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EXPLORING GENERATIVE MODELS FOR REMOTE SENSING: A COMPREHENSIVE REVIEW

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Abstract. *Remote sensing enables systematic observation of the Earth's surface through aerial and satellite imagery, supporting a wide range of applications from environmental monitoring to urban planning. Recent advances in deep learning models have significantly enhanced the analysis of remote sensing data; however, these models often require large volumes of high-quality labelled data, which are difficult and costly to obtain due to limitations in sensor resolution and data acquisition. Generative Adversarial Networks (GANs), a class of deep generative models, have emerged as a transformative solution by synthesizing realistic data and improving model robustness in data-scarce environments. In addition to data augmentation, GANs facilitate critical remote sensing tasks such as image super-resolution, cloud removal, cross-modal translation, and change detection. Their ability to model complex data distributions and perform adversarial training makes them particularly effective for addressing challenges such as noise, resolution gaps, and domain discrepancies. This review provides a comprehensive overview of GAN architectures, explores their diverse applications in remote sensing, discusses relevant evaluation metrics, and highlights key challenges and opportunities for future research.*

Keywords: data augmentation, data enhancement, generative adversarial models, image super-resolution, remote sensing

ANALIZA MODELI GENERATYWNYCH W TELEDETEKCJI: PRZEGLĄD KOMPLEKSOWY

Streszczenie. *Teledetekcja umożliwia systematyczną obserwację powierzchni Ziemi za pomocą zdjęć lotniczych i satelitarnych, znajdując szerokie zastosowanie w wielu dziedzinach, od monitorowania środowiska po planowanie urbanistyczne. Ostatnie postępy w modelach głębokiego uczenia znacznie poprawiły analizę danych teledetekcyjnych; jednak modele te często wymagają dużych ilości wysokiej jakości danych oznaczonych, które są trudne i kosztowne do uzyskania ze względu na ograniczenia rozdzielczości czujników i pozyskiwania danych. Generatywne sieci przeciwstawne (Generative Adversarial Networks – GAN), klasa głębokich modeli generatywnych, stały się przełomowym rozwiązaniem poprzez syntezę realistycznych danych i poprawę odporności modeli w środowiskach o ograniczonej ilości danych. Oprócz rozszerzenia danych, sieci GAN ułatwiają realizację kluczowych zadań teledetekcyjnych, takich jak superrozdzielczość obrazu, usuwanie chmur, tłumaczenie multimodalne i wykrywanie zmian. Ich zdolność do modelowania złożonych rozkładów danych i przeprowadzania uczenia przeciwstawnego sprawia, że są one szczególnie skuteczne w radzeniu sobie z wyzwaniami, takimi jak szum, luki w rozdzielczości i rozbieżności między dziedzinami. Niniejszy przegląd zawiera kompleksowy opis architektur sieci GAN, bada ich różnorodne zastosowania w teledetekcji, omawia odpowiednie wskaźniki oceny oraz podkreśla kluczowe wyzwania i możliwości dla przyszłych badań.*

Słowa kluczowe: rozszerzanie danych, wzbogacanie danych, generatywne modele przeciwstawne, superrozdzielczość obrazów, teledetekcja

Introduction

The rapid advancement of deep learning over the past decade has significantly transformed numerous fields, including the domain of remote sensing. Deep learning has emerged as a powerful and popular approach for analysing remote sensing data due to its remarkable ability to extract complex patterns and hierarchical features from large volumes of high-dimensional input data [1].

Deep learning techniques, particularly those based on artificial neural networks with multiple layers, commonly referred to as deep neural models have demonstrated superior performance in a wide range of computer vision tasks. These tasks include object recognition, image classification, and scene understanding. In the context of remote sensing, such capabilities are essential for various geospatial analysis applications, including land cover classification, semantic segmentation, object detection, and change detection [2, 10, 24, 28].

Among the most successful architectures in this domain are Convolutional Neural Networks (CNNs) and, to a lesser extent, Recurrent Neural Networks (RNNs). CNNs, in particular, are well-suited for image-based tasks due to their ability to capture local spatial hierarchies through convolutional operations. As most remote sensing data is acquired in the form of imagery, whether from optical sensors, radar, or multispectral instruments, the transition from traditional image processing methods to deep learning-based models is both logical and effective.

Despite these advancements, deep learning models typically require large-scale annotated datasets to train effectively. The performance of such models is often directly correlated with the quantity and diversity of the training data. However, collecting and labelling large volumes of remote sensing data poses significant challenges. These challenges include high acquisition costs, temporal limitations, atmospheric interferences, and the intensive labour required for accurate ground truth labelling. Consequently, the lack of sufficient training data has become a major bottleneck in scaling deep learning applications within remote sensing.

To mitigate this issue, researchers have developed various data augmentation strategies aimed at artificially expanding the available dataset [9]. These include techniques such as image flipping, rotation, scaling, cropping, and colour jittering. While these traditional augmentation methods are useful, they are often limited in their ability to introduce genuine diversity into the dataset [19].

A more recent and promising approach to data augmentation involves the use of Generative Adversarial Networks (GANs) [6]. They represent a class of deep generative models designed to learn and replicate the underlying data distribution of a given training set, thereby enabling the synthesis of realistic data samples. Originally proposed by Goodfellow et al. [6], GANs comprise two neural networks: a generator and a discriminator. These networks engage in a competitive minimax game, wherein the generator strives to create synthetic data indistinguishable from real data, while the discriminator aims to accurately differentiate between authentic and generated samples. Through this adversarial process, the generator learns to create high-quality, realistic samples that closely resemble those in the original dataset.

In the context of remote sensing, GANs can be particularly valuable for generating synthetic satellite or aerial imagery that mimics real-world observations. These synthetic samples can supplement limited datasets, improve the robustness of classification models, and enable new tasks such as domain translation (e.g., converting SAR to optical imagery) and resolution enhancement.

This paper provides a comprehensive review of the role of GANs in remote sensing. Section 1 discusses the basic architecture of GANs and examines the most commonly used variants tailored for remote sensing tasks. Section 2 explores the diverse applications of GANs in this field, including data augmentation, image super-resolution, cross-domain translation, and change detection. Section 3 evaluates the performance of GAN-based models using both quantitative and qualitative metrics relevant to remote sensing. Section 4 discusses about the results. Finally, Section 5 presents conclusions of the work.

1. Generative Adversarial Networks

Generative Adversarial Network (GAN), proposed by Goodfellow et al., comprises two neural networks, one is generator (G) and a discriminator (D), that compete in a two-player minimax game [6]. The generator takes a noise as input and learns to produce realistic data samples G(z), while the discriminator receives both real and generated samples and attempts to distinguish between the two. The training objective is given in equation 1. This architecture is shown in Fig. 1.

$$min_G max_D \mathrm{V}(\mathrm{D}, \mathrm{G}) = E_x \log(D(x)) + E_z \log\left(1 - D(G(z))\right) \quad (1)$$

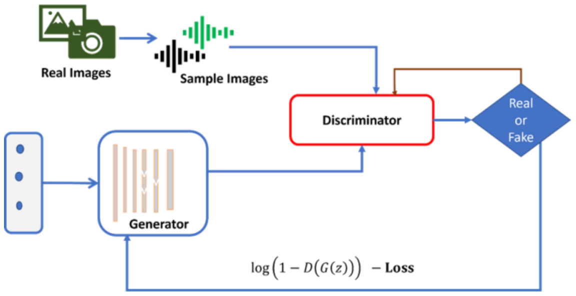

Fig. 1. Architecture of GAN

The latent space, or noise vector, is denoted as *z*, which is used as input to the generator G. The generator produces synthetic images, which are then fed into the discriminator *D* along with real images from the dataset. The discriminator's output for a real image *x* is written as *D(x)*, while its output for a generated image *G(z)* is denoted as *D(G(z))*. Here, E_x represents the expectation over the distribution of real data, and E_z denotes the expectation over the distribution of the latent noise z.

1.1. Conditional GAN

Conditional GANs extend the Vanilla GAN by conditioning both the generator and discriminator on auxiliary information *y* (e.g., class labels, segmentation maps, or another image) [18]. The input to the generator becomes *G(z*|*y)*, and the discriminator also receives y as an additional input to enforce consistency. The architecture of cGAN model is shown in Fig. 2.

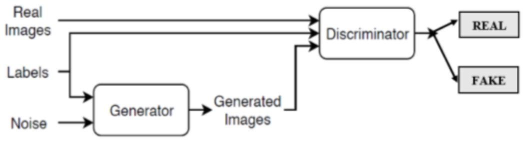

Fig. 2. Architecture of cGAN

cGANs are widely used for supervised image-to-image translation, including land cover classification, semantic segmentation, cloud removal, and pan-sharpening, where the conditional input improves the spatial and spectral coherence of generated outputs.

1.2. Cycle GAN

Cycle-Consistent Generative Adversarial Networks (Cycle GANs) have emerged as a powerful deep learning framework for unpaired image-to-image translation, particularly advantageous in remote sensing applications where aligned data pairs are often unavailable. The architecture comprises two generator-discriminator pairs that learn forward and inverse mappings between two image domains, optimized jointly using adversarial and cycle-consistency losses to ensure semantic fidelity during translation. In remote sensing, Cycle GANs have been effectively employed in tasks such as cloud removal, by translating cloudy optical images into their clear-sky counterparts, and SAR-to-optical image translation, which enhances the interpretability of radar imagery for human analysts.

Cycle GANs enable unsupervised image-to-image translation by simultaneously training two GAN models, each responsible for learning the bidirectional mapping between two distinct visual domains, such as summer (X) and winter (Y) landscapes [27]. The architecture incorporates two generators and two discriminators: one generator translates images from domain X to domain Y, while the corresponding discriminator evaluates the authenticity of the generated Y images relative to real samples. Similarly, a second generator learns the reverse mapping from domain Y to domain X, with its discriminator performing analogous authenticity assessments. A key innovation of Cycle GAN is the addition of a cycle consistency loss, which works alongside the adversarial loss. This loss ensures that when an image is transformed from one domain to another and then converted back, it remains very similar to the original image. This constraint ensures semantic coherence during domain translation. For instance, in translating a summer scene to a winter one, the generator $G_{X \to Y}$ produces a winter image from a given summer input, which is then passed through $G_{Y \to X}$ to reconstruct the original summer image. The discrepancy between the reconstructed and original images is penalized by the cycle loss, thereby guiding the network to learn faithful transformations. The architecture and the concept of cycle consistency are illustrated in Fig. 3.

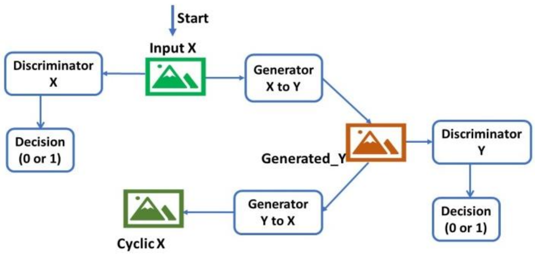

Fig. 3. Cycle GAN Architecture

1.3. Style GAN

StyleGAN (Style-Based Generator Architecture for GANs, introduced by Karras et al. in 2019, represents a significant advancement in generative adversarial networks by enabling high-resolution, highly controllable image synthesis through a novel architectural design [14]. Unlike traditional GANs that map a latent vector z directly to image space, StyleGAN employs a mapping network that transforms z into an intermediate latent vector w, which is then used to modulate feature maps in the synthesis network via Adaptive Instance Normalization. This style-based modulation allows independent control over visual attributes at different levels of abstraction – coarse (e.g., structure), middle (e.g., features), and fine (e.g., texture). The synthesis network begins from a learned constant and progressively up samples through convolutional layers, incorporating both style and stochastic variation via per-layer noise inputs to enhance realism. The discriminator, structured as a conventional CNN, is trained adversarially to distinguish between real and generated images. A unique feature of StyleGAN is style mixing, where styles from multiple latent vectors can be applied at different layers to produce diverse and controllable outputs. Subsequent improvements in StyleGAN2 and StyleGAN3 addressed artifacts and aliasing, enhancing spatial consistency and image fidelity. In remote sensing, StyleGAN has been utilized for high-resolution image generation, synthetic data augmentation, semantic-to-image translation, and unsupervised anomaly detection, proving especially useful in scenarios where labelled data are scarce or fine-grained control over generated content is required [17].

StyleGAN's ability to generate high-resolution, semantically controlled images has made it valuable for various remote sensing tasks. It is widely used for synthetic data augmentation, enhancing training datasets by producing realistic satellite imagery for under-represented classes. Additionally, StyleGAN enables semantic-to-image translation, converting land cover maps into photorealistic images to support urban planning and environmental monitoring. Its hierarchical style modulation also facilitates super-resolution and image enhancement, improving the quality of low-resolution or noisy data. Furthermore, StyleGAN's modelling of complex data distributions aids unsupervised anomaly detection, identifying environmental changes such as deforestation or illegal construction. These applications highlight StyleGAN's potential to advance remote sensing analysis where data quality and availability are critical challenges.

2. Generative Adversarial Networks for remote sensing tasks

GANs have demonstrated significant potential across various remote sensing tasks, offering novel solutions to challenges related to data scarcity, image quality, and classification accuracy. This section reviews key applications of GANs within the remote sensing domain, highlighting their impact on data generation, cloud removal, object detection, and land cover classification.

2.1. Data generation

Data scarcity and imbalance remain critical challenges in remote sensing, particularly when dealing with high-dimensional and heterogeneous datasets. To address this, Lin et al. [16] proposed a multi-layer GAN framework, MARTA GANs, designed to learn interpretable and meaningful feature representations in a fully unsupervised manner, even when trained on complex remote sensing imagery. This approach enables the generation of synthetic data that preserves the intrinsic spatial and spectral characteristics of the source domain, thereby enriching datasets without requiring manual annotation. Complementing this, Han et al. [8] introduced a high-resolution scene and image generation technique leveraging the Wasserstein GAN (WGAN) framework, which mitigates common GAN training issues such as mode collapse and distortion artifacts. Their approach improves the realism and diversity of synthetic or fake remote sensing images, facilitating more effective training of downstream models.

2.2. Land cover classification

Improving the generalizability of land cover classifiers is paramount for accurate and scalable scene interpretation in remote sensing. GAN-based augmentation strategies have been applied to address this by generating realistic variations of training images that cover boundary cases and rare classes. Some researchers proposed the use of dual classifiers in conjunction with a GAN framework to refine land cover classification outcomes [12]. This dual-classifier setup helps to reduce ambiguity near decision boundaries by cross-validating classification confidence, leading to more precise and reliable predictions when models are applied to heterogeneous target datasets. Such techniques exemplify the role of GANs not only in augmenting data quantity but also in enhancing the qualitative aspects of classification models.

2.3. Image super-resolution

GANs have been extensively used to enhance the spatial resolution of low-resolution satellite images, a task known as super-resolution. Models like SRGAN (Super-Resolution GAN) learn to reconstruct high-frequency details lost during down sampling, significantly improving the visual quality and interpretability of remote sensing imagery [13]. This is crucial for applications requiring fine-grained spatial detail, such as urban monitoring and infrastructure mapping [25].

2.4. Object detection

The robustness and accuracy of object detection models in remote sensing can be substantially improved through GAN-based data augmentation. Zhu *et al.* [26] introduced a multi-branch convolutional GAN (MCGAN) architecture that generates a diverse set of synthetic samples tailored for object detection tasks. The model includes a primary classification branch that predicts the classes of input objects alongside multiple adversarial branches tasked with generating realistic, varied false samples. To further ensure the quality and relevance of synthetic data, the authors implemented a dynamic sample selection mechanism that filters out artificially generated images whose distributions deviate significantly from real-world data. This selective augmentation enhances detector training by enriching data variability without compromising model generalization.

2.5. Cloud haze removal

Cloud contamination is a pervasive problem in optical remote sensing imagery, often obscuring critical information and complicating image analysis. Traditional cloud removal techniques rely on multi-temporal image composites or manual pixel replacement, which are labour-intensive and may introduce inconsistencies. To automate and improve this process, Cloud-GAN [23] employs a cycle-consistent adversarial framework that learns to map cloudy images to their cloud-free counterparts without requiring paired training data. This method effectively removes thin clouds partial obstructions that allow some information to pass through by reconstructing underlying scene details while preserving spectral integrity. Handling thick clouds, which completely obscure ground features, remains more challenging; however, Cycle GAN based models provide a promising direction for enhancing cloud mitigation in satellite imagery [20].

2.6. Terrain and elevation modelling

GANs have also been applied to generate realistic digital elevation models (DEMs) or 3D terrain surfaces from 2D satellite imagery. Conditional GANs can learn mappings from optical images to elevation data, allowing for elevation prediction in areas lacking LiDAR or radar coverage [15]. This supports tasks in hydrology, geomorphology and flood modelling.

2.7. Image fusion

GANs have been used to perform multi-modal or multi-sensor image fusion, where images from different sensors (e.g., optical and SAR, or panchromatic and multispectral) are integrated into a single, high-quality composite [22]. GAN-based fusion models can effectively learn cross-sensor relationships, preserving spectral fidelity while enhancing spatial features. This is particularly useful in improving the performance of classification and segmentation tasks [3]. Performance of GANs shown in Table 1.

Table 1 (part 1). Advantages of GANs and its applications

reference	type of GANs	application	use cases
Lin et al. [13]	MARTA GANs	data generation	To learn interpretable and meaningful feature representations in a fully unsupervised manner
Han et al. [14]	Wasserstein GAN (WGAN)	data generation	Improves the realism and diversity of synthetic or fake remote sensing images
Jia et al. [16] and Wang et al. [17]	SRGAN (Super-Resolution GAN)	image super resolution	Reconstruct high-frequency details lost during down sampling, significantly improving the visual quality and interpretability of remote sensing imagery
Zhu et al. [18]	multi-branch convolutional GAN (MCGAN)	object detection	Generates a diverse set of synthetic samples tailored for object detection tasks

Table 1 (part 2). Advantages of GANs and its applications

reference	type of GANs	application	use cases
Singh et al. [19]	Cloud-GAN	cloud haze removal	Removes thin clouds partial obstructions that allow some information to pass through by reconstructing underlying scene details while preserving spectral integrity
Li et al. [21]	Conditional GANs	terrain and elevation modelling	Learn mappings from optical images to elevation data, allowing for elevation prediction in areas lacking LiDAR or radar coverage

3. Evaluation metrics and datasets

The evaluation of GAN-based models in remote sensing involves a range of quantitative and qualitative metrics [21]. These assessments are essential for verifying image quality, validating model performance in downstream tasks and ensuring generalizability across diverse sensing scenarios.

3.1. Evaluation metrics

3.1.1. Qualitative measures

Peak Signal-to-Noise Ratio (PSNR): It measures the pixel-level similarity between the generated and reference images, commonly used in super-resolution and image restoration tasks. Higher PSNR indicates better image fidelity.

Fréchet Inception Distance (FID): The quality and diversity of generated images are measured by comparing how similar the features of real images and generated images are. These features are taken from a pre-trained Inception network, which is used to analyse images. A lower FID means that the generated images are closer to real images.

Inception Score (IS): It is originally designed for natural images, IS measures both the quality and diversity of generated images. It is less commonly used in remote sensing due to domain-specific limitations but remains relevant in general-purpose evaluations given in equation 2.

$$IS = \exp(E_x[D_{KL}(p(y/x)\|p(y))]) \tag{2}$$

here x and y are vectors of spectrum of real image and generated images respectively. D_{KL} is the KL divergence and E_x denotes expectation.

Spectral Angle Mapper (SAM): This automatically identifies the spectral similarity between image pixels and reference spectra which are acquired either through laboratory analysis, in situ spectrometer measurements, by computing the angular distance between their respective spectral vectors given in (3). Here x and y are vectors of spectrum of real image and generated images respectively.

$$SAM = \arccos\frac{x.y}{\|x\|\|y\|} \tag{3}$$

3.1.2. Quantitative measures

Kappa Coefficient: It measures the agreement between predicted and ground truth classifications while accounting for the agreement that could occur by chance. It is especially useful in multi-class classification problems common in land cover mapping given in equation 4.

$$k = \frac{p_o - p_e}{1 - p_e} \tag{4}$$

where p_o is the observed accuracy and p_e is the expected accuracy.

Intersection over Union (IoU): This is also known as the Jaccard Index, and it is one of the widely used metrics in image segmentation and change detection tasks. It quantifies the similarity between the predicted segmentation mask and the ground truth by computing the ratio of their intersection to their union. This is particularly relevant in semantic segmentation and change detection tasks given in (5).

$$IoU = \frac{|A \cap B|}{|A \cup B|} \tag{5}$$

Where A is the predicted region and B is the ground truth region.

3.2. Datasets

3.2.1. EuroSAT Dataset

This study utilizes the EuroSAT dataset, which comprises 27,000 labeled satellite images categorized into 10 distinct land use and land cover classes. Each class contains approximately 2,000 to 3,000 images. The categories include vegetation, herbaceous plants, roads, industrial sites, grasslands, annual crops, residential areas, and water bodies [11].

3.2.2. BigEarthNet

The BigEarthNet dataset comprises over 590,000 image patches (120×120 pixels) derived from Sentinel-2 satellite imagery [5]. Each image is annotated with multi-label land cover classes based on the CORINE Land Cover (CLC) Level-3 nomenclature. The dataset offers a large-scale resource for multi-label classification and is increasingly used in self-supervised and generative tasks to enhance label efficiency and generalization.

3.2.3. xBD Dataset

xBD dataset is one of the most comprehensive remote sensing datasets available for assessing building damage resulting from natural disasters [7]. It classifies building damage into four levels: undamaged, minor damage, major damage, and destroyed. The dataset includes 22,068 satellite images covering 19 types of disaster events, with annotations for approximately 850,736 individual buildings. The imagery is sourced through the Maxar/DigitalGlobe Open Data Program.

3.2.4. NWPU-RESISC45 Dataset

NWPU-RESISC45 dataset contains 31,500 satellite images categorized into 45 scene classes, with each class comprising roughly 700 images [4]. This dataset is widely used for remote sensing scene classification tasks and includes diverse categories such as airports, harbours, commercial areas, and residential neighbourhoods.

4. Results and discussion

The original image is enhanced using GAN and StyleGAN as shown in Fig. 4b and Fig. 4c respectively. The performance of these generated images is evaluated using PSNR and SAM. This can be seen in Table 2. The less the SAM, the better the quality of the image. StyleGAN enhanced image shows a better performance in terms of PSNR and SAM compared to GAN based generated image.

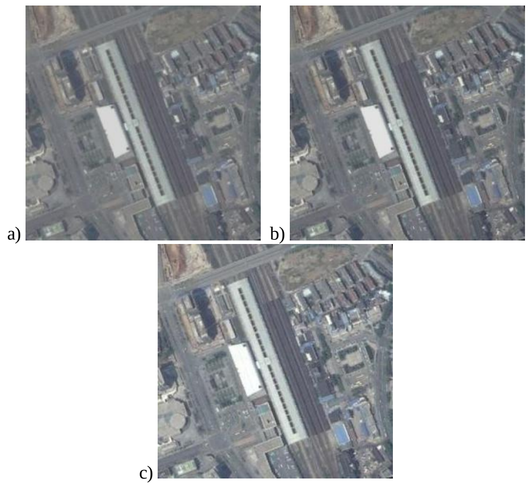

Fig. 4. Original image (a), enhanced image using GAN (b), enhanced image using SR GAN (c)

Table 2. Performance of generated images using GAN and Style GAN

Method	PSNR	SAM
GAN	28.3	5.3
StyleGAN	32.4	3.5

5. Conclusions

This paper provides an overview of the GANs in remote sensing applications, along with its basic principles and relevant studies. Generative Adversarial Networks (GANs) have shown great promise in addressing important challenges in remote sensing, such as limited labelled data and low image resolution. This review also focusses on various applications of GANs in remote sensing and the types of GANs that are used in remote sensing applications along with the datasets used. Among the various GAN architectures, StyleGAN performs better due to its ability to generate higher quality images with better detail and more accurate spectral information. The results presented here demonstrate that StyleGAN achieves higher PSNR values, indicating clearer and sharper images, and lower SAM values, reflecting improved preservation of spectral characteristics, compared to traditional GAN models. These strengths make StyleGAN particularly useful for remote sensing applications like image super-resolution. Future work can focus on integrating sensor-specific physical constraints and radiometric calibration mechanisms into StyleGAN-based frameworks to enhance spectral consistency and cross-sensor generalization. In addition, further research extend the evaluation of StyleGAN models to large-scale, multi-modal remote sensing datasets, including hyperspectral, SAR, and LiDAR data, and assess their performance in real-world operational scenarios.

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