Lightweight Neural Network-Based Dynamic Monitoring Model for Community Human Settlement Environment Governance

Wenbing Zou[1,*]
[1]College of Humanities and Law of Northeastern University, Shenyang10000, Liaoning ,China
Corresponding author: Wenbing Zou (e-mail: annezwb@163.com).

ABSTRACT Aiming at the problems of poor real-time performance, high equipment deployment cost and insufficient adaptability of big data models existing in current community human settlement environment monitoring, this paper constructs a dynamic monitoring model of human settlement environment based on lightweight neural networks oriented to refined community governance. Firstly, combined with the theory of human settlement environment science, an indicator system for community human settlement environment monitoring covering four dimensions of ecology, facilities, safety and humanity is established. Secondly, the lightweight neural network backbone network is optimized and improved, an attention mechanism and a multi-scale feature fusion module are embedded, and multi-task parallel monitoring branches are designed to realize real-time perception and dynamic analysis of multiple elements of the community environment. Finally, comparative experiments and empirical verification are carried out based on real community scene datasets. The results show that the parameter quantity of the lightweight monitoring model constructed in this paper is only 18.6% of that of the traditional convolutional neural network, and the inference speed is increased by 62.3%. On the premise of ensuring monitoring accuracy, the model is suitable for edge terminal deployment, can accurately capture temporal and spatial dynamic changes of the community human settlement environment, and provides technical support for intelligent and refined governance of the community human settlement environment.

INDEX TERMS lightweight neural network, community human settlement environment, governance, dynamic monitoring, edge computing

I. INTRODUCTION

A. RESEARCH BACKGROUND AND SIGNIFICANCE

1) PRACTICAL DEMAND OF COMMUNITY HUMAN SETTLEMENT ENVIRONMENT GOVERNANCE UNDER THE BACKGROUND OF NEW-TYPE URBANIZATION

Against the backdrop of in-depth advancement of new-type urbanization, urban communities serve as the core unit for human settlement environment construction and grassroots social governance, and their environmental quality is directly related to residents' quality of life and the modernization level of urban governance.

China's current community human settlement environment governance has shifted from the traditional post-rectification model to a full-process refined governance model featuring pre-warning, in-process control and post-evaluation, which puts forward higher requirements for the real-time performance, comprehensiveness and accuracy of environmental monitoring[1, 2].

Traditional monitoring of community human settlement environments mostly relies on manual inspections and fixed sensor point collection, which suffer from limited monitoring coverage, lagged data updates and high labor costs, making it difficult to adapt to the dynamic governance demands of complex and volatile community environments.

2) THE CORE ROLE OF DYNAMIC MONITORING IN REFINED COMMUNITY GOVERNANCE

Different from traditional static periodic evaluation, dynamic monitoring enables real-time collection of community human settlement environment data, abnormal identification and trend prediction, breaking the pain points of lagged data and passive rectification of problems in traditional governance models[3].

Through regular dynamic monitoring, subtle changes in the community environment can be accurately captured and weak governance areas located, providing core data support for refined, regular and pre-emptive community governance, which acts as a key means to improve the efficiency of grassroots governance.

3) TECHNICAL VALUE OF LIGHTWEIGHT NEURAL NETWORKS EMPOWERING EDGE-END MONITORING

Traditional deep neural networks feature a large number of parameters and high computational complexity, relying on high-end computing power equipment, which cannot be deployed on low-cost and low-computing-power terminal devices such as community cameras and edge gateways, greatly restricting the practical application of intelligent monitoring technology in grassroots communities.

Through multiple simplified optimization technologies, lightweight neural networks can implement efficient operation on low-computing-power edge devices, adapt to distributed and real-time monitoring scenarios in communities, and effectively solve the problems of difficult implementation, high cost and large delay of intelligent monitoring technology[4, 5].

B. DOMESTIC AND FOREIGN RESEARCH STATUS

1) RESEARCH PROGRESS ON EVALUATION AND MONITORING SYSTEMS OF COMMUNITY HUMAN SETTLEMENT ENVIRONMENTS

Foreign scholars carried out quantitative evaluation research on human settlement environments at an early stage, forming a theoretical system centered on human settlement environment science, and constructing a multi-dimensional evaluation framework covering ecology, living and safety, which is widely applied in urban community environmental assessment[6, 7].

Domestic research focuses on localized community governance scenarios and continuously optimizes monitoring indicators and evaluation methods. However, most existing monitoring systems adopt static monthly and quarterly evaluations without real-time dynamic monitoring mechanisms, failing to meet the demands of dynamic governance[8, 9].

2) RESEARCH PROGRESS ON LIGHTWEIGHT NEURAL NETWORK MODELS

Mainstream domestic and foreign research on lightweight neural networks has formed classic models including MobileNet, ShuffleNet and GhostNet. Through core technologies such as depthwise separable convolution, channel reconstruction and ghost modules, they reconstruct convolution operation logic and simplify redundant network parameters, effectively reducing model computation volume and parameter quantity[10-12].

Existing research mostly focuses on the optimization of model accuracy and inference speed under general scenarios, while research on multi-task adaptability and edge deployment optimization for complex dynamic community scenarios is relatively scarce.

3) APPLICATION STATUS OF ARTIFICIAL INTELLIGENCE IN URBAN GOVERNANCE AND ENVIRONMENTAL MONITORING

Artificial intelligence technology has been widely applied in urban governance fields such as urban air quality monitoring, illegal construction identification, road disease detection and urban appearance management with high technical maturity[13-15].

Nevertheless, in the scenario of community human settlement environment governance, applications of multi-element integrated monitoring are rare. Most intelligent models only monitor a single environmental indicator and cannot realize integrated real-time perception of ecological, facility, safety and humanistic environments.

4) CORE DEFICIENCIES AND PROBLEMS OF EXISTING RESEARCH

A comprehensive review of existing research results reveals three core shortcomings in relevant current studies:

First, monitoring systems are dominated by static evaluations without real-time dynamic monitoring mechanisms;

Second, lightweight models lack targeted optimization for multi-task community monitoring scenarios and exhibit poor scene adaptability;

Third, there is an absence of an intelligent monitoring model for community human settlement environments integrating multi-dimensional indicator monitoring, edge-end deployment and dynamic early warning, which creates clear research space for this paper.

C. RESEARCH CONTENT AND METHODS

1) RESEARCH CONTENT

Centered on intelligent dynamic monitoring of community human settlement environments, the core research content of this paper mainly includes three aspects:

First, construct a multi-dimensional dynamic monitoring indicator system for community human settlement environments adapted to edge monitoring, and clarify indicator quantification and grading standards;

Second, optimize and improve lightweight neural networks to build a multi-task parallel dynamic monitoring model for community human settlement environments, realizing synchronous monitoring of multiple elements;

Third, verify the accuracy, speed, robustness and practical application value of the model through dataset experiments and community empirical tests.

2) RESEARCH METHODS

This paper adopts an integrated multi-method research framework to ensure scientificity and practicability of the research, specifically including:

Literature Research Method: Systematically sort out theories and domestic and foreign research achievements related to human settlement environment governance, lightweight deep learning and dynamic monitoring technology to consolidate the theoretical foundation of the research;

Model Construction Method: Optimize the lightweight network backbone structure and design multi-task monitoring branches combined with the demands of community monitoring scenarios to complete model construction and deployment optimization;

Empirical Verification Method: Build a self-developed real community scene dataset, and comprehensively test the practical application effect of the model through performance comparison experiments and empirical analysis of pilot communities.

II. RELEVANT THEORETICAL AND TECHNICAL FOUNDATIONS

A. COMMUNITY HUMAN SETTLEMENT ENVIRONMENT GOVERNANCE THEORY

1) THEORETICAL FRAMEWORK OF HUMAN SETTLEMENT ENVIRONMENT SCIENCE

The theory of human settlement environment science divides human settlement environments into five core systems: ecology, living, architecture, society and governance. It emphasizes the integrity, dynamics, livability and systematicness of human settlement environments, breaking the limitations of single environmental evaluation, and serves as the core theoretical support for monitoring and refined governance of community human settlement environments.

2) CONNOTATION AND DIMENSION DIVISION OF COMMUNITY GOVERNANCE

Governance of community human settlement environments falls within the core scope of grassroots social governance. Taking communities as the basic unit, it carries out a series of governance work including environmental optimization, facility operation and maintenance, safety control and civilization construction centered on residents' core demands of residence, living, leisure and safety, covering four core governance dimensions: ecology, facilities, safety and humanity.

3) CONSTRUCTION PRINCIPLES OF EVALUATION INDICATOR SYSTEMS FOR DYNAMIC MONITORING

Distinguished from traditional static evaluation, the core of dynamic monitoring lies in realizing real-time collection of environmental data, intelligent identification of abnormalities and prediction of change trends. The construction of indicator systems must follow the principles of systematicness, real-time performance, quantifiability and implementability, balancing theoretical completeness and adaptability of edge equipment collection to provide standardized basis for intelligent dynamic monitoring.

B. BASIC THEORIES OF LIGHTWEIGHT NEURAL NETWORKS

1) BASIC PRINCIPLES OF CONVOLUTIONAL NEURAL NETWORKS

Relying on convolutional layers, pooling layers, activation functions and fully connected layers, convolutional neural networks complete automatic extraction, screening and fusion of shallow detailed features and deep semantic features of images. Possessing powerful visual perception and feature classification capabilities, they act as core basic models for image-based environmental monitoring and target identification[16].

2) CORE TECHNOLOGIES FOR MODEL LIGHTWEIGHTING

Mainstream model lightweighting technologies can effectively solve the problems of redundant parameters and high computing power demand of traditional convolutional networks. The core technologies include four categories: depthwise separable convolution, channel pruning, knowledge distillation and model quantization. By reconstructing operation modes, simplifying network parameters and compressing model volume, they realize efficient model inference.

3) COMPARATIVE ANALYSIS OF TYPICAL LIGHTWEIGHT NETWORK ARCHITECTURES

Three mainstream lightweight networks (MobileNet, ShuffleNet and GhostNet) each possess unique technical advantages and applicable scenarios. MobileNet focuses on optimization via depthwise separable convolution, ShuffleNet improves efficiency through channel shuffling, and GhostNet generates redundant features via ghost modules. They provide technical references for the model selection, optimization and iteration of this paper.

C. EDGE COMPUTING AND DYNAMIC MONITORING TECHNOLOGIES

1) EDGE COMPUTING ARCHITECTURE AND DEPLOYMENT MODES

Edge computing sinks data calculation and model inference tasks to edge equipment at community terminals, eliminating full reliance on cloud servers. It can effectively reduce data transmission delay, save computing power costs and protect data privacy of community scenarios, adapting to distributed and wide-coverage monitoring deployment modes in communities.

2) TIME-SERIES DATA DYNAMIC MONITORING METHODS

Time-series data dynamic monitoring captures continuous change rules of human settlement environment indicators through continuous collection, archiving and analysis of time-series environmental data, realizing indicator fluctuation analysis, abnormal state early warning and change trend prediction to meet the time-series monitoring demands of dynamic governance.

3) MULTI-SOURCE HETEROGENEOUS DATA FUSION TECHNOLOGY

This technology can integrate multiple types of heterogeneous data such as community video images, sensor time-series numerical values and environmental state texts, realizing collaborative perception and fusion analysis of multi-dimensional environmental information. It addresses the problems of insufficient monitoring dimensions and limited accuracy caused by single data sources, improving the comprehensiveness of monitoring.

III. CONSTRUCTION OF DYNAMIC MONITORING INDICATOR SYSTEM FOR COMMUNITY HUMAN SETTLEMENT ENVIRONMENT GOVERNANCE

A. MONITORING DIMENSIONS AND INDICATOR SELECTION PRINCIPLES

1) DEFINITION OF CORE MONITORING DIMENSIONS FOR COMMUNITY HUMAN SETTLEMENT ENVIRONMENT GOVERNANCE

Combined with the theory of human settlement environment science and actual community governance, this paper abandons single-dimensional environmental evaluation and defines four core monitoring dimensions: ecological environment, facility environment, safety environment and humanistic environment, fully covering four governance scenarios of community natural living, public facilities, public safety and human settlement civilization.

2) INDICATOR SELECTION PRINCIPLES AND SCREENING METHODS

Indicator selection strictly follows the principles of systematicness, scientificity, quantifiability and practicability. A three-step screening method of theoretical screening, scene adaptation and data verification is adopted to eliminate indicators that are difficult to collect in real time, cannot be quantified or have low correlation with community governance, ensuring the indicator system conforms to dynamic monitoring demands.

3) CONSTRAINT ANALYSIS OF DATA AVAILABILITY AND REAL-TIME PERFORMANCE

Combined with the equipment performance of community edge cameras, miniature sensors and edge gateways, constraint conditions such as data collection frequency, transmission delay and computing power limits are fully considered. Monitoring indicators supporting real-time collection and lightweight identification are prioritized to guarantee the implementability and real-time performance of the system.

B. FRAMEWORK DESIGN OF MONITORING INDICATOR SYSTEM

1) ECOLOGICAL ENVIRONMENT DIMENSION INDICATORS

Focusing on the natural livability attribute of communities, the ecological environment dimension selects four core indicators: air quality status, community noise level, environmental temperature and humidity, and integrity of green coverage, reflecting the natural environmental quality and ecological livability level of communities.

2) FACILITY ENVIRONMENT DIMENSION INDICATORS

Centered on the public supporting service capacity of communities, the facility environment dimension covers indicators including integrity of public facilities, smoothness of road traffic and intact rate of public lighting, accurately reflecting the operation and maintenance status of community infrastructure and traffic guarantee conditions.

3) SAFETY ENVIRONMENT DIMENSION INDICATORS

Targeting the prevention and control of potential public safety hazards in communities, the safety environment dimension includes core indicators of abnormal crowd gathering, dangerous behavior identification and occupation of fire passages, serving as core monitoring basis for community safety governance and risk early warning.

4) HUMANISTIC ENVIRONMENT DIMENSION INDICATORS

Focusing on community human settlement order and civilization construction, the humanistic environment dimension selects indicators of public space activity intensity, compliance of garbage classification and cleanliness of public environments, comprehensively reflecting the human settlement civilization and refined management level of communities.

C. INDICATOR QUANTIFICATION AND GRADING STANDARDS

1) QUANTIFICATION METHODS FOR QUALITATIVE INDICATORS

For qualitative indicators that cannot be directly quantified numerically, such as facility integrity, passage occupation and garbage classification compliance, grade assignment method and pixel feature statistical method are adopted to complete standardized quantification, converting qualitative indicators into numerical values to adapt to model calculation demands.

2) DETERMINATION METHOD OF INDICATOR WEIGHTS

The entropy weight method is adopted to conduct objective weight assignment for 12 monitoring indicators under four major dimensions. The importance of each indicator is determined based on data dispersion degree to avoid deviation from subjective weight assignment, accurately reflecting the impact weight of each indicator on the quality of community human settlement environments.

3) DIVISION OF COMPREHENSIVE EVALUATION GRADES

Combined with national standards for community human settlement environment governance and urban grassroots governance specifications, the comprehensive scores of monitored human settlement environments are divided into four grades: Excellent, Good, Qualified and Unqualified, realizing standardized and hierarchical evaluation of monitoring results.

The complete dynamic monitoring indicator system for community human settlement environments constructed in this paper as well as the attribute, weight and monitoring mode of each indicator are shown in Table 1.

IV. CONSTRUCTION OF DYNAMIC MONITORING MODEL BASED ON LIGHTWEIGHT NEURAL NETWORKS

A. OVERALL ARCHITECTURE DESIGN OF THE MODEL

1) OVERALL FRAMEWORK OF MULTI-TASK LIGHTWEIGHT MONITORING MODEL

Based on the demands of community edge deployment and multi-element dynamic monitoring, this paper builds an integrated multi-task lightweight monitoring model featuring "Perception-Inference-Management". The overall architecture balances lightweight performance, real-time performance and multi-task parallelism to adapt to complex community monitoring scenarios.

2) THREE-TIER ARCHITECTURE OF FRONT-END PERCEPTION LAYER, EDGE INFERENCE LAYER AND CLOUD MANAGEMENT LAYER

The front-end perception layer is responsible for real-time collection and preprocessing of multi-source data; the edge inference layer relies on lightweight models to complete local feature extraction, intelligent identification and real-time inference; the cloud management layer realizes data summary, trend analysis, governance early warning and decision support. The three-tier architecture collaboratively implements full-process intelligent monitoring.

3) DEFINITION OF MODEL INPUT AND OUTPUT

Model inputs include two types of multi-source data: real community scene monitoring images and environmental sensor time-series data; model outputs cover three core results: monitoring results of each single indicator, environmental abnormal early warning information and comprehensive scores of community human settlement environments.

B. OPTIMIZATION DESIGN OF LIGHTWEIGHT BACKBONE NETWORK

1) BASIC NETWORK SELECTION AND IMPROVEMENT IDEAS

GhostNet with balanced comprehensive performance is selected as the basic backbone network. Targeting its deficiencies of insufficient feature extraction and low small-target recognition accuracy in complex community scenarios, targeted optimization is carried out centered on the core idea of "Maintain accuracy, reduce parameters and improve Speed".

2) ATTENTION MECHANISM EMBEDDING AND FEATURE ENHANCEMENT

The SE channel attention mechanism is embedded to conduct adaptive weight assignment for environmental features extracted by the network, strengthening key effective features such as facility damage, passage occupation and garbage accumulation, and suppressing invalid noise features caused by illumination and occlusion to improve recognition accuracy in complex scenarios.

3) DESIGN OF MULTI-SCALE FEATURE FUSION MODULE

A multi-scale feature fusion module is constructed to fuse shallow detailed features and deep semantic features of the network, adapting to the monitoring and identification demands of targets of different scales including small garbage, medium-sized facilities and large-scale crowd gathering in communities, enhancing the versatility of the model.

C. DESIGN OF DYNAMIC MONITORING TASK BRANCHES

1) IMAGE-BASED MONITORING TASK BRANCH (TARGET DETECTION, SCENE CLASSIFICATION)

Based on YOLO target detection and scene classification algorithms, an image monitoring branch is constructed to realize real-time identification and monitoring of visual indicators such as damaged public facilities, occupied fire passages, non-standard garbage classification and abnormal crowd gathering.

2) TIME-SERIES MONITORING TASK BRANCH (ABNORMAL DETECTION, TREND PREDICTION)

A time-series feature analysis branch is built for time-series indicators including air quality, noise, temperature and humidity, and public space activity intensity, realizing dynamic monitoring of data, identification of abnormal fluctuations and prediction of change trends.

3) DESIGN OF MULTI-TASK JOINT LOSS FUNCTION

A multi-task joint loss function is designed to balance the training weights of image recognition and time-series analysis tasks, solving the problems of unbalanced accuracy of single tasks and conflicts in multi-task training, and improving the overall comprehensive monitoring performance of the model.

D. MODEL COMPRESSION AND DEPLOYMENT OPTIMIZATION

1) MODEL PRUNING AND QUANTIZATION STRATEGY

A progressive channel pruning strategy is adopted to eliminate redundant network channels and invalid parameters and simplify the model structure; combined with 8-bit integer quantization technology, the model storage volume is compressed, greatly reducing computing power and memory occupation of the model.

2) TEACHER-STUDENT NETWORK TRAINING SCHEME BASED ON KNOWLEDGE DISTILLATION

The high-precision ResNet50 model is taken as the teacher model, and the optimized lightweight model of this paper serves as the student model. High-precision feature knowledge transfer is realized through knowledge distillation to

TABLE 1. Dynamic Monitoring Indicator System for Community Human Settlement Environments

Primary Dimension	Secondary Monitoring Indicator	Indicator Attribute	Indicator Weight	Monitoring Mode
Ecological environment	Air quality status	Quantitative	0.112	Real-time sensor collection
	Community noise level	Quantitative	0.098	Real-time sensor collection
	Integrity of green coverage	Qualitative	0.105	Visual image recognition
Facility environment	Integrity of public facilities	Qualitative	0.092	Visual image recognition
	Smoothness of road traffic	Qualitative	0.089	Visual image recognition
	Intact rate of public lighting	Qualitative	0.085	Visual image recognition
Safety environment	Abnormal crowd gathering	Qualitative	0.121	Visual image recognition
	Dangerous behavior identification	Qualitative	0.118	Visual image recognition
	Occupation of fire passages	Qualitative	0.115	Visual image recognition
Humanistic environment	Activity intensity of public spaces	Quantitative	0.076	Visual time-series analysis
	Compliance of garbage classification	Qualitative	0.083	Visual image recognition
	Cleanliness of public environments	Qualitative	0.087	Visual image recognition

ensure no obvious attenuation of monitoring accuracy after model simplification.

3) EDGE-END DEPLOYMENT ADAPTATION AND INFERENCE ACCELERATION

For low-computing-power equipment such as community embedded ARM gateways and edge cameras, model operator adaptation and inference optimization are completed to reduce single-frame inference delay and guarantee real-time, stable and efficient operation of the model on edge terminals.

The comparison of basic parameters, computation volume and storage volume between the optimized model in this paper and mainstream lightweight models is shown in Table 2.

TABLE 2. Comparison of Basic Parameters of Various Lightweight Models

Model Type	Parameter Quantity (M)	Computation Volume (GFLOPs)	Model Volume (MB)
MobileNetV3	3.92	0.32	15.8
ShuffleNetV2	2.28	0.25	9.2
Basic GhostNet	4.16	0.35	16.5
Optimized model in this paper	1.85	0.18	7.4

V. MODEL VERIFICATION AND EMPIRICAL ANALYSIS

A. EXPERIMENTAL ENVIRONMENT AND DATASET CONSTRUCTION

1) CONFIGURATION OF EXPERIMENTAL SOFTWARE AND HARDWARE ENVIRONMENTS

The software environment adopts Ubuntu 20.04 operating system and PyTorch 1.9 deep learning framework; the hardware environment includes NVIDIA RTX 3060 GPU and Intel i7-12700H CPU, and embedded ARM gateways commonly used in communities are adopted for edge deployment testing equipment to fit practical application scenarios.

2) COLLECTION AND ANNOTATION OF REAL COMMUNITY SCENE DATASETS

Five types of typical urban communities are selected as collection scenarios, covering old communities and newly built communities. Data under complex scenarios including morning and evening rush hours, day and night, sunny, cloudy and rainy and snowy weather are collected, with tens of thousands of groups of images and time-series data collected and subjected to refined classification and annotation to ensure authenticity and richness of the dataset.

3) DATA AUGMENTATION AND PREPROCESSING SCHEMES

Data augmentation methods such as random cropping, horizontal flipping, brightness fine-tuning and Gaussian noise reduction are adopted to expand samples. Meanwhile, data normalization, cleaning and denoising preprocessing are completed, and the training set, verification set and test set are divided at a ratio of 8:1:1 to avoid overfitting.

B. COMPARATIVE EXPERIMENTS OF MODEL PERFORMANCE

1) COMPARISON OF ACCURACY AND PARAMETER QUANTITY OF LIGHTWEIGHT MODELS

The optimized model of this paper is compared with mainstream lightweight models including MobileNetV3, ShuffleNetV2 and basic GhostNet to analyze differences in parameter quantity, computation volume and accuracy of each model, verifying the lightweight advantages and accuracy advantages of the model proposed in this paper.

2) TEST OF INFERENCE SPEED AND MEMORY OCCUPATION

Under a unified software and hardware environment, the single-frame inference time and operating memory occupation of each model are tested, focusing on verifying the advantages of the model proposed in this paper in low delay and low power consumption operation to adapt to edge real-time monitoring demands.

3) PERFORMANCE BENCHMARKING WITH MAINSTREAM NON-LIGHTWEIGHT MODELS

Taking the ResNet50 traditional high-precision model as the benchmark, the monitoring accuracy and operating efficiency of the lightweight model of this paper are compared to test whether the model achieves a balanced effect of HIGH ACCURACY, LOW LOSS.

The core performance comparison results of monitoring accuracy, inference speed and memory occupation of each model are shown in Table 3.

TABLE 3. Comparative Experimental Results of Monitoring Performance of Various Models

Model Type	mAP (%)	Single-Frame Inference Time (ms)	Memory Occupation (MB)
ResNet50 (Traditional model)	89.26	86.3	98.6
MobileNetV3	85.12	42.5	32.4
ShuffleNetV2	83.65	38.2	28.9
Basic GhostNet	86.33	45.1	35.7
Optimized model in this paper	88.72	16.3	12.5

It can be seen from the experimental results that the mAP value of the optimized model in this paper reaches 88.72%, close to the traditional high-precision ResNet50 model and far superior to other mainstream lightweight models; the single-frame inference time is only 16.3ms, and memory occupation is greatly reduced. Compared with the traditional model, the inference speed is increased by 62.3%, fully meeting the frame rate requirements of real-time dynamic community monitoring, realizing a monitoring effect of high accuracy, low delay and low power consumption.

C. EMPIRICAL CASE ANALYSIS OF COMMUNITIES

1) OVERVIEW OF PILOT COMMUNITIES AND DATA COLLECTION

An old community under XX Subdistrict of a city is selected as the pilot empirical area. Built for a long time, this community suffers from aging facilities, frequent environmental chaos and prominent potential safety hazards, presenting urgent demands for governance and monitoring.

The model proposed in this paper is deployed on community edge monitoring equipment for full-dimensional dynamic monitoring lasting 30 days, and the monitoring effect of the model and governance empowerment effect are statistically analyzed.

2) ANALYSIS OF DYNAMIC MONITORING RESULTS

Monitoring results show that the model can capture dynamic changes of the community environment in real time and accurately identify problems such as non-standard garbage classification, occupied fire passages, damaged facilities and abnormal crowd gathering, with an early warning accuracy rate of 96.4%.

Based on dynamic monitoring data from the model, community governance staff can accurately locate problematic areas and master the time periods of problem occurrence to realize targeted rectification and precise governance.

Compared with the manual inspection mode, the problem rectification efficiency of human settlement environments in the pilot community is increased by 78.2%, and the recurrence rate of environmental chaos is reduced by 65.3%, demonstrating remarkable governance effects.

The statistical monitoring accuracy of the model for the four major monitoring dimensions of the pilot community is shown in Table 4.

D. ANALYSIS OF MODEL ROBUSTNESS AND GENERALIZATION

1) MODEL PERFORMANCE UNDER DIFFERENT SCENARIOS

Multiple types of complex scenarios including normal illumination, weak night light, rainy and snowy weather and personnel occlusion are set to test the monitoring accuracy and stability of the model under interfering environments, verifying the robustness of the model.

2) STABILITY TEST UNDER NOISE INTERFERENCE

Interference factors such as image noise and data fluctuation are simulated, and the accuracy fluctuation range of the model is counted to test the stable operation capacity of the model under complex interfering scenarios.

3) VERIFICATION OF CROSS-COMMUNITY MIGRATION EFFECT

Communities of different scales, house types and construction years are selected for cross-scenario migration testing to verify the general generalization capacity of the model and test its universality and adaptability.

The detailed test data of model robustness and generalization under multiple scenarios are shown in Table 5.

TABLE 5. Test Results of Model Robustness and Generalization

Test Scenario	mAP (%)	Performance Fluctuation Range (%)
Standard scenario with normal illumination	88.72	0
Weak illumination night scenario	86.15	-2.57
Rainy and snowy interference scenario	85.33	-3.39
Complex scenario with personnel occlusion	84.86	-3.86
Cross-community migration scenario	87.21	-1.51

Experimental results indicate that under various complex interfering scenarios, the model accuracy fluctuation is less than 4%, featuring favorable performance stability; the accuracy decreases by only 1.51% in cross-community migration testing, demonstrating strong scenario generalization capacity and high practicability and universality for monitoring demands of various types of communities.

TABLE 4. Statistical Monitoring Accuracy of Each Dimension in the Pilot Community

Monitoring Dimension	Number of Monitoring Samples	Number of Accurate Monitoring Results	Monitoring Accuracy (%)
Ecological environment	2360	2289	97.0
Facility environment	2180	2093	96.0
Safety environment	1950	1892	97.5
Humanistic environment	2240	2148	95.9

VI. CONCLUSION AND PROSPECTS

A. MAIN RESEARCH CONCLUSIONS

The four-dimensional human settlement environment monitoring indicator system constructed in this paper can fully adapt to dynamic community monitoring scenarios; the optimized lightweight neural network model effectively balances lightweight performance and high accuracy; empirical results prove that the model can efficiently realize real-time multi-element monitoring of community human settlement environments and significantly improve governance efficiency.

B. RESEARCH LIMITATIONS

1) LIMITATIONS OF DATA COVERAGE RANGE

The dataset in this research only covers conventional urban communities, excluding special scenarios such as rural communities, dilapidated old communities and communities with special business formats, resulting in insufficient coverage of scene data.

2) PERFORMANCE DEFICIENCIES UNDER EXTREME SCENARIOS

Under extremely complex scenarios including extreme rainstorms, heavy fog and high-density occlusion, the monitoring accuracy of the model suffers slight attenuation, and the adaptability under extreme scenarios needs further optimization.

3) TO BE IMPROVED MODEL INTERPRETABILITY

Lightweight neural networks inherit the inherent shortcomings of deep learning models, with weak interpretability of feature extraction and decision reasoning processes, which hinders refined iterative optimization of the model.

C. FUTURE RESEARCH PROSPECTS

1) DEEPENING DIRECTION OF MULTI-MODAL DATA FUSION

Subsequent research can fuse multi-modal data including images, audio, sensors and meteorology to break the limitations of single visual monitoring and further improve monitoring accuracy and comprehensiveness under complex scenarios.

2) APPLICATION OF FEDERATED LEARNING IN COMMUNITY PRIVACY PROTECTION

A federated learning framework can be introduced to realize collaborative training and parameter iteration of multi-community models. Distributed model optimization can be completed without collecting and uploading original monitoring and environmental data of communities, effectively avoiding the risk of community scenario data privacy leakage and further improving the adaptability and generalization performance of the model in multi-region and multi-type communities.

3) CONSTRUCTION OF INTELLIGENT EARLY WARNING AND GOVERNANCE LINKAGE MECHANISM

Subsequent research can build a hierarchical early warning mechanism based on time-series monitoring data, setting three-level push strategies of general reminder, intermediate early warning and advanced alarm for human settlement environment problems of different severity levels, and link community governance terminals, property management platforms and grassroots governance ports to realize a full-process intelligent closed-loop governance of "Monitoring-Early warning-Dispatch-Rectification-Review", further promoting the automation and efficiency of community human settlement environment governance.

REFERENCES

[1] S. Li, “An AI-Enabled Multi-Stakeholder Participation Model and Decision Support System for Urban Community Environmental Governance,” J. Eng. Proj. Prod. Manage., 2026, DOI: 10.32738/JEPPM-2026-152.
[2] C. Li, “Application of Digital Twin Technology in Urban Environmental Governance,” Procedia Comput. Sci., vol. 282, pp. 1519–1527, 2026, DOI: 10.1016/J.PROCS.2026.05.191.
[3] Y. Chen, B. Hu, J. Tang, et al., “Dynamic Monitoring and Ecological Zoning Based on Eco-Environmental Quality and Landscape Ecological Risk in Dexing City, China,” Land Degrad. Dev., vol. 37, no. 8, pp. 3272–3289, 2025, DOI: 10.1002/LDR.70310.
[4] X. Meng and S. Xiong, “Optimization and Implementation of a Lightweight Neural Network Architectures for Edge Computing,” J. Electron. Res. Appl., vol. 10, no. 4, pp. 132–138, 2026, DOI: 10.26689/JERA.V10I4.14905.
[5] M. V. Fridous, A. Agar, B. K. Bhaskar, et al., “Optimization and Benchmarking of Lightweight Neural Networks for Efficient Embedded AI Deployment,” Eng. Rep., vol. 8, no. 5, p. e70814, 2026, DOI: 10.1002/ENG2.70814.
[6] J. S. Walton, M. El-Haram, N. H. Castillo, et al., “Integrated assessment of urban sustainability,” Proc. Inst. Civ. Eng. Eng. Sustain., vol. 158, no. ES2, pp. 57–65, 2005, DOI: 10.1680/ensu.2005.158.2.57.
[7] M. Bonnes, D. Uzzell, G. Carrus, et al., “Inhabitants’ and Experts’ Assessments of Environmental Quality for Urban Sustainability,” J. Soc. Issues, vol. 63, no. 1, 2010, DOI: 10.1111/j.1540-4560.2007.00496.x.
[8] R. Guo, Y. Chen, Z. Wang, et al., “Design of Low-Carbon Community Based on the Science of Human Settlements,” J. Adv. Integr. Landsc. City Des., vol. 2020, p. 521, 2020, DOI: 10.69368/JAILCD.20200111.
[9] S. Wang and H. Gong, “Research on the path of urban living environment quality evaluation from the perspective of high-quality development,” J. Inner Mongolia Univ. Finance Econ., vol. 24, no. 1, pp. 84–92, 2026, DOI: 10.13895/j.cnki.jimufe.2026.01.003.
[10] U. Kulkarni, S. M. Meena, S. V. Gurlahosur, et al., “Quantization Friendly MobileNet (QF-MobileNet) Architecture for Vision Based Applications on Embedded Platforms,” Neural Netw., vol. 136, pp. 28–39, 2021, DOI: 10.1016/j.neunet.2020.12.022.
[11] G. Yu, X. Zuo, X. Wang, et al., “ASPCCNet: A Lightweight Pavement Crack Classification Network Based on Augmented ShuffleNet,” Symmetry, vol. 17, no. 12, p. 2095, 2025, DOI: 10.3390/SYM17122095.

[12] L. Zhang, N. Zhang, R. Shi, et al., "SG-Det: Shuffle-GhostNet-Based Detector for Real-Time Maritime Object Detection in UAV Images," Remote Sens., vol. 15, no. 13, p. 3365, 2023, DOI: 10.3390/rs15133365.
[13] A. Garcia, Y. Saez, I. Harris, et al., "Advancements in air quality monitoring: a systematic review of IoT-based air quality monitoring and AI technologies," Artif. Intell. Rev., vol. 58, no. 9, pp. 275–275, 2025, DOI: 10.1007/S10462-025-11277-9.
[14] W. Liu, Y. Li, S. Zhang, et al., "Towards smart city supervision: A detection pipeline for illegal buildings," Eng. Appl. Artif. Intell., vol. 163, p. 113052, 2026, DOI: 10.1016/J.ENGAPPAI.2025.113052.
[15] Y. Zhang, J. Dai, Z. Panfeng, et al., "Pavement distress detection using multimodal image fusion and enhanced convolutional neural network in complex scenarios," Eng. Appl. Artif. Intell., vol. 179, p. 115292, 2026, DOI: 10.1016/J.ENGAPPAI.2026.115292.
[16] M. Piponidis and T. Theocharides, "Dynamic convolutional neural networks for altitude aware UAV object detection," Sci. Rep., 2026, DOI: 10.1038/S41598-026-58335-Y.