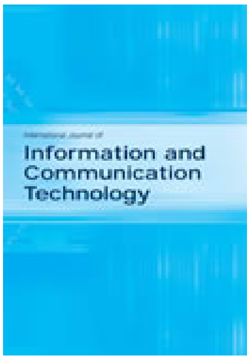
INDERSCIENCE PUBLISHERS
Linking academia, business and industry through research



International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

Intelligent optimisation of traditional village element layout using generative adversarial networks

Bin Yu, Ying Yang, Xie Liu

DOI: 10.1504/IJICT.2025.10072530

Article History:

Received:	02 June 2025
Last revised:	16 June 2025
Accepted:	16 June 2025
Published online:	30 July 2025

Intelligent optimisation of traditional village element layout using generative adversarial networks

Bin Yu

College of Landscape Architecture,
Central South University of Forestry and Technology,
Changsha 410004, China
and
College of Tourism and Urban-Rural Planning,
Xichang University,
Xichang 615013, China
Email: henry8554@163.com

Ying Yang*

China Construction Fifth Engineering Division Corporation Limited,
Changsha 410001, China
Email: auricyy@163.com
*Corresponding author

Xie Liu

College of Tourism and Urban-Rural Planning,
Xichang University,
Xichang 615013, China
and
Faculty of Design and Architecture,
University Putra Malaysia,
Selangor 43400, Malaysia
Email: gs62057@student.upm.edu.my

Abstract: The conservation and optimisation of traditional villages has progressively been a major focus for intelligent applications with the fast development of artificial intelligence and information technology. Combining spatial multi-dimensional constraints to intelligibly optimise the layout of traditional villages through the adversarial training of generators and discriminators, this paper proposes a traditional village element layout optimisation method GAN-PLS based on generative adversarial network (GAN) model. Introduced into the GAN-PLS model, the gradient penalty technique helps to increase the stability of the training process and optimisation effect. Particularly outperforming conventional optimisation techniques in terms of convergence speed, generation effect and stability, the GAN-PLS model shows good performance in spatial layout optimisation, cultural element retention and ecological conservation by means of comparison studies. At last, this work addresses the shortcomings of the model and suggests future directions like dataset expansion, computational efficiency enhancement, and multi-dimensional constraints addition.

Keywords: generative adversarial network; GAN; intelligent optimisation of layout; traditional village; gradient penalty.

Reference to this paper should be made as follows: Yu, B., Yang, Y. and Liu, X. (2025) 'Intelligent optimisation of traditional village element layout using generative adversarial networks', *Int. J. Information and Communication Technology*, Vol. 26, No. 30, pp.60–80.

Biographical notes: Bin Yu received his Master's degree from the Fujian Agriculture and Forestry University in June 2013. He is currently pursuing his PhD at the Central South University of Forestry and Technology. Currently, he works as a Lecturer at the Xichang University. His research interests include landscape architecture planning and generative adversarial networks.

Ying Yang received his PhD from the Chongqing University in 2004. He is currently a Senior Engineer at the research level of the China Construction Fifth Engineering Bureau Co., Ltd. His research interests include architecture and landscape planning.

Xie Liu received her Master's degree from the China Agricultural University in 2013. She is currently pursuing her PhD at the Putra University in Malaysia. She is currently a Lecturer at the Xichang University, and her research interests include nature education, rural design and deep learning.

1 Introduction

1.1 Background of study

Generative adversarial network (GAN), as a novel machine learning model, has progressively drawn great interest in academia and business as information technology, especially the broad application of deep learning and artificial intelligence technology, develops rapidly. By building the adversarial process between the generator and the discriminator, GAN can efficiently create realistic images, text, audio and other kinds of data (Dash et al., 2023). It has been applied in the domains of image generation, image restoration, data enhancement and other spheres. But the possibilities of GANs extend much beyond this; their use in spatial design and planning particularly in the optimisation of traditional villages has not yet been properly investigated.

Traditional villages have a special spatial layout and cultural significance since they are a significant type of human residence bearing historical legacy and local features. But as modernism accelerates, traditional communities are experiencing a few issues including population decline, resource depletion and slow removal of traditional characteristics (Li et al., 2023). Thus, given the preservation of the core of traditional culture, how best to maximise the spatial layout and resource allocation of villages using modern technologies. Conventional approaches of layout optimisation can depend on empirical design or rule-based algorithms, which lack flexibility and intelligence and are challenging to reach exact optimisation objectives.

GAN's great generative capacity has been progressively used in many design and planning disciplines in recent years, particularly in architectural design and urban planning and which offers special benefits. The intelligent optimisation strategy of GAN allows a layout plan that satisfies the features of traditional villages to be automatically produced based on historical data, spatial layout needs and cultural elements, so ensuring accurate spatial optimisation and resource allocation. Consequently, the intelligent optimisation of the layout of conventional village elements depending on GAN has become a subject of tremendous research relevance and practical promise.

1.2 Significance of study

This work provides an intelligent optimisation model based on GAN, i.e., GAN-PLS, and investigates the application of GAN in the optimising of the layout of traditional village components. The study has theoretical and pragmatic importance as follows:

1 Promote the application of GAN in spatial layout optimisation: Though GAN has been extensively applied in domains including picture production, studies on spatial layout optimisation of traditional villages are still in their early years. GAN-PLS not only stretches the possibilities of the application of GAN but also offers a creative answer for the field of spatial design by merging GAN with village plan optimisation (Alam, 2024).

2 Promote the cultural protection and inheritance of traditional villages: Apart from their rich historical legacy and geographical features, traditional communities also show the particular social structure and way of life. Modern spatial optimisation can be accomplished while preserving the core of traditional culture by means of intelligent optimisation of GAN-PLS, therefore enabling the inheritance and development of traditional villages.

3 Enhance the efficiency and accuracy of layout optimisation: Usually depending on manual experience or regular algorithms, the layout optimisation of traditional villages is less efficient and lacks personalism. Learning historical data and spatial requirements helps GAN-PLS to automatically create optimal layout solutions that satisfy traditional cultural traits, so considerably improving the accuracy and efficiency of optimisation and satisfying the needs of every village.

4 Promote the construction of smart villages and sustainable development: Given the idea of smart cities and sustainable development, smart optimisation of classic villages is especially crucial. In terms of resource allocation, ecological environment and cultural protection, GAN-PLS presents fresh solution routes for the sustainable development of rural regions and a data-driven spatial optimisation means for the building of smart villages.

In general, the application of GAN-PLS in the layout optimisation of traditional village elements not only promotes the development of GAN technology but also offers creative solutions for cultural heritage protection and village space optimisation, which has significant academic value and practical relevance.

1.3 Methodology of study

This work presents GAN-based layout optimisation model for conventional village components, GAN-PLS. Three main phases define the research approach: data collecting and pre-processing; model building and training; layout optimisation strategy design.

First, the study created a multi-dimensional dataset by compiling information on geographic location, architectural layout and historical background together with data on the spatial arrangement and cultural features of traditional communities. To give correct data support for model training, all data were preprocessed to guarantee consistent format and noise elimination.

The generator and the discriminator make up the two components of the GAN-PLS model then. Based on historical layout data, the generator creates a spatial layout scheme that satisfies the optimisation goal; the discriminator assesses whether the produced layout conforms to the cultural traits and spatial rationality. Adversarial training lets the generator, and the discriminator iterate with one other to always maximise the layout generating impact (Karras et al., 2020).

Finally, a set of spatial layout optimisation techniques is meant to guarantee that the produced layouts satisfy contemporary spatial challenges and satisfy conventional cultural needs. These techniques involve imposing physical and cultural limitations to guarantee that the produced layouts maintain conventional village features and improve the quality of life. Including a feedback system helps designers to adjust the produced outcomes to maximise the layout plan.

2 Generative adversarial networks

Comprising two neural networks, GAN is a novel deep learning paradigm whereby the two networks interact adversally during training to reach optimisation. GAN's design concept is that the generator is progressively made capable of producing pseudo-data quite similar to the distribution of the real data while the discriminator tries to differentiate between the generated data and the real data by means of adversarial training between the generator and the discriminator.

GAN's basic mechanism is a zero-sum game, in which the generator and the discriminator are rivals in the training process driving one another forward (Mohebbi Moghaddam et al., 2023). With the intention of fooling the discriminator such that the created data cannot be distinguished from the real data, the generator seeks to constantly maximise the produced false data to make it closer and closer to the distribution of the genuine data. Conversely, the discriminator aims to raise its capacity to differentiate produced data from actual data to appropriately identify which of the created data are real and which are phony ones produced by the generator. Whereas the discriminator keeps raising its discriminating accuracy, the game between the two makes the generator keep producing more real data. Eventually, after training, the generator and the discriminator find a state of equilibrium whereby the produced data nearly matches the real data.

Usually, a GAN's training method consists in optimising the generator and the discriminator's loss functions. The objectives of the discriminator are to increase its capacity to identify actual data and reduce the chance of misclassification of the produced data; so, the loss functions of the generator and the discriminator are connected. One may write the discriminator's loss function as:

$$L_D = -\mathbb{E}_{x \sim p_{data}(x)}\left[\log D(x)\right] - \mathbb{E}_{z \sim p_z(z)}\left[\log\left(1 - D\left(G(z)\right)\right)\right] \tag{1}$$

where $G(z)$ is the fake data created by the generator by inputting the noise z; $D(x)$ is the outcome of the discriminator's judgement that the input data x is real data; x denotes a sample taken from the real data distribution p_{data}, z denotes a random vector sampled from the noise distribution p_z. The discriminator keeps becoming better in discriminating between genuine and produced data by means of optimisation of its loss function (Tian et al., 2022).

Conversely, the generator aims to maximise the probability of misjudging the produced data by producing data as realistic as feasible, hence guiding the discriminator to believe that the produced data is real. The generator's loss function is:

$$L_G = \mathbb{E}_{z \sim p_z(z)} \left[\log D\left(G(z)\right) \right] \tag{2}$$

where $D(G(z))$ is the outcome of the discriminator's evaluation on the generated fake data $G(z)$ by the generator. Maximising this loss function helps the generator to produce phony data as near to the distribution of the genuine data, therefore misleading the discriminator. By alternately changing the parameters of both the generator and the discriminator, the two-way game that is their optimisation process finally results in a Nash equilibrium condition (Ma et al., 2022).

The generator and the discriminator change their parameters correspondingly using the back-propagation technique during the training period. While the discriminator continuously improves its judgement ability by minimising the loss function, the generator progressively changes its parameters to generate more and more realistic fake data. By encouraging the cooperative development of the generator and the discriminator, adversarial training helps the generator to progressively learn the possible distribution of real data and create high-quality fake data without clearly identifying the data.

GAN has the benefit in not requiring conventional supervised learning of labels; the generator can automatically learn the fundamental data structure just by training against the discriminator. GANs therefore can produce unexpected outcomes in many fields, particularly in tasks including picture generating, image restoration, style migration, etc. (Gan et al., 2024). The success of GANs also offers fresh concepts for unsupervised learning, particularly in the lack of labelled data, where GANs are nevertheless able to self-optimise via the adversarial process, producing quite strong data generating results.

Nevertheless, the GAN training process has certain difficulties as well, particularly in the unstable training process and the game between the generator and the discriminator may cause one of the models to be too strong for the other model to learn effectively, so hindering the convergence of the training. Researchers have suggested several better approaches to address these issues, including Wasserstein generative adversarial network (WGAN) and deep convolutional generative adversarial network (DCGAN), which by changing the loss function or adding new network architectures enhance the training stability and generative impact of GANs (Man et al., 2022).

All things considered, GAN's achievement has not only altered the field of generative modelling but also given strong instruments for addressing useful challenges. From image generation to speech synthesis, text generation, to cross-modal data production and other domains, GAN shows significant promise and possibilities as GAN technology develops constantly. Many new GAN variations have been presented, and the application scenarios have been increased.

3 Layout of traditional village elements

3.1 Spatial layout characteristics of traditional villages

The interaction of the geographical, cultural, social, and environmental surroundings shapes the spatial arrangement of traditional communities. Because of their distinct geography and temperature, villages all around exhibit different layouts. Whereas southern villages are typically open, with timber buildings, emphasising air and light, northern communities are mostly enclosed, with brick buildings, suited to the cold. The way the community is laid not only captures the features of the nearby natural surroundings but also the distinctiveness of the regional culture.

The social structure and culture are strongly reflected in the design of traditional villages (Chen et al., 2020). Many communities have a rigid clan or family system, with the arrangement of homes and courtyards based on blood ties or social status, therefore representing kinship unity and social order. With the orientation of buildings and the arrangement of courtyards following ideas to guarantee comfortable and safe living, some villages also have a tight relationship with the idea of feng shui. One of the main features of traditional communities is this cultural one.

The functional zoning of the village is somewhat flexible while its spatial division is based on the demands of life and the logical utilisation of natural resources. Usually, the most significant street or plaza in the town, the central axis, links public activity areas including markets and temples with residential sections, therefore enclosing the hamlet. Integrated with one another, agricultural, home, and public activity venues show the harmonic cohabitation of man and nature, and man and man. This practical design shows how well resources are used and how carefully traditional villages arrange their daily life.

Traditional village layouts also consider the cooperation of the surroundings and ecology. Many towns exploit their local natural resources to reach self-sufficiency by means of sensible layout and spatial planning. The efficient management of water resources is reflected in the design of water conservancy facilities including wells and ditches; likewise, the design of green areas, courtyards, and agricultural fields in villages not only satisfies the demands of local production and life but also advances ecological balance and sustainable development. This ecological design offers great ecological understanding and shows the adaptability and sustainability of classic settlements. Traditional villages' spatial arrangement is a complete mirror of history, culture, and society and deserves preservation and study during the modernising process.

3.2 Review of intelligent optimisation of traditional village element layout

Concerning space use, resource allocation, and environmental protection among other things, traditional village layouts present difficulties. More and more algorithms have been used in this field attempting to increase the efficiency, usefulness and sustainability of conventional village layout with the fast development of intelligent optimisation technology. Using these algorithms not only enhances the conventional layout strategies but also offers creative solutions for the challenges experienced by conventional communities during the modernising process. Several typical intelligent methods in conventional village layout optimisation are reviewed here together with their application effects, advantages and drawbacks.

Widely applied in traditional village design, particularly in the issues of space usage and resource allocation, genetic algorithm (GA) is an optimising tool based on biological evolution mechanism. GA is widely employed in the optimisation of functional areas including construction sites, road networks and public spaces in conventional village planning. For instance, the use of GA helps to optimise village road networks so enhancing road access efficiency and lowering traffic congestion issues (Dikshit et al., 2023). GA suffers from sluggish convergence, nevertheless, particularly in challenging, multi-constraint layout problems that could call for significant processing time.

Appropriate for handling path optimisation problems, ant colony algorithm (ACO) is an optimisation method that models the foraging activity of ants. ACO is typically employed in conventional village layouts for issues of resource allocation and transportation network design. Typical traditional village layouts are complicated and erratic, thus ACO can maximise the road design by means of local search to minimise space waste and traffic congestion and enhance traffic flow (Boubedra et al., 2023). ACO has the drawback, too, in that it is possible to fall into optimal local solutions, particularly in relation to large-scale complicated problems, which could produce undesirable optimising outcomes.

By simulating the activity of a flock of birds feeding or a school of fish swimming, particle swarm optimisation (PSO) searches for the best solution via group cooperation and local search. When addressing the spatial layout of traditional villages, PSO may efficiently maximise the building spacing, the layout of the public area, and change the density and shape of the road network, so enhancing the spatial utilisation rate and the quality of life of the residents (Tang et al., 2018). PSO does, nonetheless, also have certain restrictions. PSO is prone to slip into local optimal solutions when confronted with very complicated and nonlinear layout issues, particularly in cases when the search space of the problem is somewhat big and the search path of the particles may not be able to completely cover the whole optimisation space.

By progressively lowering the temperature, simulated annealing (SA) replics the physical annealing process to identify the best global solution (Liu et al., 2022). In conventional village design, SA is mostly applied in the optimisation of public space distribution, building layout, etc. SA's global search capacity is its advantage since it allows one to leap out of the local optimal solution and identify a layout scheme nearer the global optimal solution. SA's convergence speed is slow, nevertheless, particularly in cases of large-scale optimisation challenges that can call for more computing time. Furthermore, SA is more sensitive to the choice of the starting solution, hence the outcome of final optimisation could change.

Deep learning and neural network methods have progressively taken front stage in conventional village design in recent years. Particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, deep learning models may provide effective layout solutions and discover intricate patterns from large-scale data (Alzubaidi et al., 2021). CNNs can be used, for instance, to extract spatial elements of villages from satellite photos, and LSTMs can be used to examine the dynamic activity patterns of the residents and so optimise the building and traffic flow path distribution inside communities. Deep learning algorithms' strength resides in their capacity to solve large-scale, challenging nonlinear problems and yield quite accurate optimisation outcomes. Deep learning approaches have certain difficulties, though. First, deep learning models typically depend on strong computational resources, and the training process is long and complicated, which may restrict their application in the optimisation of traditional village layouts. Besides, these models depend mostly on a great volume of high-quality training data, which is often lacking or of poor quality related to traditional villages.

Emerging as a deep learning model, GAN has lately been used in the optimisation of conventional village design. GAN may optimise the site of buildings, the direction of roads, the distribution of public space, etc.; it can also replicate the layout of ancient villages in many historical periods and cultural settings. GAN has the benefit in that it can automatically create a layout design satisfying the requirements free from human involvement. Particularly in terms of preservation of local culture and historical inheritance, GAN can offer imaginative and culturally significant village layouts.

All things considered, the optimisation issue of conventional village design has grown to be a major focus for investigation of intelligent optimisation methods. While new algorithms, including deep learning, have showed great promise in creative layout and data-driven optimisation, conventional optimisation techniques, such GA, ACO, PSO, SA, etc., have achieved spectacular outcomes in spatial planning and resource allocation.

3.3 The need for optimisation in the layout of traditional villages

The spatial use, natural environment, cultural legacy, and infrastructure of traditional villages suffer several difficulties as modernism advances. While traditional villages have great historical and cultural significance, how to reach their sensible optimisation in the framework of modernisation has become a pressing problem. While satisfying the needs of modern society for the protection and development of traditional culture, intelligent optimisation not only increases the efficiency of space utilisation but also improves the living environment and boosts ecological sustainability.

Low space use efficiency and scattered building designs of traditional villages make it challenging to adjust with population increase and functional needs. Concurrently with these developments in the external environment and human activities, the ecological environment has suffered damage; issues including water resource scarcity and vegetation degradation have grown ever more important. By means of data analysis and model prediction, intelligent optimisation may rationally modify the building plan and increase land use efficiency; use IoT and artificial intelligence technologies to monitor environmental data in real time, optimise and repair the ecosystem and guarantee ecological sustainability (Miller et al., 2025).

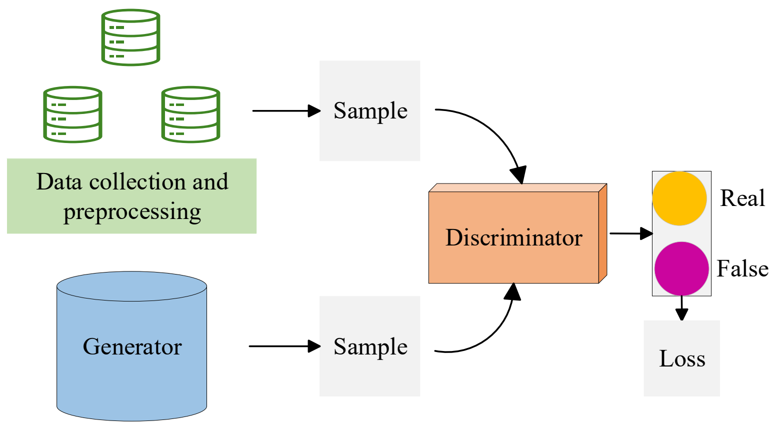
Another difficult task for traditional communities is striking the equilibrium between functional requirements and cultural legacy. Many communities have seen a slow erosion of cultural traits as modern lifestyles become more prevalent. By means of artificial intelligence algorithms and massive data analysis, intelligent optimisation can forecast resident demands and create spatial layout solutions that satisfy contemporary life while conserving traditional culture. Furthermore, unable to satisfy modern society's needs are the infrastructure and traffic of old settlements. By use of traffic flow analysis and intelligent resource management systems, intelligent optimisation can maximise the road network and infrastructure, so improving the general operational efficiency of villages.

All things considered, traditional communities desperately need clever optimisation technology to undergo change. Intelligent optimisation can offer creative ideas to help traditional villages to increase the efficiency of space use, improve the ecological environment, protect the cultural legacy, and optimise the traffic and infrastructure in the process of modernisation, to achieve sustainable development.

4 Intelligent optimisation model based on GANs

This work presents GAN-based layout optimisation model for conventional village components, GAN-PLS. See Figure 1 for three main steps: data collecting and pre-processing, model creation and training, and layout optimisation strategy design; the model performs intelligent optimisation of traditional village layout.

Figure 1 GAN-PLS model architecture (see online version for colours)



4.1 Data collection and pre-processing

Data collecting and pre-processing form the foundation for effective training and model optimisation prior to the GAN-PLS model construction. Traditional village layouts and associated cultural element data contain complicated multidimensional qualities spanning geography, architecture, history, culture and other elements. Thus, the main steps to reach layout optimisation are correct pre-processing of the data and precise and thorough collecting of pertinent data.

Common issues in the gathered raw data are inconsistent format, missing numbers, and noise interference. Comprehensive preparation of the data is necessary to raise the quality of the data and the efficacy of the training paradigm. Data pre-processing includes actions in data format standardisation, data cleansing, feature extraction and selection, as well as data normalisation and standardisation. First, all the geographic information, building layout data, and cultural aspects data need to be standardised if we are to unite the form of the heterogeneous data from several sources. Z-score normalisation approach with the following formula handles data normalisation:

$$X_{norm} = \frac{X - \mu}{\sigma} \tag{3}$$

where X is the original data; X_{norm} is the normalised data; μ and σ are respectively the mean and standard deviation of the data.

K-nearest neighbours (KNN) algorithm fills in missing values during data cleaning (Lee and Styczynski, 2018). By means of similar data points and mean values of adjacent points, KNN algorithm fills in the missing data. The computation is:

$$X_{filled} = \frac{1}{K}\sum_{i=1}^{K} X_{neighbour,i} \tag{4}$$

where X_{filled} is the filled data; $X_{neighbour,i}$ is the i^{th} eigenvalue of the K surrounding points; K is the number of chosen neighbours.

Important further phases in data preparation are feature extraction and selection. By means of key feature extraction from a vast volume of raw data, the study concentrates on extracting geographic features (topographic slope, land use type, etc.), architectural features (building height, distance between buildings, etc.), and cultural features (location of historical sites, areas of folklore activities, etc.). Training of the GAN-PLS model will use these characteristics as input data. All data must also be normalised and normalised if we are to increase the training effect; this model employs the min-max normalisation approach with the formula:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{5}$$

where $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of the features in the dataset correspondingly, X_{norm} is the normalised data.

By means of these data pretreatment techniques, the study guaranteed a high-quality, homogeneous, uniformly formatted and information-rich dataset for the GAN-PLS model. This lays a strong basis for later model development and conventional village planning enhancement. The improved data can improve the effect of layout optimisation and help the generator to thoroughly examine the geographical features and cultural connotations in layout production.

4.2 Model construction

The GAN-PLS model is built with the design of the generator and discriminator of the GAN, the definition of the optimisation objective and the adversarial training of the two. By means of adversarial training between the generator and the discriminator, the model is able to attain the optimisation of the spatial layout of conventional villages and develop a traditional village layout plan that satisfies the optimisation target.

The key component of the GAN-PLS model is the generator, whose job is to create a conventional village layout plan satisfying the optimisation goal depending on the input historical layout data and cultural element data. Multi-dimensional data including architectural layout data, geography information, cultural element data, etc. forms the generator's inputs. By means of deep neural networks, the generator creates a layout satisfying both spatial and cultural needs. To reach this aim, the generator uses a structure combining CNN and LSTM. While LSTM can capture the time-series links in the layout data, which is especially appropriate for characterising the laws of traditional village layout evolution over time (Yang et al., 2019), CNN can efficiently extract local features in spatial layouts. Usually shown as a hypothetical layout scheme, the generator produces:

$$G(z; \theta_G) = \hat{X} \tag{6}$$

where the generator is G; the input potential vector or noise is z; the generator's parameter is θ_G; the produced layout scheme is $\hat{X}$. The generator's output has to satisfy ecological preservation, cultural legacy, and spatial rationality standards.

The discriminator's job is to assess if the produced layout scheme follows actual traditional village layout statistics. Its purpose is to evaluate the produced layout against the actual layout and provide input to the generator via the discriminator therefore fostering its optimisation. The discriminator evaluates the environmental and cultural adaptation as well as the spatial rationality of the design. Using multi-layer convolutional processes, the discriminator gathers features from layout images using a deep convolutional neural network (DCNN) architecture, therefore judging the legitimacy of the layout scheme (Dargan et al., 2020). Apart from depending just on spatial characteristics, the discriminator examines the retention of cultural aspects holistically. For instance, whether the design can mirror architectural components in ancient towns, cultural activity venues and historical relics. One may represent the discriminator's output as:

$$D(\hat{X}; \theta_D) = p(\hat{X}) \tag{7}$$

where D is the discriminator; $\hat{X}$ is the produced layout; θ_D is the discriminator's parameter; $p(\hat{X})$ is the authenticity probability of the layout scheme, thereby indicating if the layout adheres to the features of the authentic layout.

The GAN-PLS model's goal is to create a conventional village plan that fits both cultural features and spatial rationality. Several optimisation loss functions are created to reach this aim covering the features of spatial rationality of layout, retention of cultural elements and protection of the environment. The spatial rationality loss function is used to measure the location of buildings, the smoothness of the road network, and the effective use of public space in the generated layout; the cultural heritage loss function is used to measure the degree of retention of elements such as historical sites, cultural activity areas, and traditional buildings in the layout; and the ecological environment loss function focuses on the environmental impacts of the generated layout, such as the green space area and the density of the buildings, etc. Comprising the elements of the optimisation function, the final total optimisation loss function defines.

The weighted sum of every component of the final total loss function defines it; the expression is:

$$L = \lambda_1 L_{space} + \lambda_2 L_{culture} + \lambda_3 L_{ecology} \tag{8}$$

where L_{space} is the loss of spatial reason; $L_{culture}$ is the loss of cultural legacy; $L_{ecology}$ is the loss of protection of the ecology; λ_1, λ_2 and λ_3 are the weights of each loss function.

The generator and discriminator are continuously changed in the training process using this loss function formulation to get intelligent traditional village plan design (Yuanliang and Zhe, 2024).

4.3 Training and layout optimisation strategies

The training program mainly uses generative confrontation training, in which the generator and discriminator are updated to maximise the layout. This method uses a gradient penalty technique to stabilise the training process therefore avoiding issues including pattern collapse and gradient vanishing. By limiting the discriminator's gradient, the gradient penalty helps to prevent instability in the training process so guarantee that the output of the discriminator stays smooth throughout the sample space (Lei et al., 2024).

By penalising the gradient deviation between the generated samples and the discriminator, the gradient penalty guarantees that the gradient of the discriminator stays smooth over the data distribution. The gradient penalty term LGP is computed especially as follows:

$$L_{GP} = \mathbb{E}_{\hat{x}\sim P_{\hat{x}}}\left[\left(\left\|\nabla_{\hat{x}} D(\hat{x})\right\|_2 - 1\right)^2\right] \tag{9}$$

where $\nabla_{\hat{x}} D(\hat{x})$ is the gradient of the discriminator over this sample; $||\cdot||^2$ signifies the two-parameter number; $\mathbb{E}_{\hat{x}\sim P_{\hat{x}}}$ is the expectation over all interpolated samples; $\hat{x}$ is the sample acquired by means of interpolation between the real and produced data distributions. This loss function guarantees that the discriminator's gradient keeps near to 1 over the data space, therefore enabling stable generator and discriminator training.

Combining the gradient penalty term with the adversarial loss of the generator and discriminator will help to maximise the final loss function. Using weighted summation, the resultant loss function is:

$$L_{final} = \lambda_1 L_{space\text{-}culture\text{-}ecology} \tag{10}$$

Among them, $L_{space\text{-}culture\text{-}ecology}$ is a loss function that combines spatial rationality, cultural legacy and ecological protection, λ_1 and λ_2 are the weights of each part of the loss function respectively, which are used to balance the influence of spatial, cultural and ecological factor with gradient penalty.

While the discriminator can more precisely evaluate the rationality and authenticity of the layout, the generator is able to create a more optimal traditional village layout in every round of training by means of this loss function optimisation.

First, the design of the generator considers the integration of modernism needs, so enabling the generated traditional village layout to not only preserve the traditional cultural qualities but also fit the demands of modern life. First, the road system in the layout adopts modern traffic demand prediction methods in order to optimise the road planning of the traditional village, so resulting in a smoother traffic flow and a high degree of access efficiency; second, the building distribution and green space design take into account the principle of ecological protection, so avoiding over-development and increasing the area of green space, so enhancing the eco-friendliness of the village. Furthermore, given particular attention is the protection of historical sites to guarantee the efficient preservation of the cultural legacy and that some pragmatic issues in the framework of modernism are resolved by means of the rational spatial distribution (Wen et al., 2023).

Strategic design of the optimisation process guarantees that the conventional village plan is balanced between spatial rationality, cultural legacy and ecological preservation.

By means of a feedback mechanism, the designers can fine-tune the produced layout scheme, enabling multiple iterations to progressively maximise the layout results in multiple iterations, so ensuring that the generated layout meets the spatial requirements, but also effectively transmits the culture and protects the environmental surroundings to the maximum extent.

By using these intelligent optimisation procedures, the final model is able to provide a conventional village layout that satisfies spatial rationality, cultural legacy, and ecological protection, thereby offering an intelligent optimisation tool for the protection and planning of traditional communities. Apart from enhancing the design efficiency of conventional village layout, this intelligent optimisation model offers technical support and creative ideas for the sustainable development of communities.

5 Experiments and analysis of results

5.1 Experimental data

The fundamental data source for the traditional village layout optimisation model in this work is OpenStreetMap (OSM) dataset. Globally open-source geographic information system (GIS) OSM provides a broad spectrum of geographic aspects in cities and towns, including road networks, building distribution, natural landscapes, cultural heritage locations, transportation facilities, etc. With great degree of openness and global coverage, OSM data are extensively applied in GISs, urban planning, navigation systems, etc.

In this work, the geographical data supplied by OSM will be utilised for intelligent optimisation of conventional village plans by aggregating the cultural and ecological aspects of conventional villages. Table 1 compiles the fundamental details of the OSM dataset applied in this work.

Table 1 OSM dataset

Dataset name	*OpenStreetMap (OSM)*
Data type	Geographic dataset, including roads, buildings, green spaces, landmarks and natural landscapes
Data source	User-contributed, open data platform
Coverage	Global (with the option to extract data from specific regions)
Data format	XML (.osm), PBF (.osm.pbf), GeoJSON, Shapefile, etc.
Tools used	Overpass API, OSM website, Geofabrik, etc.
Update frequency	Continuous updates (data is updated in real time based on user contributions)
Application areas	GIS, urban planning, transportation management, environmental analysis, etc.

This work will extract spatial layout information of traditional communities using an OSM dataset. More especially, we will concentrate on applying the following statistics: road layout, including main streets, alleys, trails, etc., to provide data support for optimising the traffic flow in traditional villages; building distribution, including architectural information such as residences, stores, cultural sites, etc., which will be used to generate the location and structure of the buildings in the layout; natural landscapes, such parks, green areas, lakes, etc., which will be used as a basis for ecological environmental protection; cultural sites, including historical sites, cultural landmarks, etc., which will be used to help maintain the cultural characteristics of traditional villages. Processing and analysis of this data will help the GAN-PLS model to give data assistance for intelligent layout optimisation of conventional villages.

5.2 Experimental setup

For this experiment, a high-performance computer cluster with multi-core CPUs and NVIDIA GPUs provides the computing environment to guarantee effective model training (Ravikumar and Sriraman, 2023). Table 2 shows the running system as Ubuntu 20.04 and the deep learning framework as PyTorch 1.10.0.

Table 2 Experimental hardware configuration environment

Hardware	*Description*
CPU	Intel Xeon 2.4 GHz (16 cores)
GPU	NVIDIA Tesla V100 16 GB
Memory	64 GB
Storage	1 TB SSD
OS	Ubuntu 20.04

Table 3 shows the collection of the following important hyperparameters during the model training procedure.

Table 3 Experimental parameter settings

Hyperparameter	*Value*
Batch size	32
Learning rate	0.0002
Generator hidden layers	128
Discriminator hidden layers	128
Epochs	1,000
Optimiser	Adam ($\beta_1 = 0.5$, $\beta_2 = 0.999$)

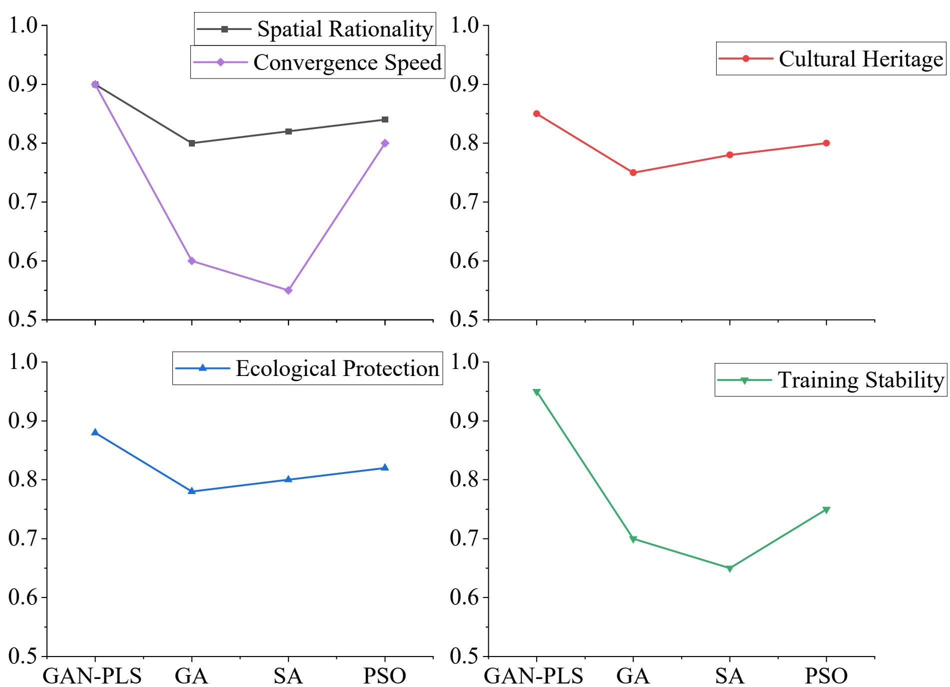
5.3 Comparative experiments with traditional layout optimisation models

This experiment intends to confirm in traditional village layout optimisation the performance difference between GAN-PLS model and conventional layout optimisation models (e.g., GA, SA, PSO). Every one of these methods is extensively applied in conventional layout optimisation and has greater global optimisation capacity. Examining spatial rationality, cultural legacy, ecological preservation, training stability, and convergence speed helps one to fully weigh the benefits and drawbacks of various optimising techniques.

The two models' optimisation effect is evaluated in this paper using the following assessment indices.

By means of the arrangement of buildings, road planning, and public space use, spatial rationality gauges if the produced layout satisfies the actual demands of traditional communities. Cultural legacy evaluates if the produced design preserves the historical sites, traditional architectural forms, etc. of the old community. Ecological environmental protection gauges the area of green space, building density, and ecological coordination of the produced design. Quantifying the stability of the training process helps one to assign a value of 0 to 1. This helps notably to avoid issues such disappearing gradients and model collapse by 1 representing a stable training process and 0 reflecting instability. With values from 0 to 1 reflecting the speed of convergence, convergence speed is to evaluate the speed of convergence of the model; 1 indicates fast convergence and 0 indicates slow convergence. Figure 2 shows the experimental outcomes.

Figure 2 Comparison experiment of different layout optimisation models (see online version for colours)



With a score of 0.90, the GAN-PLS model showed the best spatial rationality. This approach generates extremely optimal layouts in terms of building distribution, road planning and public space use, therefore guaranteeing effective use of space devoid of waste. Though they also performed better in terms of spatial structure, GA (0.80), SA (0.82), and PSO (0.84), failed to completely optimise space, thereby producing some wasted space and illogical distribution in the design. PSO improves spatial rationality more than GA and SA, although its optimisation accuracy is still not like that of GAN-PLS.

Regarding cultural legacy, GAN-PLS's performance stands out as excellent, with 0.85. Crucially important to preserving the cultural integrity of villages, the approach can effectively conserve the cultural elements of traditional towns including the conservation of historical places and the integration of traditional architectural forms. On cultural transmission, GA, SA, and PSO are less successful, in comparison. These conventional optimisation techniques lack cultural elements, which results in produced layouts that fail to fully reflect the cultural traits of traditional villages, particularly in the lack of performance in the design of historical heritage protection areas and cultural activity areas. Although they are able of global optimisation.

Regarding environmental preservation, GAN-PLS showed outstanding optimisation capacity with 0.88. The model guarantees that the plan satisfies the criteria of ecological protection by optimising green areas, building density, and ecological compatibility during designing. On ecological preservation, GA (0.78), SA (0.80), and PSO (0.82) did rather poorly. These algorithms optimise the plan, but they neglect to completely include ecological protection, thereby producing layouts with issues with green space allocation and environmental coordination and fail to attain an optimal ecological balance.

GAN-PLS obtained a high score of 0.95, indicating great training stability, and the gradient penalty approach avoids the typical problems of gradient disappearance and pattern collapse during training. Conversely, especially in large-scale data processing, which is prone to gradient instability or non-convergence of the training process, GA (0.70), SA (0.65) and PSO (0.75) have rather low training stability. GAN-PLS is more efficient in producing the ideal layout as, in terms of the convergence speed, it has 0.90, far faster than the other algorithms (GA: 0.60, SA: 0.55, PSO: 0.80).

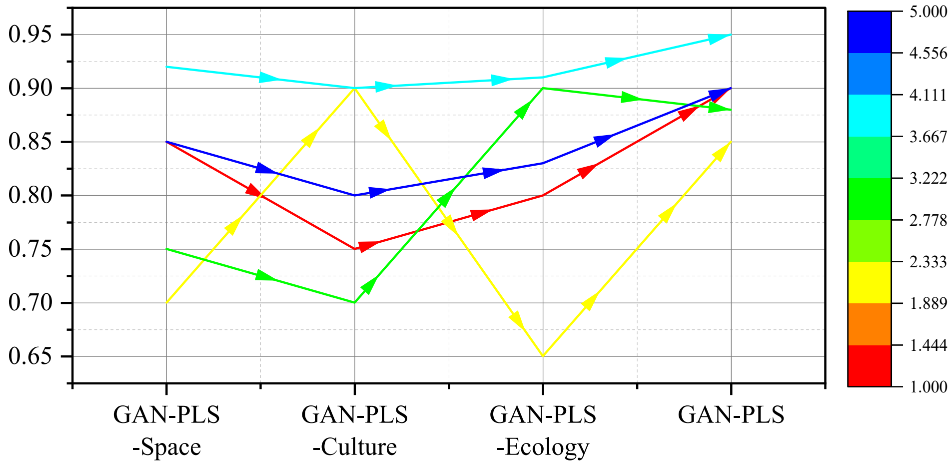
GAN-PLS performs well in many dimensions, including spatial rationality, cultural legacy, ecological protection, etc., and its training stability and convergence speed are much higher than those of conventional optimisation techniques when compared with GA, SA and PSO approaches. This shows the efficiency and creativity of applying GAN (particularly the gradient penalty-introducing training method) for conventional village layout improvement.

5.4 *Impact of different optimisation strategies on the effectiveness of layout optimisation*

Aiming to investigate the impact of several limitations, such spatial rationality, cultural legacy, and ecological conservation, four distinct optimisation procedures are setup in this experiment. First, to guarantee the spatial rationality and seamless flow of the layout, the spatial optimisation approach (GAN-PLS-Space) concentrates on improving building distribution, road planning and public space. Second, GAN-PLS-Culture stresses the preservation of historical monuments, traditional architectural styles and cultural activity areas to guarantee that the layout corresponds with the cultural traits of the conventional village. Focusing on the coordination of green space, building density and ecological environment to satisfy the objectives of ecological protection, the ecological optimisation approach (GAN-Pls-Ecology) At last, the complete optimisation strategy (GAN-PLS) integrates the spatial, cultural, and ecological optimisation goals to improve all facets of the layout in an integrated manner, so ensuring that the produced layout satisfies the spatial rationality and maintains the cultural features while so preserving the ecological environment.

The exact experimental results of this experiment are displayed in Figure 3; its evaluation index is the same as that of Experiment 1.

Figure 3 Comparison of optimisation effect of different optimisation strategies (see online version for colours)



With a score of 0.85 GAN-PLS-Space excels in terms of spatial rationalities. This approach guarantees appropriate spatial structure and flow design by concentrating on the best possible placement of buildings, road planning and public areas. Conversely, GAN-PLS-Culture (0.75) and GAN-PLS-Ecology (0.80) perform somewhat worse in terms of spatial rationality mostly because both methods concentrate more on cultural components and ecological conservation demands than on spatial layout as the major optimisation target.

With 0.90, GAN-PLS-Culture excels in terms of cultural legacy. The approach stresses the preservation of cultural elements in traditional villages, including historical places, traditional architectural styles and areas for cultural events, therefore allowing the produced layout to properly pass on traditional culture. Given their optimisation focus did not offer in-depth design around cultural features, GAN-PLS-Space (0.70) and GAN-PLS-Ecology (0.65) scored weakly in terms of cultural legacy.

GAN-PLS-Ecology scored 0.90 to show best in terms of ecological preservation. The approach provided more of a contribution to maximising the area of green space, building density and compatibility with the natural surroundings, therefore guaranteeing that the produced designs better fit needs for ecological preservation. Lower ecological protection scores for GAN-PLS-Space (0.75) and GAN-PLS-Culture (0.70) indicate that the designs produced under a single strategy fail to balance ecological protection with other variables well.

With scores of spatial rationality (0.90), cultural legacy (0.85), and ecological protection (0.88), GAN-PLS shows overall good performance in all evaluation criteria. This outcome confirms the benefits of the integrated optimisation technique under several limitations, thereby balancing the spatial, cultural, and ecological needs to provide a traditional village plan that satisfies the real requirements. In terms of training stability (0.95) and convergence speed (0.90), GAN-PLS also shows great flexibility of the model under challenging challenges.

6 Conclusions

6.1 Summary and shortcomings of the study

In this work, an intelligent optimisation model GAN-PLS is suggested to optimise the arrangement of conventional village parts depending on GAN. To attain the intelligent optimisation of the layout of traditional villages, the model is trained via adversarial training of generator and discriminator and integrates numerous constraints including spatial rationality, cultural inheritance and ecological conservation. Specifically, the gradient penalty approach is implemented into the GAN-PLS model and helps to avoid issues including gradient disappearance and pattern collapse, so improving the stability of the training process and hence the training efficiency and generating quality of the model. By means of data collecting, model training and layout optimisation strategy design, the GAN-PLS model is able to keep the cultural features of traditional villages based on assuring the rationality of spatial layout, thereby meeting the needs of ecological preservation and preserving the cultural traits of traditional villages. The experimental findings reveal that in terms of spatial rationality, cultural inheritance, and ecological preservation the model delivers a more desirable optimisation impact. GAN-PLS shows the significant possibilities of the model in real applications since it performs well in all the evaluation measures.

There are still certain flaws even if the outcomes of this study have certain validity in theory and practice. First of all, the model mostly concentrates on the conventional village layout data in particular areas, hence having some restrictions in terms of the diversity and breadth of the dataset. Second, in very complicated and large-scale layout optimisation challenges, the training time and computing cost of the model may still be considerable notwithstanding a steady training process. Furthermore, this study mostly addresses the optimisation of spatial, cultural, and ecological features of traditional villages; but the intelligent optimisation of traditional village layouts goes much beyond that.

6.2 Directions for future research

Future study can be conducted in the following ways depending on the given constraints:

1. Extending the diversity and coverage of the dataset: By incorporating more kinds of traditional village data, including villages with various geographic settings, cultural backgrounds and historical periods, future study can improve the generalisation capacity of the model. This will not only maximise the model's adaptability but also make it valuable in more various application contexts.

2. Improving training efficiency and computational resource optimisation: Future studies can concentrate on maximising the computational efficiency of the model, for example, by means of methods such as model pruning and quantisation, lowering the demand for hardware resources and hence the amount of computation during the training process, so improving the operability of the model in practical applications.

3. Introduce more dimensional constraints: Combining economic rewards, social requirements, sustainable development, and other elements will help the practicality and comprehensiveness of the model to be much enhanced in the future (Breuer

et al., 2018). By means of multi-objective optimisation techniques, considering additional dimensional limitations, it can create conventional village layouts more in line with pragmatic demands.

4 Strengthening the model's adaptive ability and dynamic adjustment mechanism: Future studies can investigate how to make the model adaptable and automatically change the optimisation objectives depending on real-time data during the process of creating layout plans (Lăzăroiu et al., 2022). This will improve the long-term sustainability of conventional village layouts and help create more adaptable and changeable ones.

5 Extension to cross-domain applications: Future studies can investigate how to expand the model to these fields and evaluate the use in several kinds of spatial layout optimisation chores. This will not only improve the applications scenarios of GAN in spatial optimisation but also offer intelligent solutions for several kinds of architectural planning and design.

All things considered, this work advances the use of GAN in the field of spatial optimisation and offers a fresh concept and approach for the preservation and planning of traditional communities. Notwithstanding certain constraints, the GAN-PLS model is projected to be more important in the optimisation of the layout of conventional villages and the larger area of building design as the technology is always developing and optimising.

Acknowledgements

This work is supported by the Xichang University Fund Project (No. YBS202415).

Declarations

All authors declare that they have no conflicts of interest.

References

Alam, T. (2024) 'Metaverse of things (MoT) applications for revolutionizing urban living in smart cities', *Smart Cities*, Vol. 7, No. 5, pp.2466–2494.

Alzubaidi, L., Zhang, J., Humaidi, A.J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M.A., Al-Amidie, M. and Farhan, L. (2021) 'Review of deep learning: concepts, CNN architectures, challenges, applications, future directions', *Journal of Big Data*, Vol. 8, pp.1–74.

Boubedra, S., Tolba, C., Manzoni, P., Beddiar, D. and Zennir, Y. (2023) 'Urban traffic flow management on large scale using an improved ACO for a road transportation system', *International Journal of Intelligent Computing and Cybernetics*, Vol. 16, No. 4, pp.766–799.

Breuer, H., Fichter, K., Lüdeke-Freund, F. and Tiemann, I. (2018) 'Sustainability-oriented business model development: principles, criteria and tools', *International Journal of Entrepreneurial Venturing*, Vol. 10, No. 2, pp.256–286.

Chen, X., Xie, W. and Li, H. (2020) 'The spatial evolution process, characteristics and driving factors of traditional villages from the perspective of the cultural ecosystem: a case study of Chengkan Village', *Habitat International*, Vol. 104, p.102250.

Dargan, S., Kumar, M., Ayyagari, M.R. and Kumar, G. (2020) 'A survey of deep learning and its applications: a new paradigm to machine learning', *Archives of Computational Methods in Engineering*, Vol. 27, pp.1071–1092.

Dash, A., Ye, J. and Wang, G. (2023) 'A review of generative adversarial networks (GANs) and its applications in a wide variety of disciplines: from medical to remote sensing', *IEEE Access*, Vol. 12, pp.18330–18357.

Dikshit, S., Atiq, A., Shahid, M., Dwivedi, V. and Thusu, A. (2023) 'The use of artificial intelligence to optimize the routing of vehicles and reduce traffic congestion in urban areas', *EAI Endorsed Transactions on Energy Web*, Vol. 10, pp.1–13.

Gan, W., Zhao, Z., Wang, Y., Zou, Y., Zhou, S. and Wu, Z. (2024) 'UDGAN: a new urban design inspiration approach driven by using generative adversarial networks', *Journal of Computational Design and Engineering*, Vol. 11, No. 1, pp.305–324.

Karras, T., Aittala, M., Hellsten, J., Laine, S., Lehtinen, J. and Aila, T. (2020) 'Training generative adversarial networks with limited data', *Advances in Neural Information Processing Systems*, Vol. 33, pp.12104–12114.

Lăzăroiu, G., Andronie, M., Iatagan, M., Geamănu, M., Ștefănescu, R. and Dijmărescu, I. (2022) 'Deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms in the internet of manufacturing things', *ISPRS International Journal of Geo-Information*, Vol. 11, No. 5, p.277.

Lee, J.Y. and Styczynski, M.P. (2018) 'NS-kNN: a modified k-nearest neighbors approach for imputing metabolomics data', *Metabolomics*, Vol. 14, pp.1–12.

Lei, T., Pei, Z., Pan, F., Li, B., Xu, Y., Shao, H. and Zhao, K. (2024) 'A novel data augmentation method for steering mechanism fault diagnosis based on variational autoencoding generative adversarial networks with self-attention', *Measurement Science and Technology*, Vol. 35, No. 5, p.055115.

Li, Q., Subica, A., Kendra, J. and Ali, S.H. (2023) 'Tradition or modernization? The dilemma of Chinese indigenous communities', *International Journal of Heritage Studies*, Vol. 29, No. 5, pp.382–397.

Liu, Y., Heidari, A.A., Cai, Z., Liang, G., Chen, H., Pan, Z., Alsufyani, A. and Bourouis, S. (2022) 'Simulated annealing-based dynamic step shuffled frog leaping algorithm: optimal performance design and feature selection', *Neurocomputing*, Vol. 503, pp.325–362.

Ma, W., Hu, J., Yao, L., Fu, Z., Morais, H. and Marinelli, M. (2022) 'New technologies for optimal scheduling of electric vehicles in renewable energy-oriented power systems: a review of deep learning, deep reinforcement learning and blockchain technology', *Energy Conversion and Economics*, Vol. 3, No. 6, pp.345–359.

Man, C.K., Quddus, M., Theofilatos, A., Yu, R. and Imprialou, M. (2022) 'Wasserstein generative adversarial network to address the imbalanced data problem in real-time crash risk prediction', *IEEE Transactions on Intelligent Transportation Systems*, Vol. 23, No. 12, pp.23002–23013.

Miller, T., Durlik, I., Kostecka, E., Kozlovska, P., Łobodzińska, A., Sokołowska, S. and Nowy, A. (2025) 'Integrating artificial intelligence agents with the internet of things for enhanced environmental monitoring: applications in water quality and climate data', *Electronics*, Vol. 14, No. 4, p 696.

Mohebbi Moghaddam, M., Boroomand, B., Jalali, M., Zareian, A., Daeijavad, A., Manshaei, M.H. and Krunz, M. (2023) 'Games of GANs: game-theoretical models for generative adversarial networks', *Artificial Intelligence Review*, Vol. 56, No. 9, pp.9771–9807.

Ravikumar, A. and Sriraman, H. (2023) 'Computationally efficient neural rendering for generator adversarial networks using a multi-GPU cluster in a cloud environment', *IEEE Access*, Vol. 11, pp.45559–45571.

Tang, C., He, Y., Zhou, G., Zeng, S. and Xiao, L. (2018) 'Optimizing the spatial organization of rural settlements based on life quality', *Journal of Geographical Sciences*, Vol. 28, pp.685–704.

Tian, Y., Su, D., Lauria, S. and Liu, X. (2022) 'Recent advances on loss functions in deep learning for computer vision', *Neurocomputing*, Vol. 497, pp.129–158.

Wen, Y., Haider, S.A. and Boukhris, M. (2023) 'Preserving the past, nurturing the future: a systematic literature review on the conservation and revitalization of Chinese historical town environments during modernization', *Frontiers in Environmental Science*, Vol. 11, p.1114697.

Yang, B., Yin, K., Lacasse, S. and Liu, Z. (2019) 'Time series analysis and long short-term memory neural network to predict landslide displacement', *Landslides*, Vol. 16, pp.677–694.

Yuanliang, W. and Zhe, Z. (2024) 'Integration effect of artificial intelligence and traditional animation creation technology', *Journal of Intelligent Systems*, Vol. 33, No. 1, p.20230305.