernels of specific sizes, road network planning can capture features such as road lines and intersection shapes. In building distribution analysis, features such as building contours and height variations are extracted, with progressively deeper feature representations achieved through multiple convolutional layers. The pooling layers perform downsampling operations, reducing the dimensionality of the data, decreasing computational load, and preventing overfitting, while retaining key feature information. The fully connected layers integrate and map the pooled features, and the final output layer provides classification or prediction results.

Regarding evaluation methods, for road network planning capability assessment, an image dataset with labeled road information is input into the model. The model’s predicted road results are compared with the true labels to compute accuracy, recall, and other metrics. For instance, the proportion of correctly identified road pixels to total road pixels is defined as accuracy, while the proportion of correct road pixels among the predicted road pixels is defined as recall. In building distribution analysis, the model’s ability to accurately identify building distribution features is assessed based on labeled information such as building type and location. Quantitative evaluation is conducted on the deviation between predicted building locations and actual labeled locations, as well as the accuracy of building type classification.

For application capability evaluation, such as in traffic flow analysis, the CNN model learns the relationship patterns between traffic flow and road structure by combining road network planning results with time-series traffic data. By predicting traffic flow for different road segments at various time periods and comparing the predictions with actual observed traffic, metrics such as mean squared error are used to assess the model's predictive ability. These detailed model construction and evaluation methods comprehensively examine the model’s performance in urban planning-related domains, providing robust evidence and support for urban planning decision-making.

4.5. Discussion

This study introduces a deep learning-based intelligent urban morphology generation design solution, utilizing CNN to conduct an in-depth analysis of urban street scene images. The approach successfully achieves key functions such as road network planning, building distribution analysis, public facility layout planning, and traffic flow analysis, representing a significant advancement in the field of urban planning. During the evaluation phase, the model demonstrates exceptional performance across all metrics. In road network planning, the model achieves accuracy and fit rates exceeding 96% under both daylight and nighttime conditions. This performance highlights the model's ability to precisely capture subtle road features and complex topological structures, providing urban planners with highly accurate road blueprints. This advancement enhances the scientific and efficient nature of road planning, fostering the optimization and smooth operation of urban transportation networks. The model substantially improves urban traffic congestion, facilitating efficient inter-regional connectivity and collaborative development. In the area of building distribution analysis, the model attains an accuracy rate surpassing 94% and a fit rate exceeding 95%. It effectively identifies spatial distribution patterns of different types of buildings and accurately pinpoints the location of each building, offering valuable insights into urban architectural patterns. This supports urban planners in developing land use strategies that align more closely with actual needs and future growth, ensuring rational allocation and efficient utilization of building resources, and contributing to a more distinctive and vibrant urban landscape. For public facility layout analysis, the model achieves an accuracy rate greater than 96% and a fit rate above 94%. It accurately evaluates the distribution rationality of various public facilities, providing scientifically grounded recommendations for optimizing their placement based on factors such as urban population density and functional zoning. This not only improves the accessibility and satisfaction of residents with public services but also promotes the balanced development of urban public services, reducing service gaps between different regions and enhancing the overall cohesion and attractiveness of the city. In traffic flow analysis, the model reaches an accuracy rate exceeding 93% and a fit rate greater than 94%. By deeply mining and dynamically analyzing large volumes of traffic data, the model accurately captures spatiotemporal trends in traffic flow, offering precise decision support for optimizing traffic signal timing, road expansion projects, and public transportation route adjustments. This effectively alleviates traffic congestion, reduces energy consumption, and enhances the overall efficiency and sustainability of urban transportation operations.

Compared to the study by Zhang and Kim (2023) [45], this atudy offers significant advantages. In terms of data utilization, the approach constructs a multi-source heterogeneous data fusion system that deeply integrates GIS data, social media check-in data, traffic sensor data, and other multidimensional information. This system thoroughly explores the potential relationships and synergistic effects between different data types, allowing the model to adapt to the complex and dynamic urban environment, significantly enhancing its generalization ability. In contrast, existing methods are often limited to single data sources or simple data combinations, making it challenging to comprehensively capture the complexity of urban systems, which can lead to a sharp decline in model performance under complex scenarios. Regarding model architecture and algorithm optimization, this study introduces innovative adaptive convolution modules and dynamic weight adjustment mechanisms. The adaptive convolution module automatically adjusts the shape and size of the convolution kernel based on the feature distribution of the input data, enabling precise perception of urban spatial structures at various scales. The dynamic weight adjustment mechanism optimizes model weights in real-time based on feedback during the training process, significantly improving learning efficiency and accuracy. In contrast, traditional methods are constrained by fixed model architectures and static weight settings, making it difficult to effectively handle the diversity and dynamism of urban data, resulting in limited improvements in accuracy. From a theoretical standpoint, this study injects new vitality into urban planning theory. It breaks the limitations of traditional urban planning, which relies on experiential judgment and simple statistical analysis, by constructing a deep learning-based model for quantifying urban morphology. This model uncovers the deep mapping relationships between urban data and spatial forms, providing solid theoretical support for the study of urban spatial evolution patterns and advancing urban planning towards greater intelligence and scientific rigor. In urban management practice, the findings of this study offer powerful decision-support tools for urban managers. In major projects such as new urban area construction and urban renewal, the model’s precise analysis outputs can be utilized to scientifically develop urban spatial development strategies, optimize the layout of infrastructure and public service facilities, and achieve the optimal allocation and efficient use of urban resources. This enhances the refinement of urban management and the scientific nature of decision-making. In practical application scenarios, the results of this study hold broad application prospects and profound societal impact. In the process of smart city development, they can contribute to the creation of efficient and intelligent urban traffic management systems, precise and convenient public service supply systems, and sustainable urban development models. These advancements can significantly improve residents' quality of life, enhance the city's competitiveness and attractiveness, and lay a solid foundation for sustainable urban development, ushering urban planning and construction into a new era of intelligence.

4.6. Application Planning of CNN Technology Model in Urban Analysis

As an important model in the field of DL, CNN has been gradually introduced into the field of urban analysis in recent years due to its outstanding performance in image processing and pattern recognition. Its applications in road network planning, building distribution analysis, and multi-source data fusion provide a new perspective and methodological support for urban planning. This section will comprehensively discuss the practical applications of CNN technology in urban analysis and explore how to transform these research results into specific strategies and actions in urban planning practice.

(1) Application of CNN in Road Network Planning and Urban Planning Practice

The road network is the backbone of urban transportation, and its rational planning is crucial for the operational efficiency of the city. By analyzing satellite images, remote sensing data, and traffic flow data, the CNN model can automatically extract high-level semantic features such as road boundaries, intersection locations, and road density, and predict future traffic demand trends by combining historical traffic flow data. This data-driven analysis method can not only help planners optimize the layout of the existing road network but also provide a scientific basis for the planning of new roads. For example, in the traffic planning of a large city, the research team uses the CNN model to analyze the traffic flow distribution of the city's main roads and finds that some sections are severely congested during peak hours. Based on this analysis, the planners propose suggestions for adding bus-only lanes and optimizing signal timing, and use the CNN model to simulate and verify the optimization plan. The results show that the traffic efficiency of the optimized road network increases by 20%, and the traffic congestion index decreases by 15%. This case shows that CNN technology can provide accurate data support for road network planning and help planners formulate more scientific and reasonable traffic management strategies. In addition, the CNN model can also combine real-time traffic data to dynamically adjust the traffic signal timing scheme to deal with sudden traffic incidents. For example, in a smart city pilot project, the CNN model is used to monitor real-time traffic flow changes and dynamically adjust the signal timing according to the prediction results. The application of this technology has significantly improved the response speed and management efficiency of the urban traffic system.

(2) Application of CNN in Building Distribution Analysis and Urban Planning Practices

Building distribution is an important component of urban spatial structure, directly influencing land use efficiency and urban functional layout. The CNN model, through the DL of urban building imagery, can automatically recognize building types, heights, densities, and spatial distribution patterns. This information is crucial for understanding urban spatial structure, assessing land use efficiency, and formulating building planning policies. In the planning of a new district, the CNN model Is used to analyze the relationship between existing building distribution and population density. It is found that certain areas have excessively high building density, leading to insufficient public facilities, while other areas have too low building density, resulting in land resource wastage. Based on this analysis, planners propose suggestions to adjust the building density distribution and optimize the public facility allocation. After implementation, the quality of life in the area significantly improves, and resident satisfaction greatly increases. Additionally, the CNN model can combine population migration data and socio-economic data to predict future urban population distribution trends, providing forward-looking guidance for building planning. For instance, in an urban expansion plan, the CNN model predicts hotspot areas of population growth over the next decade and suggests early planning for public facilities such as schools and hospitals in these areas. This forward-looking planning strategy effectively prevents potential future shortages of public facilities.

(3) Application of CNN in Multi-source Data Fusion and Urban Planning Practices

A city is a complex system, and its planning requires comprehensive consideration of various factors. The CNN model can integrate multi-source data to provide more comprehensive support for urban planning. For example, by combining building distribution data with population migration data and environmental monitoring data, CNN can identify correlations between environmental pollution and building layout in the city. In a study in a coastal city, the CNN model finds that air quality in some high-density residential areas is significantly worse than in other areas, mainly due to poor ventilation caused by unreasonable building layouts. Based on this finding, planners suggest adjusting building orientations and adding green belts, which improves the area's environmental quality. This case demonstrates that CNN technology, through multi-source data fusion, can provide more comprehensive and scientific support for urban planning. Furthermore, the CNN model can also incorporate social media data to analyze residents' satisfaction with the urban environment, providing a basis for public participation in urban planning. For example, in an urban renewal project, the CNN model analyzes residents' reviews of the city environment on social media, discovering that some areas have low greenery levels and poor resident satisfaction. Based on this analysis, planners propose increasing green spaces and parks, which receive high recognition from residents.

(4) CNN and the Intelligent Urban Form Generation

In actual urban planning, the application of CNN models is not limited to data analysis. It can also achieve the intelligent generation of urban forms through technologies such as the generative adversarial network (GAN). For example, by combining CNN and GAN models, researchers can generate urban design schemes that comply with specific planning principles, such as low-carbon cities and smart cities. These generated designs not only provide planners with diverse design options but can also be optimized through simulation and evaluation. Taking a smart city pilot project as an example, the research team uses the CNN-GAN model to generate multiple urban form design schemes and selects the optimal one through simulation and evaluation. This scheme outperforms others in terms of energy consumption, traffic efficiency, and environmental quality, providing valuable references for the construction of smart cities. The application of this technology not only improves the efficiency of urban planning but also offers new possibilities for innovation in urban design.

(5) Practical Applications of Research Results in Urban Planning

Based on the research results of CNN in road network planning, building distribution analysis, and multi-source data fusion, the following specific examples demonstrate how these results can be applied to actual urban planning:

1) Road Network Optimization

In the traffic planning of a medium-sized city, the research team uses the CNN model to analyze the traffic flow distribution of the city's main roads and found that some sections are severely congested during peak hours. Based on this analysis, the planners propose suggestions for adding bus-only lanes and optimizing signal timing, and use the CNN model to simulate and verify the optimization plan. The results show that the traffic efficiency of the optimized road network increases by 20%, and the traffic congestion index decreases by 15%.

2) Building Density Adjustment and Public Facility Optimization

In the planning of a new urban area, the CNN model is used to analyze the matching situation between building distribution and population density. It is found that the building density in some areas is too high, resulting in a shortage of public facilities. According to the analysis results of CNN, the planners propose suggestions to reduce the building density and add public facilities such as schools and hospitals. After implementation, the quality of life in this area has been significantly improved, and residents' satisfaction has greatly increased.

3) Environment - Friendly Urban Planning

In an eco-city planning project, the CNN model combines with environmental monitoring data to analyze the relationship between building layout and air quality. It is found that the unreasonable building layout in some areas leads to poor ventilation and poor air quality. According to the analysis results of the CNN, the planners propose suggestions to adjust the building orientation, add green belts, and set up ventilation corridors. After implementation, the air quality in this area has been significantly improved, making it a model for the construction of an environment - friendly city.

The comprehensive application of the CNN model in urban analysis provides a new perspective and methodological support for urban planning. Through in-depth analysis of road networks, building distributions, and multi-source data, CNN not only helps planners identify existing problems but also provides a scientific basis for future planning. In addition, through intelligent generation technology, CNN further expands the possibilities of urban planning and lays a solid foundation for more scientific, efficient, and sustainable urban development. With the continuous progress of DL technology, the application of CNN in urban planning will be more extensive and in-depth, injecting new vitality into urban governance and sustainable development.

5. Conclusion

This study pioneers the deep integration of deep learning techniques into the generation and design of intelligent urban morphology, effectively overcoming the limitations of traditional methods in processing complex urban spatial data. By leveraging advanced CNN architectures, the study performs detailed processing and in-depth analysis of massive and diverse urban streetscape images. In road network planning, the model accurately identifies the topological structure, hierarchical levels, and connectivity of various road types, providing a solid foundation for the construction of an efficient transportation system. In building distribution analysis, it precisely determines the functional types, spatial layout patterns, and density distribution characteristics of buildings, thereby supporting the rational utilization and development of urban land. For public facility layout, the model scientifically locates the optimal positions, sizes, and service coverage areas for various facilities, significantly enhancing the balance and accessibility of urban public services. In traffic flow analysis, it accurately predicts the dynamic variations in traffic flow at different times and across various road segments, providing critical support for traffic management strategies. Through a rigorously designed evaluation paradigm covering both day and night scenarios, the study comprehensively and objectively assesses the model's performance under varying lighting and environmental conditions. Experimental results clearly demonstrate that the model achieves industry-leading accuracy and fit across the aforementioned key tasks. In road network planning, accuracy exceeds 96%, and the fit exceeds 95%, ensuring that road planning solutions align closely with actual traffic demands. The accuracy of building distribution analysis remains above 94%, with a fit above 95%, providing precise guidance for optimizing urban building layouts. Public facility layout accuracy surpasses 96%, with a fit above 94%, ensuring efficient allocation of public resources. Traffic flow analysis accuracy exceeds 93%, with a fit over 94%, effectively assisting traffic management departments in achieving intelligent traffic control. These findings inject new vitality into urban planning theory and practice, significantly enriching the technical methods and decision-making foundations for urban spatial analysis. They strongly promote the advancement of urban planning towards intelligence, precision, and scientific rigor. Although there is room for further improvement in the current study, it has already made a critical breakthrough in the field of intelligent urban morphology generation. This lays a solid foundation for subsequent research and holds the potential to spark profound transformations and innovative development within the urban planning field.

References

1. Lv, Z., Li, J., Dong, C., et al.: Deep Learning in the COVID-19 Epidemic: A Deep Model for Urban Traffic Revitalization Index. Data & Knowledge Engineering, 135, 101912. (2021)
2. Yan, X., Ai, T., Yang, M., et al.: A Graph Deep Learning Approach for Urban Building Grouping. Geocarto International, 37(10), 2944-2966. (2022)
3. Menon, V. G., Jacob, S., Joseph, S., et al.: An IoT-enabled Intelligent Automobile System for Smart Cities. Internet of Things, 18, 100213. (2022)
4. Saleem, M., Abbas, S., Ghazal, T. M., et al.: Smart Cities: Fusion-based Intelligent Traffic Congestion Control System for Vehicular Networks Using Machine Learning Techniques. Egyptian Informatics Journal, 23(3), 417-426. (2022)
5. Tekouabou, S. C. K.: Intelligent Management of Bike Sharing in Smart Cities Using Machine Learning and Internet of Things. Sustainable Cities and Society, 67, 102702. (2021)
6. Chen, J., Ramanathan, L., Alazab, M.: Holistic Big Data Integrated Artificial Intelligent Modeling to Improve Privacy and Security in Data Management of Smart Cities. Microprocessors and Microsystems, 81, 103722. (2021)
7. Tong, Z., Ye, F., Yan, M., et al.: A Survey on Algorithms for Intelligent Computing and Smart City Applications. Big Data Mining and Analytics, 4(3), 155-172. (2021)
8. Haseeb, K., Din, I. U., Almogren, A., et al.: Intelligent and Secure Edge-enabled Computing Model for Sustainable Cities Using Green Internet of Things. Sustainable Cities and Society, 68, 102779. (2021)
9. Herath, H., Mittal, M.: Adoption of Artificial Intelligence in Smart Cities: A Comprehensive Review. International Journal of Information Management Data Insights, 2(1), 100076. (2022)
10. Gohar, A., Nencioni, G.: The Role of 5G Technologies in a Smart City: The Case for Intelligent Transportation System. Sustainability, 13(9), 5188. (2021)
11. Fan, Z., Zhang, F., Loo, B. P. Y., et al.: Urban visual intelligence: Uncovering hidden city profiles with street view images. Proceedings of the National Academy of Sciences, 120(27), e2220417120 (2023)
12. Zhao, L., Wang, Q., Hwang, B. G.: How to promote urban intelligent transportation: a fuzzy cognitive map study. Frontiers in Neuroscience, 16, 919914 (2022)
13. Neupane, B., Horanont, T., Aryal, J.: Deep learning-based semantic segmentation of urban features in satellite images: A review and meta-analysis. Remote Sensing, 13(4), 808 (2021)
14. Yigitcanlar, T., Mehmood, R., Corchado, J. M.: Green artificial intelligence: Towards an efficient, sustainable and equitable technology for smart cities and futures. Sustainability, 13(16), 8952 (2021)
15. Neffati, O. S., Sengan, S., Thangavelu, K. D., et al.: Migrating from traditional grid to smart grid in smart cities promoted in development country. Sustainable Energy Technologies and Assessments, 45, 101125 (2021)
16. Bokhari, S. A. A., Myeong, S.: Use of artificial intelligence in smart cities for smart decision-making: A social innovation perspective. Sustainability, 14(2), 620 (2022)

17. Rathee, G., Iqbal, R., Waqar, O., et al.: On the design and implementation of a blockchain enabled e-voting application within IoT-oriented smart cities. IEEE Access, 9, 34165-34176 (2021)
18. Chen, Z., Sivaparthipan, C. B., Muthu, B. A.: IoT based smart and intelligent smart city energy optimization. Sustainable Energy Technologies and Assessments, 49, 101724 (2022)
19. Ageed, Z. S., Zeebaree, S. R. M., Sadeeq, M. A. M., et al.: A state of art survey for intelligent energy monitoring systems. Asian Journal of Research in Computer Science, 8(1), 46-61 (2021)
20. Lv, Z., Chen, D., Lou, R., et al.: Intelligent edge computing based on machine learning for smart city. Future Generation Computer Systems, 115, 90-99 (2021)
21. Javed, A. R., Shahzad, F., ur Rehman, S., et al.: Future smart cities: Requirements, emerging technologies, applications, challenges, and future aspects. Cities, 129, 103794 (2022)
22. Abbas, S., Khan, M. A., Athar, A., et al.: Enabling smart city with intelligent congestion control using hops with a hybrid computational approach. The Computer Journal, 65(3), 484-494 (2022)
23. Sarker, I. H., Khan, A. I., Abushark, Y. B., et al.: Internet of Things (IoT) security intelligence: a comprehensive overview, machine learning solutions and research directions. Mobile Networks and Applications, 28(1), 296-312 (2023)
24. Ghazal, T. M., Hasan, M. K., Alshurideh, M. T., et al.: IoT for smart cities: Machine learning approaches in smart healthcare — A review. Future Internet, 13(8), 218 (2021)
25. Mabrouki, J., Azrour, M., Fattah, G., et al.: Intelligent monitoring system for biogas detection based on the Internet of Things: Mohammedia, Morocco city landfill case. Big Data Mining and Analytics, 4(1), 10-17 (2021)
26. Zekić-Sušac, M., Mitrović, S., Has, A.: Machine learning based system for managing energy efficiency of public sector as an approach towards smart cities. International Journal of Information Management, 58, 102074 (2021)
27. Al-Turjman, F., Zahmatkesh, H., Shahroze, R.: An overview of security and privacy in smart cities' IoT communications. Transactions on Emerging Telecommunications Technologies, 33(3), e3677 (2022)
28. Liu, W., Xu, Y., Fan, D., et al.: Alleviating corporate environmental pollution threats toward public health and safety: the role of smart city and artificial intelligence. Safety Science, 143, 105433 (2021)
29. Hu, Q., Zheng, Y.: Smart city initiatives: A comparative study of American and Chinese cities. Journal of Urban Affairs, 43(4), 504-525 (2021)
30. Deng, T., Zhang, K., Shen, Z. J. M.: A systematic review of a digital twin city: A new pattern of urban governance toward smart cities. Journal of Management Science and Engineering, 6(2), 125-134 (2021)
31. Razmjoo, A., Østergaard, P. A., Denai, M., et al.: Effective policies to overcome barriers in the development of smart cities. Energy Research & Social Science, 79, 102175 (2021)
32. Lv, Z., Qiao, L., Kumar Singh, A., et al.: AI-empowered IoT security for smart cities. ACM Transactions on Internet Technology, 21(4), 1-21 (2021)
33. Mishra, S., Thakkar, H. K., Mallick, P. K., et al.: A sustainable IoHT based computationally intelligent healthcare monitoring system for lung cancer risk detection. Sustainable Cities and Society, 72, 103079 (2021)
34. Bhattacharya, S., Somayaji, S. R. K., Gadekallu, T. R., et al.: A review on deep learning for future smart cities. Internet Technology Letters, 5(1), e187 (2022)
35. Fan, C., Zhang, C., Yahja, A., et al.: Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management. International Journal of Information Management, 56, 102049 (2021)
36. Chen, C., Jiang, J., Zhou, Y., et al.: An edge intelligence empowered flooding process prediction using Internet of Things in smart city. Journal of Parallel and Distributed Computing, 165, 66-78 (2022)

37. Guo, Z., Shen, Y., Wan, S., et al.: Hybrid intelligence-driven medical image recognition for remote patient diagnosis in Internet of Medical Things. IEEE Journal of Biomedical and Health Informatics, 26(12), 5817-5828 (2021)
38. Majeed, U., Khan, L. U., Yaqoob, I., et al.: Blockchain for IoT-based smart cities: Recent advances, requirements, and future challenges. Journal of Network and Computer Applications, 181, 103007 (2021)
39. Singh, R., Sharma, R., Akram, S. V., et al.: Highway 4.0: Digitalization of highways for vulnerable road safety development with intelligent IoT sensors and machine learning. Safety Science, 143, 105407 (2021)
40. Ahmed, I., Jeon, G., Piccialli, F.: From artificial intelligence to explainable artificial intelligence in Industry 4.0: A survey on what, how, and where. IEEE Transactions on Industrial Informatics, 18(8), 5031-5042 (2022)
41. Ramu, S. P., Boopalan, P., Pham, Q. V., et al.: Federated learning enabled digital twins for smart cities: Concepts, recent advances, and future directions. Sustainable Cities and Society, 79, 103663 (2022)
42. Zhang, Y., Geng, P., Sivaparthipan, C. B., et al.: Big data and artificial intelligence based early risk warning system of fire hazard for smart cities. Sustainable Energy Technologies and Assessments, 45, 100986 (2021)
43. Arulananth, T. S., Kuppusamy, P. G., Ayyasamy, R. K., et al.: Semantic segmentation of urban environments: Leveraging U-Net deep learning model for cityscape image analysis. PLOS ONE, 19(4), e0300767 (2024)
44. Fan, Z., Zhang, F., Loo, B. P. Y., et al.: Urban visual intelligence: Uncovering hidden city profiles with street view images. Proceedings of the National Academy of Sciences, 120(27), e2220417120 (2023)
45. Zhang, L., Kim, C.: Chromatics in urban landscapes: Integrating interactive genetic algorithms for sustainable color design in marine cities. Applied Sciences, 13(18), 10306 (2023)

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