

Research on the Method of Landform Feature Recognition based on Deep Learning

Zeyu Jin^a, Lele Cui^a, Zhifa Wang^a, Zien Zhang^a, Chang Liu^a, Guangwei Zhang^{a, b, *}

^a School of Mechatronics Engineering, Beijing Institute of Technology, China

^b Science and Technology on Electromechanical Dynamic Control Laboratory, China

* Corresponding author

758743342@qq.com, 3120240256@bit.edu.cn, 3397073817@qq.com, 1732955442@qq.com, liuchang0118@bit.edu.cn, 6120240118@bit.edu.cn

Abstract— This research proposes a deep learning-based method for geomorphic feature recognition, aiming to achieve high-precision classification of complex geomorphic echo signals through deep learning techniques. First, a GAN-based geomorphic feature recognition model is established, incorporating a multi-layer fully connected discriminator and generator, optimized for generalization capability via adversarial training. To address the small-sample problem, an improved generative adversarial network is employed for data augmentation and feature alignment, generating typical geomorphic power spectra with echo characteristics. A three-layer neural network classification module is designed to identify different geomorphic types, while techniques such as cosine annealing, attention mechanisms, label smoothing, and global normalization are applied to mitigate overfitting and gradient oscillation. Finally, the adversarial capability of the proposed GAN is validated using a simulated dataset, with the data split into 7:3 training and testing sets to evaluate the model's classification performance. The results demonstrate that the proposed method achieves over 90% recognition accuracy for various geomorphic types on both simulated and real-world datasets, confirming the effectiveness of the GAN-based geomorphic feature recognition model.

Keywords— Deep Learning, Generative Adversarial Network, Geomorphic Feature Recognition, Data Augmentation, Classification Accuracy

I. INTRODUCTION

In recent years, deep learning networks have achieved revolutionary breakthroughs in deep feature extraction and multimodal fusion, significantly advancing landform feature recognition. Traditional methods rely on manually designed algorithms like Fourier transform and wavelet transform for signal feature extraction. While effective, these approaches often lack robustness when processing complex signals in noisy environments. In contrast, deep learning models such as convolutional neural networks (CNN) and generative adversarial networks (GAN) can autonomously learn intricate patterns from large-scale training data, substantially improving the accuracy of geomorphic feature identification while eliminating the need for handcrafted feature extractors.

Each natural spatial entity with distinct visual and physical characteristics is shaped by long-term environmental processes of varying intensity [1]. Terrain recognition

involves classifying landforms like soil, grassland and water bodies through surface feature analysis. Deep learning-based methods adapt to complex scenarios by automatically learning terrain features from large-scale survey data. Conventional approaches, however, depend on rule-based systems and manual feature extraction requiring expert knowledge and implicit regional experience [2]. Typical preprocessing techniques like noise suppression, environmental clutter filtering, image enhancement, and focal plane array dynamic range expansion aim to mitigate interference from precipitation or infrared decoys to enhance target-to-background signal-to-noise ratios. Most existing methods utilize single-modal data: (1) digital elevation models (DEMs) or geomorphic variables (slope aspect, gradient, curvature) for physical attributes [3], or (2) texture features from topographic maps or remote sensing imagery for visual characteristics [4–5]. DEMs excel in distinguishing mountainous/hilly terrains, while texture/imagery data better classify plains/plateaus [6]. However, their reliance on heuristic rules and unimodal data limits universal applicability.

Early detection studies employed manually designed texture features such as Local Binary Patterns [7], Local Ternary Patterns [8], Scale-Invariant Feature Transform, and Histograms of Oriented Gradients for classification. These methods often exhibited weak robustness against environmental noise, illumination variations, and geometric distortions. The emergence of Speeded-Up Robust Features (SURF) marked a turning point. For instance, Filitchkin et al. implemented real-time terrain classification on the LittleDog robot using SURF-based Bag-of-Words models [9], while Kim and so developed an invariant feature framework via linear-filtered image statistical analysis [10].

Recent advancements highlight multi-sensor fusion and AI integration. In 2021, Wang et al. pioneered a machine learning framework in Geoscience Frontiers combining optical imagery with DEMs, where SVM and random forest algorithms established benchmarks for landslide detection [11].

Generative adversarial networks, proposed in 2014, have gained widespread adoption. Combining LSTM gating mechanisms [12] with Transformer positional encoding [13], GANs address challenges like ECG periodicity modelling and

geomorphic recognition. In 2022, Chen Weitao's team proposed the JAGAN framework [14], which significantly improved the accuracy of land cover classification in mining areas by integrating a joint channel-spatial attention mechanism with a generative adversarial network. This model achieved fine-grained interpretation of complex land features on the domestic GF-5 hyperspectral imagery dataset. In 2023, Li Jing's team developed GPR-GAN [15], addressing the issue of insufficient training samples in ground-penetrating radar data by constructing a conditional GAN-based terrain data augmentation system. The model generated synthetic data across varying antenna frequencies, covering scenarios such as road pavements, railway subgrades, and tunnel linings.

This study simulates echo signals with scenario-specific parameters and analyses them via deep learning to distinguish terrains based on power spectral features. Field measurements further validate the method's feasibility and accuracy in identifying reflective surfaces.

II. GAN-BASED GEOMORPHIC FEATURE RECOGNITION MODEL NETWORK STRUCTURE

A. Model Principle

Generative Adversarial Networks constitute a class of deep learning models that have emerged as one of the most promising approaches for unsupervised learning on complex data distributions in recent years. The framework operates through an adversarial process involving at least two core components: a generative model (G) tasked with synthesizing data samples, and a discriminative model (D) that evaluates their authenticity. Through iterative adversarial training—where G and D engage in a minimax game—the system progressively refines its output quality. The overarching architecture is illustrated in Figure 1.

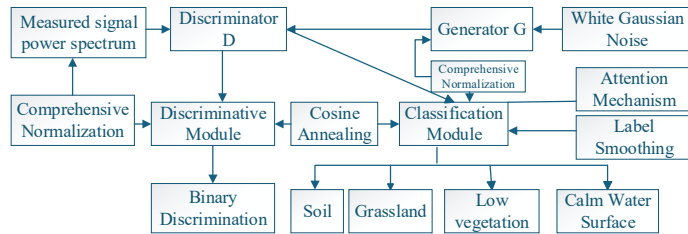


Figure 1. Generative Adversarial Network Architecture

First, input the power spectral signal data and corresponding labels of different terrains into the model, and train the input signals according to task categories. For discrimination tasks: The GAN undergoes unsupervised training. The generator produces 256-dimensional power spectral signals by fully connecting and mapping 100-dimensional Gaussian white noise. The discriminator receives either real or generated 256-dimensional spectral signals, extracts 128-dimensional pre-discrimination features, and inputs them into a discrimination module that outputs a 1D confidence score to evaluate similarity. Comprehensive

normalization is applied across all data paths to enhance training stability. For classification tasks: The GAN operates under supervised training. The discriminator jointly encodes terrain labels and real spectral signals into pre-classification features. A classification module, integrated with an attention mechanism, correlates labels with features to generate a 4D probability distribution. Label smoothing improves cross-entropy loss, while cosine annealing dynamically balances discrimination and classification weights. The pre-classification feature layer also employs comprehensive normalization to ensure feature consistency.

B. Model Structure

The Generative Adversarial Network framework based on a fully connected network is illustrated in Figure 2. Its core components consist of two subnetworks: the Generator and the Discriminator. The generator network G takes 1×100 -dimensional Gaussian noise as input and outputs a 1×256 -dimensional synthetic signal through multi-layer fully connected processing. The model employs a composite loss function design: During forward propagation, the generator loss is defined as the discrimination loss when the generated signal passes through D. The discriminator loss is divided into a discrimination probe loss and a classification probe loss. The discriminator network D receives 1×256 -dimensional data samples (either real or generated data). The discrimination probe uses a dual-branch output structure to compute the discrimination loss for real samples and generated samples, respectively. Meanwhile, the classification probe outputs a classification loss after training with labelled real data. The discrimination probe loss is averaged from the real sample discrimination loss and generated sample discrimination loss. Cosine annealing is applied to dynamically adjust the weight ratio between the discrimination probe loss and the classification probe loss within the total discriminator loss, ensuring simultaneous convergence of both the discrimination probe and the classification probe (based on the discriminator).

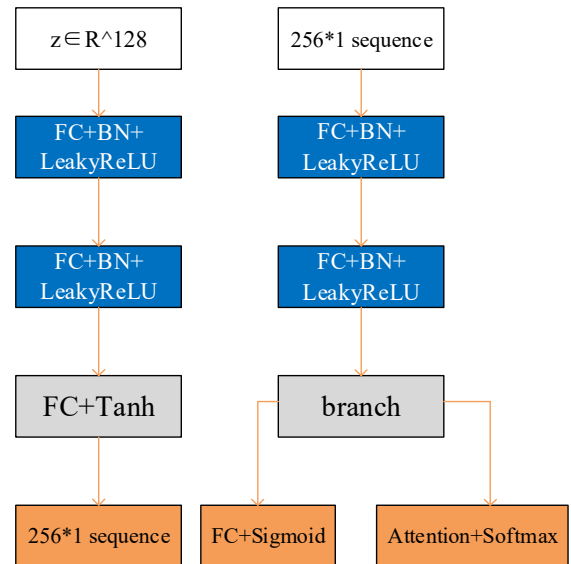


Figure 2. Generative Adversarial Network Framework

In the discriminator schematic diagram on the right side of Figure 2, the "FC + Sigmoid" serves as the main discrimination path. This branch takes a 256×1-dimensional spectral feature vector as input and processes it through a three-layer fully connected network (with progressively decreasing node counts: 128→64→32) for feature compression. The LeakyReLU activation function (negative slope coefficient $\alpha=0.2$) is employed to mitigate gradient vanishing issues. The final fully connected layer maps the output to a single neuron, and the Sigmoid activation function constrains the value range to [0, 1], quantitatively representing the estimated probability that the input sample belongs to the real data distribution. The feature space learned by this path primarily focuses on global differences in data distribution. The "Attention + Softmax" functions as the classification probe, enabling multi-category recognition. The front end of this branch shares the first two fully connected feature extraction layers with the discrimination path. The third layer reconstructs feature weight distribution via an attention mechanism. Specifically, a channel attention module is constructed in the 256-dimensional feature space to calculate the saliency weight coefficients for each channel. The features are then reduced to a 4-dimensional output (corresponding to four types of terrain) through a fully connected layer, and the Softmax function computes the category probability distribution. The introduction of the attention module significantly enhances the localization capability for frequency bands sensitive to scattering characteristics while effectively suppressing interference from irrelevant noise frequency bands.

C. Three-Layer Classification Neural Network Module

Deep learning classification networks are neural networks designed to assign input data to predefined categories, widely applied in tasks such as image classification, text classification, and speech recognition. In this study, each signal in the dataset is a 256-length electromagnetic intermediate-frequency echo signal. We propose a three-layer fully connected neural network (TL-FCN) as the discriminator's classification probe to perform classification and recognition on the dataset.

The proposed TL-FCN establishes an end-to-end classification framework specifically designed for 256-dimensional electromagnetic intermediate-frequency echo signal power spectra. The architecture comprises: (1) an input layer (512 nodes) shared with discriminative probes, (2) an attention mechanism layer for feature refinement, (3) a normalization layer, and (4) an output layer generating four-dimensional data confidence scores. The network employs cross-entropy loss function optimization and leverages fully connected structures to achieve deep learning of signal characteristics. Through this hierarchical design, TL-FCN effectively captures discriminative features across different spectral bands while maintaining computational efficiency in signal interpretation.

This study proposes an innovative approach by employing a classification network as a probe attached to the discriminator. As illustrated in Figure 2, the classification probe shares two

fully connected layers with the discriminator's primary structure. During training, the classification module processes input data through an attention mechanism to emphasize salient features, subsequently converting these features into a 4-dimensional confidence vector via softmax normalization. The category corresponding to the highest confidence value is assigned as the predicted class.

The confidence output is subjected to a cross-entropy loss function with label smoothing ($\alpha=0.1$) to mitigate overfitting. This classification loss undergoes cosine annealing scheduling before being weighted and combined with the discriminator's adversarial loss. The composite loss is then propagated forward to optimize both classification and discrimination tasks simultaneously, thereby achieving quad-class classification within the adversarial learning framework.

III. OPTIMIZATION METHOD FOR GROUND FEATURE RECOGNITION MODEL BASED ON GAN

A. GAN Model Optimization Training Module

During training, the generator model receives noise input and synthesizes simulated data, while the discriminator model strives to distinguish between real and generated samples. The system ultimately reaches discriminative equilibrium when weights stabilize without further changes. The adversarial objective function is represented as in (1):

$$\min_G \max_D V(D, G) = E_{x \sim P_{data}(x)} [\log D(x)] + E_{z \sim P_z(z)} [\log (1 - D(G(z)))] \quad (1)$$

Maximize the discrimination probability for real samples $D(x)$ while minimizing the discrimination probability for generated samples $D(G(z))$. For a fixed generator G , the optimal solution for discriminator D is expressed as in (2):

$$D^*(x) = \frac{P_{data}(x)}{P_g(x) + P_{data}(x)} \quad (2)$$

The discriminator outputs a high probability value for real samples and a low probability value for generated samples. Its discriminative loss function is the binary cross-entropy loss, expressed as in (3):

$$LD = -(\log D(x)) + \log (1 - D(G(z))) \quad (3)$$

where $D(x)$ represents the discriminator's output for real samples, and $D(G(z))$ denotes its output for generated samples. The generator's objective is to deceive the discriminator into misclassifying generated samples as real data. Its loss function is defined as in (4):

$$LG = -\log (D(G(z))) \quad (4)$$

By minimizing this loss, the generator progressively enhances the realism of the generated data.

(1) Set the number of epochs. During each epoch, alternately train the generator and discriminator. To prevent mode collapse caused by an overly powerful discriminator suppressing the generator, one can adopt strategies such as training the generator multiple times before training the discriminator once. Alternatively, training the discriminator multiple times before training the generator once within each epoch can accelerate convergence speed.

(2) After multiple update iterations, the ideal scenario is for the discriminator to be unable to distinguish whether samples originate from the generator. In the ideal convergence state, the generator and discriminator reach a Nash equilibrium point, where the Kullback-Leibler divergence between the generated distribution $p_g(x)$ and the real distribution $p_{data}(x)$ becomes zero, and the discriminator's output probability for all samples converges to $D(x)=0.5$. In practical training, alternating parameter updates between the discriminator and generator while employing adaptive learning rate algorithms (e.g., the Adam optimizer) to adjust gradient update step sizes can effectively mitigate vanishing gradient issues and drive the model toward stable evolution.

To significantly reduce the likelihood of problems like overfitting and gradient oscillation in this GAN neural network, this research employs cosine annealing, attention mechanisms, label smoothing, and global normalization methods for data preprocessing, training process optimization, and discriminator-classifier weight allocation operations.

B. Cosine Annealing

Cosine annealing is a dynamic learning rate adjustment strategy based on thermodynamic annealing principles. It periodically modulates the learning rate parameter in gradient descent algorithms to optimize the convergence performance and generalization capability of deep neural networks. The core mathematical formula can be expressed as in (5):

$$\eta_t = \eta_{\min} + \frac{1}{2}(\eta_{\max} - \eta_{\min}) \left(1 + \cos \left(\frac{t \cdot \pi}{T_{\max}} \right) \right) \quad (5)$$

This function leverages the smooth decay characteristics of the cosine curve to maintain a high learning rate during the initial training phase to accelerate convergence, then gradually reduces it to $\eta_{\min}$ for fine-grained parameter space exploration in later stages.

C. Attention Mechanisms

The attention mechanism establishes feature mapping relationships through a triplet structure (Query, Key, Value):

Query (Q): Represents the feature vector of the current processing target, determining the focus of attention.

Key (K): Serves as an index vector for input features, used to compute similarity scores with the Query.

Value (V): The raw feature vector to be weighted, encoding the actual information content.

The attention weights are computed via a Softmax-normalized similarity score matrix:

$$Attention(Q, K, V) = Softmax \left(\frac{QK^T}{\sqrt{d_k}} \right) V \quad (6)$$

The attention mechanism simulates the biologically-inspired cognitive process of selective feature extraction, endowing deep learning models with dynamic feature focusing and contextual modelling capabilities.

D. Label Smoothing

Label smoothing is a regularization technique designed to mitigate model overconfidence and overfitting in classification tasks by perturbing target label distributions. Its core principle introduces noise to soften conventional hard labels, thereby optimizing the model's probability calibration capability and generalization performance.

In traditional classification tasks, the ground-truth label y is represented in one-hot encoding, where the correct class has a probability of 1 and all other classes have a probability of 0.

Label smoothing introduces a smoothing coefficient $\alpha \in [0,1]$ to convert hard labels (one-hot) into soft labels, with the following mathematical formulation:

$$y_{smooth}^{(i)} = \begin{cases} 1 - \alpha, & \text{if } i = \text{true class} \\ \frac{\alpha}{K-1}, & \text{otherwise} \end{cases} \quad (7)$$

Label smoothing significantly reduces the model's feature norm, promoting tighter clustering of same-class samples in the feature space and enhancing the robustness of classification boundaries.

E. Global Normalization

Global normalization is a data standardization method based on global statistical measures. Its core objective is to eliminate scale differences and distribution shifts in datasets, thereby enhancing the stability and generalization capability of model training.

The mathematical formulation typically comprises two approaches:

One method is Z-Score standardization, whose mathematical formula is expressed as in (8):

$$x_{norm} = \frac{x - \mu_{global}}{\sigma_{global}} \quad (8)$$

The other method is Min-Max Scaling, whose mathematical formula is expressed as in (9):

$$x_{norm} = \frac{x - \min(X)}{\max(X) - \min(X)} \quad (9)$$

Global normalization suppresses non-stationary characteristics in feature space, creating smoother gradient propagation paths. This not only accelerates neural network convergence but also mitigates sensitivity to local optima, bolstering model robustness against noise and out-of-distribution samples. Its core value lies in constructing a data-driven reference framework, enabling deep learning models to focus on intrinsic feature learning rather than being constrained by dimensional disparities or distribution heterogeneity in raw data. This lays the foundation for improved generalization in complex tasks.

IV. EXPERIMENTS AND RESULTS

This research will utilize power spectra of distinct geomorphological features as identification characteristics.

The simulated dataset was generated via MATLAB, comprising a four-dimensional structure combining detonation height parameters (echo heights ranging from 4 to 15 m in 1 m

increments) with four types of terrain features. During preprocessing, training batches were constructed using multi-terrain samples under identical detonation height parameters. The model was trained for 100 epochs, with dynamic monitoring of the convergence characteristics of the generator loss and discriminator loss.

The generator network incorporated a Dropout layer (dropout rate = 0.2) in its hidden layers to randomly deactivate 20% of neurons, thereby reducing co-adaptation among hidden units and forcing the network to learn redundant feature representations for improved robustness. The discriminator employed a stronger Dropout (rate = 0.4) to suppress its oversensitivity to local noise features, mitigating the risk of mode collapse caused by premature discriminator convergence during adversarial training. This asymmetric configuration ensured feature complementarity between the generator and discriminator paths through a dynamic gradient-balancing mechanism.

An L2 weight decay term was added to the loss functions of both the generator and discriminator. This regularization complemented Dropout: while Dropout implicitly selected features via stochastic network pruning, L2 regularization explicitly constrained the energy distribution of weight vectors. Their synergistic effect reduced the model's tendency to overfit high-frequency noise in training samples.

As shown in Figure 3, this research employs a drone-mounted flying method to acquire measured echo data. The drone operates in a hover-scanning mode to capture multi-angle echo signals, with a hovering altitude ranging from 4 to 15 meters. Using a radio system under conditions of 1 GHz bandwidth and 50 kHz modulation frequency, vertical detection is performed on typical terrains such as soil, grassland, vegetable fields, and nylon-covered water surfaces, thereby obtaining measured echo data for different terrains.



Figure 3. Drone-mounted flight experiment

For the establishment of the measured dataset, the original time-domain signals are sampled to obtain sampled signals. The power spectra of the sampled signals are then calculated, followed by outlier elimination through filtering. Ultimately, a measured dataset with a dimension of 256×4 is constructed, containing power spectra of echoes from four types of terrains.

To achieve cross-domain feature alignment between the simulated dataset and the measured dataset, a GAN is

employed. The generator takes 100-dimensional random data as input, while the discriminator is designed as a multi-layer fully connected neural network. During training, a dynamic learning rate decay strategy is adopted, combined with a gradient penalty mechanism to enhance model generalization. Additionally, spectral normalization constraints are introduced to improve training stability and prevent overfitting through GAN optimization. Finally, the dataset is split into training and validation sets in a 7:3 ratio.

The aforementioned model was applied to identify four terrain types across a total of 1,260 samples. The actual labels and predicted labels for each sample are displayed in the figure below.

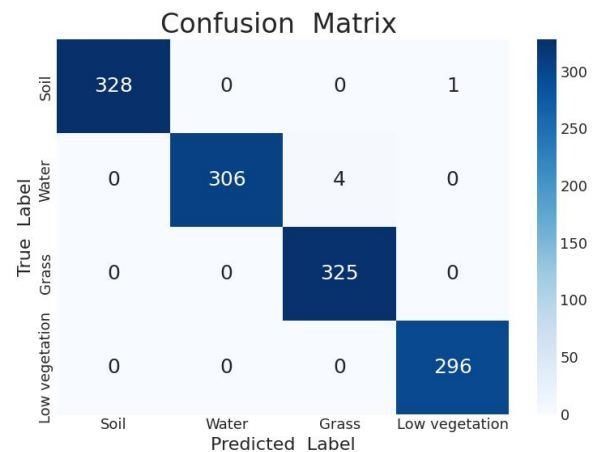


Figure 4. Confusion Matrix

Calculate the evaluation metrics of the network as shown in the table below.

TABLE 1. EVALUATION OF GAN TRAINING DATA

Evaluation data Landforms	TPR	FNR	PPV	FDR
Soil	99.70%	0.3%	100%	0%
Water	98.71%	1.29%	100%	0%
Grass	100%	0%	98.78%	1.22%
Low vegetation	100%	0%	99.66%	0.34%
Aggregate	99.60%	0.40%	99.60%	0.40%

The table data indicates that the terrain category achieves a recall rate of 99.70% with a positive predictive value (PPV) of 100%, while the water surface category attains a recall rate of 98.71% alongside a 100% PPV. Both grassland and low vegetation categories achieve perfect recall rates (100%), with PPVs of 98.78% and 99.66%, respectively. The overall model performance demonstrates a recall rate and PPV of 99.60%, with all land cover categories and aggregate evaluation metrics consistently exceeding 98% accuracy.

V. CONCLUSIONS

This research proposes a deep learning-based landform recognition method using an improved generative adversarial network. By modifying the discriminator structure—replacing the original binary classification with separate "discrimination probe" and "classification probe"—and integrating cosine annealing with attention mechanisms, the enhanced GAN demonstrates superior adversarial and classification capabilities while mitigating overfitting and mode collapse risks during training. The reconstructed GAN architecture achieves over 90% average recognition accuracy on the test set, with an overall accuracy exceeding 98% for four sample categories.

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Zeyu Jin received the BS degree in Beijing Institute of Technology in 2025. Now he is a master degree candidate in School of Mechatronical Engineering, Beijing Institute of Technology. His research interests include signal processing , signal classification , machine learning and so on.



Lele Cui received the BS degree in Mechatronical Engineering from Beijing Institute of Technology in 2024, having graduated as an undergraduate student. He is now pursuing his MS degree in School of Mechatronical Engineering at the same institution. His research interests include wireless network simulation and wireless communication.



Zhifa Wang received the BS degree from Beijing Institute of Technology in 2025. He is currently pursuing a Master's degree in the School of Mechatronical Engineering at Beijing Institute of Technology. His research interests include signal processing, signal classification, object recognition, and related applications in intelligent systems.



Zien Zhang obtained his Bachelor of Engineering degree from China Agricultural University in 2024. Currently, he is a master's student at the School of Mechatronical Engineering, Beijing Institute of Technology. His research interests include signal processing, target detection, and fuze jamming.



Chang Liu received the B.S. degree in Mechatronical Engineering from the Beijing Institute of Technology, Beijing, China, in July 2025. She is currently pursuing the M.S. degree with the School of Mechatronical Engineering, Beijing Institute of Technology. Her research interests include deep learning, signal classification, and signal processing.



Guangwei Zhang received Ph.D. degree in school of Mechatronical Engineering from Beijing Institut in 2021. He is currently pursuing the postdoctor in Beijing Institute of Technology, Beijing, China. He is working radar signal processing and intelligent detection, network simulation and emulation and so on.