Journal of Network Intelligence ©2024 ISSN 2414-8105
Taiwan Ubiquitous Information Volume **9**, Number **2**, May **2024**

Interior Scene Intelligent Generated for Smart Homes Based on GAN-ID Algorithms

Fu-Quan Zhang

1. College of Computer and Control Engineering,
Minjiang University, Fuzhou, China
2. Digital Media Art, Key Laboratory of Sichuan Province,
Sichuan Conservatory of Music, Chengdu, China
3. Fuzhou Technology Innovation Center of Intelligent Manufacturing Information System,
Minjiang University, Fuzhou, China
4. Engineering Research Center for ICH Digitalization and Multi-source Information Fusion (Fujian Polytechnic Normal University),
Fujian Province University, Fuzhou, China
zfq@mju.edu.cn

Lin-Juan Ma*

School of Computer Science and Technology,
Beijing Institute of Technology, Beijing, China
malinjuan@bit.edu.cn

Jun-Xian Zhou

College of Mathematics and Data Science (Software College),
Minjiang University, Fuzhou, China
120698031@qq.com

Run-Hong Wang

College of Computer and Control Engineering,
Minjiang University, Fuzhou, China
50397@qq.com

Guang-Zhen Zhang

Information Media School of Tianjin Technician Institute of
Mechanical & Electrical Technology, Tianjin, China
18222596267@163.com

*Corresponding author: Lin-Juan Ma
Received March 3, 2023, revised May 26, 2023, accepted October 22, 2023.

Abstract. *The purpose of this paper is to present a new GAN-ID algorithm to generate interior scene intelligently based on Artificial Intelligence of Things (AIoT). Although great progress has been made when GAN algorithm applied in smart homes and smart cities, the issue of the trade-off between the accuracy and the efficiency in interior scene has been overlooked. A number of experiments were performed to check the performance and it is indicated that the results of the proposed GAN-ID has great advantages in model sample generation than other common methods when generating interior scene intelligently, which is similar to state-of-the-art. It is meaningful when it can be applied in smart cities and smart homes filed based on AIoT in the future.*
Keywords: interior scene generated; Artificial Intelligence of Things; GAN-ID algorithm; Deep learning; Smart homes and Smart cities

1. **Introduction.** Recently, the Artificial Intelligence-Based Internet of Things is the hot topic that has received the most attention in the smart cities and smart homes filed, which can be summarized by Wu et al. [1] and Lin et al. [2]. It is well known that all kinds of intelligent devices and Internets were combined and integrated in smart cities and smart homes then to provide the efficient and convenient daily life to satisfy the society and the people and it can be referred to Wu et al. [3] and Liu et al. [4]. Despite the fact that the Artificial Intelligence of Things (AIoT) served in smart cities and smart homes has made headway, there are still existing some limitations between the efficiency and the accuracy of the generated results when it put to use. Consequently, it has become one of the primary issue to alleviate the gap between the trade-off of them.

In previous work, there are some researchers developed smart cities and smart homes filed based on deep learning methods. In literature, in 2020, Ping et al. [5] put forward to operate smart street litter detection and classification based on Faster R-CNN and edge computing. And in 2021, Araujo et al. [6] presented an end-to-end prediction of parcel delivery time with deep learning for smart-city applications to solve a real-world case of last-mile parcel delivery time prediction. During this year, Balicki et al. [7] proposed to use big data from sensor network via Internet of Things to edge deep learning for smart city. Meanwhile, Zahra et al. [8] presented a method to build an efficient salient region-based surveillance framework for smart cities which integrates a deep learning-based video surveillance technique that extracts salient regions from a video frame without information loss, and then encodes it in reduced size. At the same year, Natani et al. [9] proposed to apply sequential neural networks for multi-resident activity recognition in ambient sensing smart homes. In 2022, Avazov et al. [10] use the improved YOLOv4 network to study fire detection method in smart city environments. Then Panja et al. [11] designed a deep learning-based anomaly detection model at the edge in IoT smart home framework to efficiently detect any malicious situation to ensure the safety from any illegal hacking.

In current years, Generative Adversarial Network(GAN) plays an essential role and has become an hot issue in Artificial Intelligence-Based Internet of Things of smart cities and smart homes. In 2020, Ibitoye et al. [12] propose a GAN based approach for privacy preservation in smart homes which generates random noise to distort the unwanted machine learning-based inference. At the same year, Du et al. [13] put forward a mixed GAN network to generate the geometry and texture coordination to realize 3D building fabrication. Simultaneously, Shahid et al. [14] proposed to combine an autoencoder with a GAN to generate sequences of packet sizes that correspond to bidirectional flows for Internet of Things network traffic generation to serve for smart cities and smart homes. In 2021, Lee et al. [15] presented an eGAN model which is an edge detection for connectivity in ambient intelligence environments. Also, Soleimani et al. [16] utilizes the Generative Adversarial Network framework to perform cross-subject transfer learning in the domain of wearable sensor-based human activity recognition for smart homes.

Huge achievements has been obtained when GAN put into use in Artificial Intelligence-Based Internet of Things of smart cities and smart homes, however, it still exists some challenges as follows:1) On account of the complexity of the model, it is usually based on traditional software not intelligent algorithms to generate the scene for smart cities and homes. 2) In virtue of the redundancy in the GAN calculation, it is neglected in the transformation between the same type of models. 3) It is still a challenge to realize the trade-off between the efficiency and the accuracy when the scene for smart cities and smart homes generated by means of GAN. To address the problems aboved, a novel GAN-ID neural network based on AIoT proposed in this study to generate interior design models, which can be put into practice in smart homes and smart cities. The contributions in our study are as the following:

1. The GAN-ID algorithms based on AIoT is proposed in this study to generate interior design models intelligently.
2. A novel optimization training is presented in our GAN-ID neural network to keep it more stable.
3. A new objective function is proposed in our GAN-ID neural network to reduce the consumption of the computing resources.

In this paper, it is divided into 4 sections as follows: In section 2, it introduces the materials and methods, including the GAN-ID neural network and interior design event streams. And in section 3, the results and discussion of our study have been discussed. Finally, the study has been summed up.

2. **Materials and Methods.** As shown in Figure 1, it is the operation steps of the whole GAN-ID based AIoT to generate interior design models intelligently for smart homes. Firstly, one of several predefined styles should be selected by the user. Then according to the selected style and the data learned from the data source, a reasonable indoor configuration can be randomly arranged in the system. In the process of layout, the rationality of the relative positions of each object would be checked in the system firstly, and then the rationality of the object density would be confirmed, finally the model parameters of the corresponding style according to the pre-training for further fine-tuning would be obtained. When the scene is generated, the user can view the result from a free perspective, including zooming in, zooming out, looking down, looking up, etc.

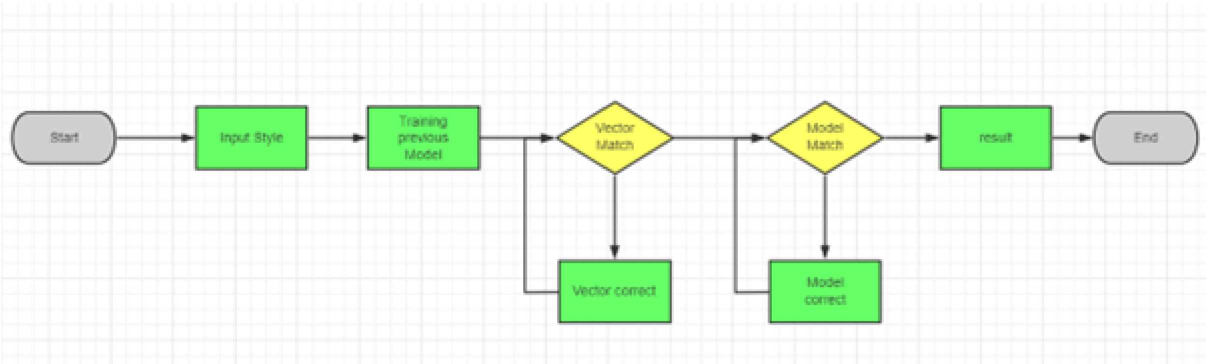

Figure 1. The event stream of GAN-ID to generate interior design intelligently

2.1. **Network Architecture.** In the proposed GAN-ID neural network, the basic neural network is GAN,which can be seen in Figure 2. It is obvious that GAN contains two models, one is a generative model and a discriminant model. Generative models is to generate instances that look natural and real, similar to the original data. Discriminant model is to judge whether a given instance appears to be naturally real or artificial. The process of judgment is similar to a zero-sum game. In layman's terms, it is similar to a businessman who makes counterfeit goods. In the process of being seen through by customers, the businessman is also constantly imitating the real product in the process of being noticed. Through repeated self-judgment and iteration. Finally, an idealized result that achieves a Nash equilibrium is generated, and it is expressed as in Equation 1.

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim P_{\text{data}(x)}}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))] \tag{1}$$

The network D is trained such that the labels of the training samples are assigned with maximum probability (maximize $\log(x)$ and $\log(1-D(G(z)))$), i.e., the loss of maximizing

D. In the training process, one party is fixed, the parameters of the other network are updated, and the other network is iterated alternately to maximize the error of the other party. Finally, G can estimate the distribution of the sample data, that is, the generated samples are more realistic. It directly understands that the loss of the G attempt to improve the general part of the calculation network $\log(1 - D(G(z)))$, and the loss of the D is $-\log(D(x)) + \log(1 - D(G(z)))$.

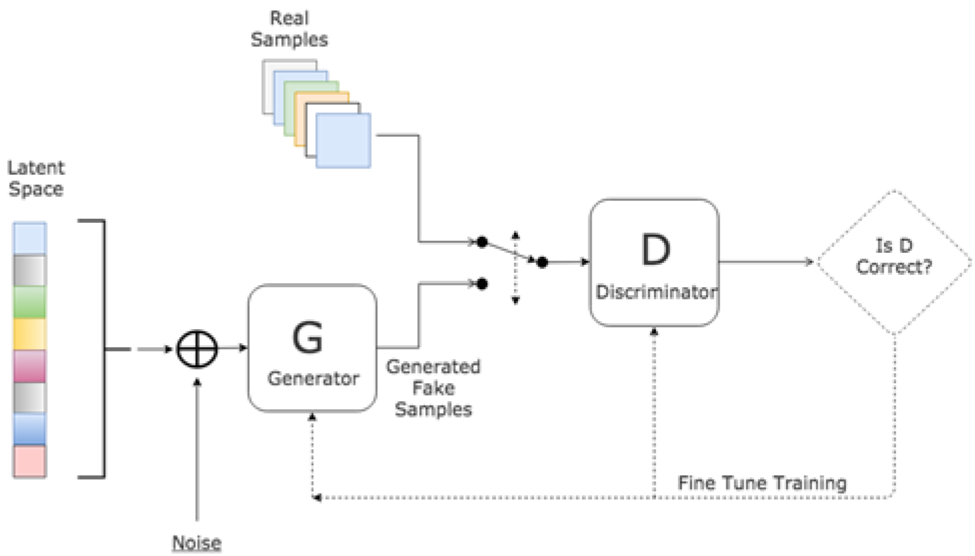

Figure 2. The architecture of the basic GAN

It is known that the training of the G network is to hope that $D(G(z))$ will be close to 1, that is, the positive class, so that the loss of G will be the smallest. The training of the D network is a 2-classification. The goal is to distinguish the real data and the generated data, that is, it is hoped that the D output of the real data is close to 1, and the output of the generated data, that is, $D(G(z))$, is close to 0 or the negative class. This is where the idea of confrontation is embodied. As the training continues, G also in turn affects the distribution of D due to the improvement of the G network. Assuming that the fixed G network does not move and train D, then the training is optimal, and it is expressed as Equation 2. Therefore, with $P_g(x)$ tend to $P_{\text{data}}(x)$, $D_g^*(x)$ will approach 0.5. The G network and the D network are in a Nash equilibrium state and cannot be further updated.

$$D_g^*(x) = \frac{P_{\text{data}}(x)}{P_{\text{data}}(x) + P_g(x)} \tag{2}$$

2.2. **Loss Function.** In our study, the model objective function was shown in Equation 3. The noise z and the condition y are fed into the generator, when the data x and the condition y are fed into the discriminator at the same time. GAN can be extended to conditional models if both the generator and the discriminator are conditioned on extra information y. And y can be any kind of auxiliary information, and performed conditioning when fed it to the discriminator and generator as an additional input layer. The result will be more directional.

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim P_{\text{data}}}[\log D(x \mid y)] + \mathbb{E}_{z\sim p(z)}[\log(1 - D(G(z \mid y)))] \tag{3}$$

The training in the original model relies too much on the randomness of the parameters, which may lead to unstable factors in the training process. It can make the running time more stable, and also greatly reduce the consumption of more useless computing resources.

In order to focus on the main direction of this experiment, our work has improved the input parameter part of the Equation 3. Inductively integrate its corresponding input condition $P_{\text{data}}(x)$ with the condition parameter y passed to the adversary G and the noise z. Unified form a parameter t with the same structure, and it is expressed as Equation 4. It is defined that t mainly contains three parts of information. Input the relative coordinate information of the furniture in the model, calculating the relative coordinate information of the furniture in the pre-model and estimate the deviation ϕ.

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim P_{\text{data}}(t)}[\log D(x \mid y)] + \mathbb{E}_{z\sim p(z)}[\log(1 - D(G(t)))] \tag{4}$$

In Equation 5, it is seen that estimating the deviation is automatically calculated when the parameters are formed. It is based on the difference sum of the relative displacements of the same type of items in the model, which is close to 0 as the standard. The magnitude of the absolute value of the bias estimator will adaptively adjust the magnitude of the random model in the process of adversarial learning to further increase the probability of effective learning. The expectation is to further save time in pre-model computation and comparison of training results.

$$\varphi = \mathbb{E}\left[\sum_{i=1}\left(t_{p(x,y,z)_i} - t_{m(x,y,z)_i}\right)\right] \tag{5}$$

2.3. **Materials and Data.** All materials are taken from the Unity Asset Store, and the materials and data source about this study in the experiment was from AssetDatabase, which is an API that allows users to access resources in the project. In addition, it provides methods for users to find and load resources, as well as create, delete, and modify resources. And the style of the objects themselves is not considered in this experiment. Just to explore the plausibility of relative positions and densities between items. In the actual application scene, we can directly replace the object in the corresponding position with the object of the same style, and it is expected to achieve good results. In Figure 3 and Figure 4, it is shown the cabinet material and the training data of our study.

Figure 3. The material of cabinet

In general, we divide indoor objects into: carpets, lamps, sofas, coffee tables, ornament tables, large cabinets, small cabinets, large potted plants, and small potted plants. These categories. In the dataset, we also manually label the corresponding objects for the initial batch of data models. Subsequent algorithms automatically label objects in subsequent datasets based on the identification of the initial batch of objects.

Figure 4. The training data

2.4. **Intelligent Scene Generated.** After the generation type determined, the "pre-model" of the corresponding style generated by the GAN confrontation generation network should be calculated firstly, and then an approximate imitation according to the arrangement of the objects in the "pre-model" should be performed. From which objects should exist, to which objects are placed where. It contains certain random parameters to ensure that the results will not be completely consistent with the "pre-model". Subsequent generated results are also saved as a separate data module to be added to the data source used to generate the "pre-model".

Next, use a dictionary to match enumerated objects with material prefabs one by one. According to the placement coordinates in space, use the prefab generation function to generate it. The conversion of coordinates should be paid attention to. It is necessary to convert the pre-calculated by GAN-ID, and it's 3-digit array coordinates into the three-dimensional vector coordinates of Vector3.

As shown in Figure 5, each prefab companied with a collider component, and it will check for position-based plausibility by going through all of the placed objects colliding with each other. For overlapping objects, it will be stored separately in a dictionary. Make it fit and calibrate the pre-model until no overlapping objects appeared.

3. **Results and Discussions.** The GAN-ID algorithms is developed based on the Unity platform, and the materials are selected from the Unity Asset Store. The training data comes from the indoor scene based on Unity provided by the network. Through repeated learning of a large amount of data, combined with reasonable algorithms, we can approximate the reasonable placement of furniture. In order to ensure that our vision is feasible, we have made a rigorous feasibility analysis of the entire project. The data comparison can be seen in Figure 6, it is obvious that our proposed GAN-ID based on AIoT has better performance than others, which is nearly 0.9. The entire scene will also perform

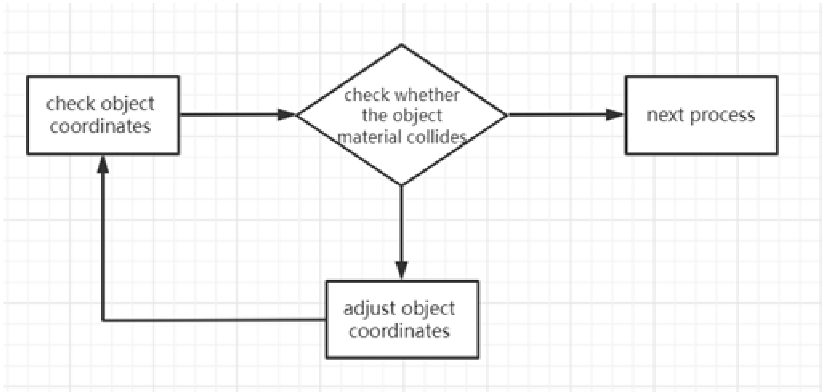

Figure 5. The flow chart of whether the material collide

model matching detection. We will judge the similarity between the generated scene and the model through the three dimensions of relative position, overall position, and regional distribution. Quantize the values of the three parts, and then adjust for the parts with a large difference. It is expected the population values approximated to a certain range. In Figure 7 and Figure 8, it shows the accuracy and the efficiency of the presented GAN-ID algorithms, which is 90% and 70%. Obviously,with the other three algorithms, the GAN-ID algorithm has a slightly obvious accuracy advantage. The most important thing is to have a very significant generation efficiency. It can be seen from the model matching rate that a very ideal approximation result has been achieved after 3 matches. If you pursue efficiency, you can choose to reduce the number of matches. If the matching rate is greater than 80, the effect will not have too obvious violation.

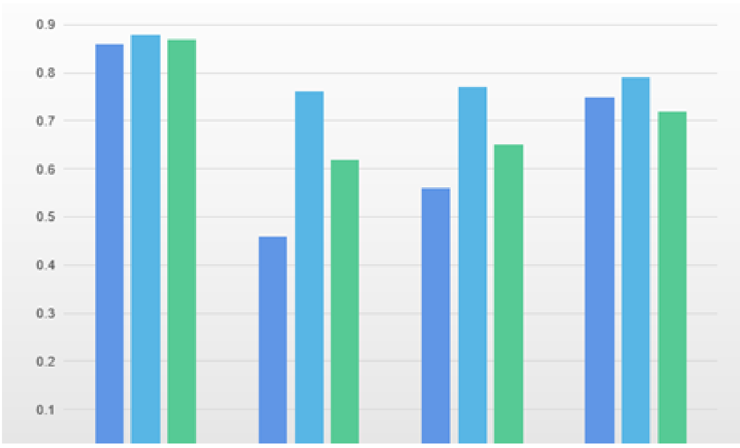

Figure 6. The data comparison

What's more, the input data as shown in Figure 9 and Figure 10, then the results of the GAN-ID can be seen in Figure 11.

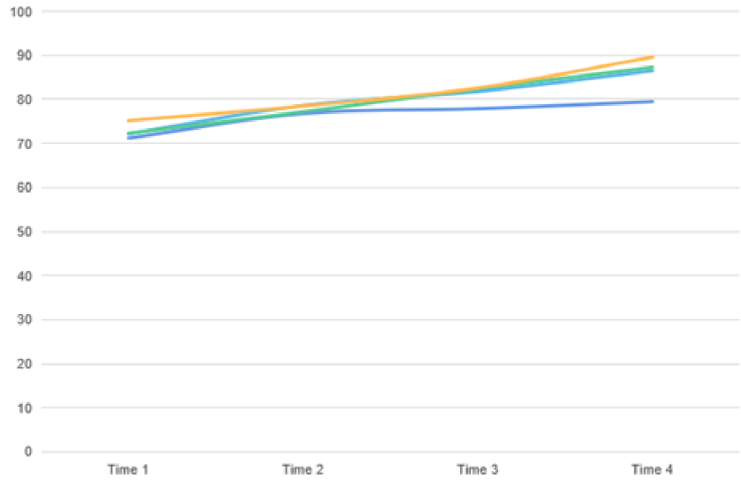

Figure 7. The accuracy comparison

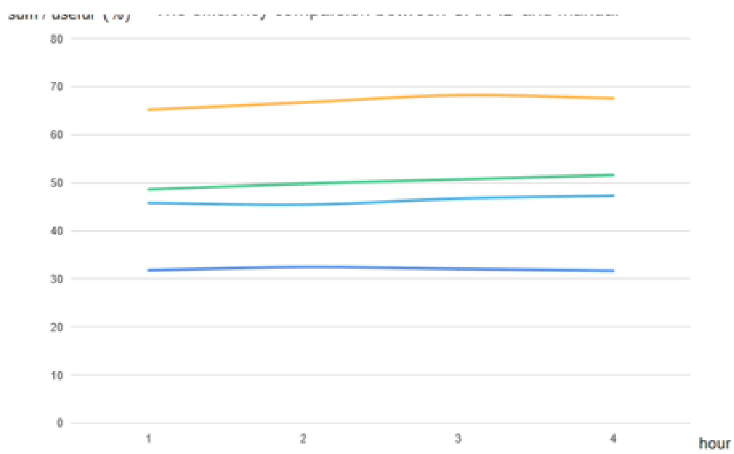

Figure 8. The efficiency comparison

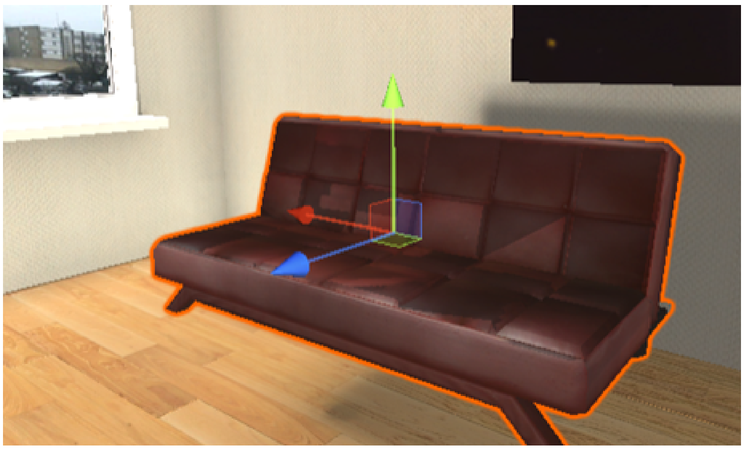

Figure 9. The input data

Figure 10. The input data

Figure 11. The generated results of the GAN-ID

4. **Conclusions.** To sum up, the presented GAN-ID algorithm based on AIoT proves to be a meaning work and can put into practice in smart homes and cities. And it is obvious that GAN-ID has great advantages in accuracy and efficiency in model sample generation than other common methods. But there are existing some challenges in GAN-ID to be addressed. The original generality of GAN algorithm can be limited by the normalized computing model, which requires a lot of tedious fine-tuning. In addition, it is limited to like unity3D environment when operating the intelligent interior design. So in the next stage of our study, it mainly focuses on the aboved problems and make improvements on the GAN-ID.

Acknowledgment. This research was funded by the Beijing Institute of Technology Project (Cancer Institute and Hospital, Chinese Academy of Medical, Project No. 201920741045); Digital Media Art, Key Laboratory of Sichuan Province (Sichuan Conservatory of Music, Project No. 21DMAKL01); the first batch of industry-university cooperation collaborative education project funded by the Ministry of Education of the People's Republic of China (Minjiang University, Project No. 202101071001); Minjiang University 2021 school-level scientific research project, (Minjiang University, Project No. MYK21011), the Open Fund Project of Fuzhou Technology Innovation Center of Intelligent Manufacturing Information System (Minjiang University, Grant No. MJUKF-FTICIMIS2022), the Open

Fund Project of Engineering Research Center for ICH Digitalization and Multi-source Information Fusion (Fujian Polytechnic Normal University, Grant No. G3-KF2204); and the Guiding Project of Fujian Province (Minjiang University, Project No. 2020H0046).

REFERENCES

[1] T.-Y. Wu et al., "Towards smart home authentication using PUF and edge computing paradigm," *Sensors*, vol. 22, no. 23, 9174, 2022.

[2] Q. Lin et al., "Smart system: Joint utility and frequency for pattern classification," *ACM Transactions on Management Information Systems*, vol. 13, no. 4, pp. 1-24, 2022.

[3] T.-Y. Wu et al., "A provably secure lightweight authentication protocol in mobile edge computing environments," *The Journal of Supercomputing*, vol. 78, no. 1, pp. 1–22, 2022.

[4] S. Liu and C.-M. Chen, "Comments on A Secure and Lightweight Drones-Access Protocol for Smart City Surveillance," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 12, pp. 25054-25058, 2022.

[5] P. Ping et al., "Smart street litter detection and classification based on Faster R-CNN and edge computing," *International Journal of Software Engineering and Knowledge Engineering*, vol. 30, no. 4, pp. 537-553, 2020.

[6] A.-C. de Araujo and A. Etemad, "End-to-end prediction of parcel delivery time with deep learning for smart-city applications," *Institute of Electrical and Electronics Engineers (IEEE)*, vol. 8, no. 23, pp. 17043-17056, 2021.

[7] J. Balicki, H. Balicka, and P. Dryja, "Big data from sensor network via internet of things to edge deep learning for smart city," in *Computer Information Systems and Industrial Management*, 20th International Conference. CISIM, 2021, pp. 357-368.

[8] A. Zahra et al., "Application of region-based video surveillance in smart cities using deep learning," *Multimedia Tools and Applications*, 2021. [Online]. Available: https://doi.org/10.1007/s11042-021-11468-w

[9] A. Natani, A. Sharma, and T. Perumal, "Sequential neural networks for multi-resident activity recognition in ambient sensing smart homes," *Applied Intelligence*, vol. 51, no. 8, pp. 6014-6028, 2021.

[10] K. Avazov et al., "Fire detection method in smart city environments using a deep-learning-based approach," *Electronics*, vol. 11, no. 1, 73, 2022.

[11] S. Panja, K. Yadav, and A. Nag, "Anomaly detection at the IoT edge in IoT-based smart home environment using deep learning," in *Proceedings of International Conference on Advanced Computing Applications*. Advances in Intelligent Systems and Computing. Springer, 2022, pp. 119-125.

[12] O. Ibitoye, A. Matrawy, and M.-O. Shafiq. "A gan-based approach for mitigating inference attacks in smart home environment," *ArXiv*, 2020. [Online]. Available: https://doi.org/10.48550/arXiv.2011.06725

[13] Z. Du et al., "3D building fabrication with geometry and texture coordination via hybrid GAN," *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 1, pp. 5177-5188, 2022.

[14] M.-R. Shahid et al., "Generative Deep Learning for Internet of Things Network Traffic Generation," in *2020 IEEE 25th Pacific Rim International Symposium on Dependable Computing (PRDC)*. IEEE, 2020, pp. 70-79.

[15] C.-Y. Lee, J.-G. Shon, and J.S. Park, "An edge detection–based eGAN model for connectivity in ambient intelligence environments," *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 10, pp. 4591-4600, 2022.

[16] E. Soleimani and E.Nazerfard, "Cross-subject transfer learning in human activity recognition systems using generative adversarial networks," *Neurocomputing*, vol. 426, no. 3, pp. 26-34, 2021.