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Generative Adversarial Networks for High Resolution Satellite Imagery Reconstruction in Urban Planning

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Abstract

Satellite imagery is used in the urban planning of land use, infrastructure monitoring, and disaster management. Nevertheless, the low-resolution satellite images do not provide the required level of detail in most cases and restrict their usefulness. The conventional techniques, such as interpolation, cannot factor in such important urban content as buildings, roads, and green areas. The current paper suggests that to resolve this problem, Generative Adversarial Networks (GANs) should be used to perform the super-resolution reconstruction of satellite images. An alternative GAN design consisting of a U-Net-based generator, residual blocks, and PatchGAN discriminator is proposed. The model employs adversarial loss, L1 loss, and perceptual loss (through VGG features) to boost the urban characteristics in high-resolution results. The usefulness of the suggested GAN model is measured based on a real-life dataset of low-resolution images of Sentinel-2 and high-resolution images of Landsat, with emphasis on urban features in Coimbatore, India. Performance is evaluated through PSNR, SSIM, and urban-specific IoU, which are used to detect buildings. The results of the experiments indicate that the GAN model is better than traditional methods and other deep learning models. In particular, the model obtained a PSNR of 35.4 dB, SSIM of 0.94, and urban IoU of 0.81, which was much better than bicubic interpolation (PSNR = 28.2 dB, SSIM = 0.82, IoU = 0.65) and SRResNet (PSNR = 32.1 dB, SSIM = 0.89, IoU = 0.72). The GAN-generated high-resolution images are more detailed and accurate of the urban features and are useful in urban planning, zoning, and disaster risk management, which illustrates the potential of GANs to enhance the satellite imagery in urban planning reality.

Keywords: GANs, Satellite Imagery, Super-Resolution, Urban Planning, Deep Learning, Building Detection, Image Reconstruction.

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Introduction

Urban planning is vital in providing growth and sustainability for cities. It entails the thoughtful planning of resources, land use, infrastructure, and services, and all these require correct and updated information concerning the urban environment. Satellite imagery is one of the most important sources of data that can be utilized by urban planners (Sangeetha et al., 2024). The city of the eyes of a bird can be seen through the satellite images, which depict key aspects of roads, buildings, vegetation, and water bodies, which are very crucial in planning and making decisions. The quality of satellite imagery, however, is usually a limiting factor to its usefulness (Dedring & Rienow, 2024). Low-resolution images are useful in giving general pictures, but they do not show finer details that are required in the analysis of cities (Crivellari et al., 2023). This weakness hinders the process of tracking and controlling urbanization, land-use, infrastructure, and environment in a precise manner.

The low-resolution satellite imagery has been one of the bottlenecks in urban planning (Niroshan & Carswell, 2022; Yue et al., 2023). The satellite images are very crucial in activities such as classifying land use, monitoring infrastructure, environmental mapping, and disaster management (Karwowska & Wierzbicki, 2022). More granular information (high-resolution imagery) is crucial to the tasks of identifying buildings and roads and green areas of the city, and measuring flood-prone lands or urban sprawl (Shang et al., 2022). However, the high-resolution satellite images might be costly and time-intensive to acquire (Ghelichkhani et al., 2023; Chen et al., 2021). Additionally, commercial satellite data resolution is usually unsatisfactory for finer city planning (Karwowska & Wierzbicki, 2023; Khan et al., 2024; Marín & Escalera, 2021). This poses a major challenge to the urban planners who require the exact information in order to make a sound decision.

The enhancement of the resolution of satellite imagery is usually done using traditional methods like interpolation (Li et al., 2022; Salgueiro Romero et al., 2020; Guo et al., 2022). These techniques seek to predict the missing pixels based on the neighboring pixels. Nonetheless, interpolation methods such as bicubic interpolation usually have the disadvantage of producing blurred images that do not capture the finer details of the features of the city. This is especially troublesome in urban planning, where a precise and acute image is vital in activities like zoning, development of infrastructure, and disaster management.

The main aim of this paper is to develop a GAN-based model of super-resolution satellite imagery, which is specifically developed for the use of urban planning. The model creates high-resolution photographs using low-resolution satellite data and maintains the important urban characteristics of buildings, roads, and green areas. The paper is also interested in testing this model in the practical setting of Coimbatore, India, when attempting to use it to solve such problems as land-use zoning, development of infrastructure, or the determination of the disaster risk. The model will be tested based on a set of low-resolution images of Landsat and high-resolution images of Sentinel-2 to evaluate the model in terms of quality improvement and the provision of practical information on urban planning.

Contributions

- An innovative GAN-based satellite imagery reconstruction architecture to improve urban structures, i.e., buildings, roads, vegetation, etc.
- Urban-oriented evaluation measures, such as the Intersection over Union (IoU), are used to detect buildings and to determine the quality of the reconstructed high-resolution images in the context of urban planning.
- When applied to a real-life dataset of Coimbatore, India, it proves that the proposed approach is applicable in practice to urban planning processes, including zoning, density mapping, and disaster risk management.
- Comparison with the conventional approach (e.g., bicubic interpolation) and the most advanced deep learning-based models (e.g., SRResNet, EDSR) to test the competence of the proposed GAN model.

This paper is structured in the following way. In section II, the literature review section covers the issues of utilizing satellite imagery in urban planning and examines the available super-resolution methods, specifically Generative Adversarial Networks (GANs). Section III provides the methodology, which includes the description of the dataset preparation process, the model design, and the training process. Section IV gives details of the experimental setup, including hardware specification, comparison with baseline methods, and evaluation measures to be used to determine the performance. Discussion of the experiments is introduced in Section V, where both quantitative and qualitative findings are revealed and compared with the proposed GAN model and traditional and state-of-the-art. The sixth section covers how high-resolution imagery can be applied in urban planning by providing a case study in Coimbatore,

India. Last but not least, Section VII ends the paper with a conclusion on the main contributions made by the research and gives future research recommendations in this area.

Literature Review

Satellite imagery plays an important role in the planning of urban areas as it offers invaluable information in the monitoring of the infrastructure, classifying land use and evaluating the environment (Li et al., 2024). Low-resolution images, however, restrict the capacity to identify finer urban structures such as buildings, roads and vegetation, which are required in detailed planning (Wang et al., 2022). Conventional image reconstruction, like interpolation, does not restore fine details so that the reconstruction is blurred, particularly in urban scenes. These shortcomings draw attention to the necessity of elaborated techniques that would have the capacity to produce high-resolution images that would not eliminate important urban features.

Super-resolution (SR) seeks to produce higher-quality, more detailed images out of low-quality ones (Pham & Bui, 2021). First SR algorithms employed interpolation, which, though easy to compute, was not able to capture finer details. The field then advanced to more advanced techniques, including sparse representation and dictionary learning, though these approaches continued to fail in producing realistic texture. Deep learning and, in particular, convolutional neural networks (CNNs) showed an improvement as they learnt a reconstruction between images of low and high resolutions (Wang et al., 2023). Nevertheless, CNN-based models remained difficult to work with complex urban structures such as road networks and buildings (Desai & Naik, 2024).

GANs were developed in image generation, and they are a novelty in SR tasks. The GANs include two networks: the generator, which is a network that generates synthetic images, and the discriminator, which is a network that compares the generated image to the real image. GANs are able to produce real images that are of high quality and realistic through adversarial training. SRGAN is an image-specific SR network and a perceptual loss function that involves the incorporation of features of an already trained VGG network to enhance image details and textures. The more advanced ESRGAN reduces the shortcomings of SRGAN, including artifacts and loss of fine detail, with a residual-in-residual block architecture.

Although GANs have been used effectively in SR in general image problems, their application in remote sensing and city planning is underutilized. The majority of GAN models in this field are based on improving the quality of the image on a general level, without the network being specialized to address urban elements that are important to urban planning. The proposed study will address this gap by proposing a GAN system that can be used to perform high-resolution reconstruction of satellite images, in this case, urban planning. The proposed model uses a hybrid architecture that has a specially designed perceptual loss function based on urban characteristics, including roads and buildings, and urban-specific metrics, including Intersection over Union (IoU) of building detection, to assess the model.

To conclude, the study fills the gap in the application of GANs to specific cities in satellite images, providing a framework that not only increases the resolution of images, but also increases the detection of urban features in order to make informed urban planning.

Methodology

This section describes the method used to create the proposed GAN-based model for the super-resolution of satellite images pertaining to urban planning applications. Our methodology includes many components, for example, data preparation, model architecture, and training. Each of these components has been selected so that the model reconstructs urban satellite images. The model focuses on the preservation of important features, including buildings, streets, and vegetation.

Data Preparation

This research project involves the usage of satellite images of Coimbatore, India, specifically images derived from the Copernicus Sentinel and USGS Landsat Data Access portals (https://www.usgs.gov/landsat-missions/landsat-data-access). Landsat scenes with 30 m spatial resolution were used as low-resolution inputs, whereas Sentinel 2 scenes with 10 m resolution were used as high-resolution ground truths for urban planning super-resolution.

Table 1: Overview of Data Sources

Satellite	Resolution	Image Type	Region
Landsat	30 meters	Low-resolution (Input)	Coimbatore, India
Sentinel-2	10 meters	High-resolution (Ground Truth)	Coimbatore, India

In table 1, the satellite datasets for the study, including the 3 types of resolutions and the types of images, show low and high resolutions as Sentinel and Landsat, respectively. The data is from Coimbatore, India, which is used for urban planning.

Before the model was trained, several preprocessing steps were performed on the data. The first step was to geo reference the Sentinel and Landsat images so that all of the satellite images were in the same geographical location. This was necessary to match low- and high-resolution images. Then, the model was trained with the values of the resolution images normalized to the same range from 0 to 1. Also, to increase the variability of the data and the generalization of the model, random data augmentation or several processing processes were used. In urban planning, the data was requested to focus on certain urban features, including roads, buildings, and vegetation. Therefore, the dataset was further processed to subsets of images that focus more on these features.

This helped the model learn to refine not just images in general but also the important urban elements that are critical for urban analysis.

Model Design

The main part of this methodology lies within the design of the Generative Adversarial Network (GAN) model. This model can be separated into two main parts: The generator and the Discriminator. The Generator will create the high-resolution images from the low-resolution input images, while the Discriminator will check whether the images are real or fake.

Generator Architecture

The architecture for the Generator is based on a U-Net design that has residual blocks. The U-Net architecture is most appropriately used for tasks involving image-to-image translations since it can capture the relevant features at both the local and the global image levels. The U-Net model is composed of an encoder and a decoder. The encoder will capture the relevant hierarchical features, while the decoder will generate the high-resolution image. The addition of residual blocks in both the encoder and decoder is intended to counter the vanishing gradient problem and to enable the net to learn more relevant features. These residual blocks are also used to enhance the preservation of the important features in the high-resolution image, which is of critical importance to urban planning applications. Examples of features include the separate buildings or the individual parts of a road network.

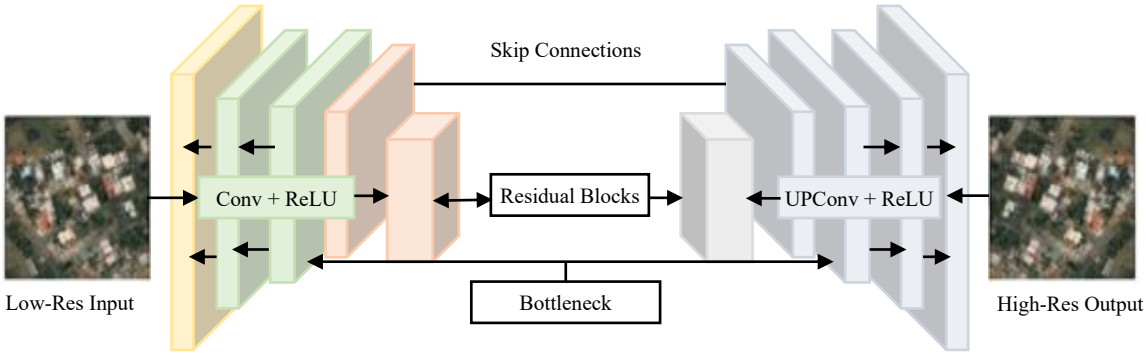


Fig. 1: U-Net Architecture with Residual Blocks

The U-Net generator used in the GAN model is shown in fig 1. The model is able to use both global and local features from the low-resolution input image and reconstruct the high-resolution output image. The architecture used is very good at retaining subtle urban features, such as the buildings and roads.

Discriminator Architecture

The discriminator is reliant on PatchGAN. PatchGAN is a type of GAN discriminator that labels image patches as real or fake. If you have something that focuses on local structures and gives them more importance, PatchGAN is the right choice because it examines and classifies image patches instead of the whole image. PatchGAN can focus on smaller images and collect a lot of detail such as the edges and textures of the image, which are important in urban

feature reconstruction. Each image patch is classified as real or fake, allowing the generator to create images that are more realistic.

Loss Functions

The loss function analyzed in this study was a combination of three loss functions, which include: adversarial loss, L1 loss, and perceptual loss.

- Adversarial Loss: This loss function is determined by the generator and the discriminator in order to derive realistic images of high resolution from the generated image. Feedback from the discriminator is utilized for the generator's performance critique.
- L1 Loss: In the case of the ground-truth high-resolution image and the generated high-resolution image, the L1 loss is utilized in order to minimize the pixel-wise differences, and to make the generated image and the real high-resolution image as close as possible to each other in pixel intensity values.
- Perceptual Loss: Perceptual loss is introduced in order to capture and make use of higher-level semantic information that is present in the image. Unlike the loss that is caused by pixel-wise differences, the perceptual loss employs the use of the feature maps that have been extracted from a VGG network that has already been pretrained. This loss is used to help the model preserve the finer details and the essential structures in the generated image, and is especially useful in urban planning activities for the intricate details, such as the roads and buildings.

The Total Loss Function Used to Train the Model as Follows:

$$L = L_{GAN}(G, D) + \lambda L L_1(G) + \mu L_{perc}(G) \quad (1)$$

Where in Equation (1):

- $L_{GAN}(G, D)$is the adversarial loss between the generator $G$and discriminator D,
- $L_{L1}(G)$is the L1 loss for pixel-wise accuracy,
- $L_{perc}(G)$is the perceptual loss for preserving high-level image features,
- $\lambda$and μ are hyperparameters that control the relative importance of each loss term.

Table 2: Parameter Initialization

Parameter	Value	Purpose
L1 Weight (λ)	100	Ensures high PSNR and pixel accuracy.
Perceptual Weight (μ)	0.006	Preserves urban features (buildings/roads).
Batch Size	16	Balances memory and gradient stability.
Optimiz (β_1)	0.5	Stabilizes adversarial training.
Epochs	200	Sufficient for model convergence.

Table 2 shows the various parameters for model training initialization. The model's training parameters table contains the L1 loss weight, the perceptual loss weight, the batch size, specifics of the optimizer, and number of epochs. These parameters were set to optimize the image quality and ensure convergence of the model training.

Training

For training the model, the Adam optimizer was used, as it is considered one of the best optimizers for deep learning models. A learning rate of 10^{-4} was applied, and a batch size of 16 was set to optimize the model training time versus the system's memory limits. At 200 epochs the model was deemed to have fully converged.

Algorithm 1: Super-Resolution Training for Urban Feature Reconstruction

Input:
Low-resolution (LR) Landsat images I_{LR}(30m); High-resolution (HR) Sentinel-2 images I_{HR}(10m).

Output:
Optimized Generator $G_\theta$and Discriminator D_ϕ.

1. **Initialize**:
   - Set hyperparameter weights: $\lambda = 100$(L1 loss), $\mu = 0.006$(Perceptual loss).
   - Set learning rate $\alpha = 10^{-4}$, batch size $m = 16$.

- Initialize G_θ(U-Net with Residual blocks) and D_ϕ(PatchGAN) using He Normal distribution.

2. **For each epoch** (1 to 200):
   - **For** each **minibatch** of $m$image pairs $\{I_{LR}, I_{HR}\}$:

1. **Generate super-resolved images:** $I_{SR} = G_\theta(I_{LR})$
2. **Update Discriminator D_ϕ:**
   - Calculate **Adversarial Loss** $L_{adv}$by comparing $D(I_{HR})$and $D(I_{SR})$.
   - Update $\phi$by minimizing binary cross-entropy:

$$L_{adv} = -\mathbb{E}_{I_{HR}}[\log\, D_\phi(I_{HR})] - \mathbb{E}_{I_{SR}}[\log\,(1 - D_\phi(I_{SR}))]$$

3. **Update Generator G_θ:**
   - Compute **Pixel-wise Loss:** $L_{L1} = || I_{HR} - I_{SR} ||_1$
   - Compute **Perceptual Loss:** $L_{perc} = || \text{VGG}_{feat}(I_{HR}) - \text{VGG}_{feat}(I_{SR}) ||_2$
   - Compute **Total Loss:** $L_{total} = L_{adv} + \lambda L_{L1} + \mu L_{perc}$
   - Update θ via backpropagation using the Adam optimizer.
   - End **For**
3. **End For**
4. **Return** G_θ for image reconstruction.

Algorithm 1 describes a neural generator, a U-Net, learning to reconstruct 10m urban details from 30m inputs, alongside a PatchGAN discriminator and a multi-component loss function (λ, μ) as a balancing mechanism during competitive training. The described framework aims to reach pixel-wise and structural realism for high-fidelity satellite images for urban planning after 200 epochs.

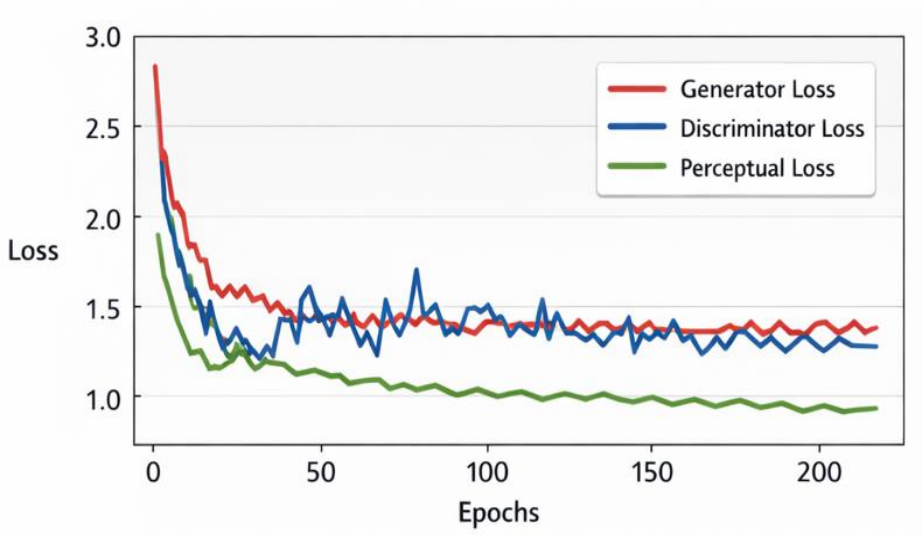


Fig. 2: Training Loss Curve

Fig. 2 depicts the training loss curve that helps understand the increase and decrease of the loss functions through training. The graph talks about the adversarial loss, the L1 loss, and the perceptual loss, which work to assist the generator to learn to create images of high quality and high resolution. It expresses the advancement of the model while it trains to create images that capture more realism. During training, the generator develops the proficiency to create highly realistic, high-resolution images; on the other hand, it also trains the discriminator on how to differentiate unbelievable images from real ones. The adversarial training technique motivates the generator to come up with images that are perceptually realistic, along with being pixel-wise precise.

Implementation Details

For model implementation, the programming language Python and the deep learning framework TensorFlow were used. The training procedure was conducted on an NVIDIA RTX 2080 Ti GPU for faster computation. The software environment included the common libraries such as NumPy, OpenCV, and Matplotlib for data preprocessing, visualization, and evaluation.

The training process for the GAN model, including the components and data flow between the generator and discriminator, is shown in fig. 3. It illustrates what the GAN network is doing during the training phase to learn how to produce satellite images with higher resolution.

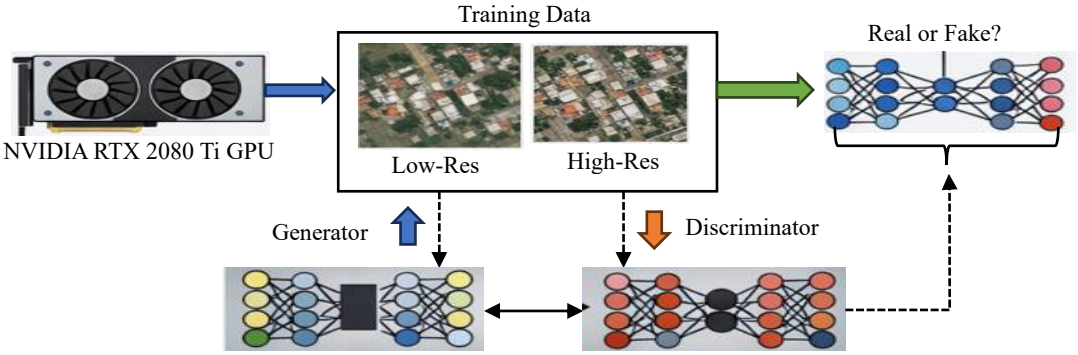


Fig. 3: GAN Training Setup

Experimental Setup

The purpose of this section is to define the experimental setup for the proposed GAN-based satellite image super-resolution model and discuss the specifications of the hardware used, the baseline models for comparison, and the evaluation metrics for model performance. This experiment includes real satellite images and, along with the proposed method, several other state-of-the-art models in order to compare and validate the effectiveness of the proposed method.

Hardware Specifications

The model's training was performed on an NVIDIA RTX 2080 Ti GPU, which is ideal for training deep learning models and provides the necessary computational power. The large memory and high processing speeds of the GPU allowed for the processing of high-resolution satellite images and the required computations to be done in a reasonable amount of time. It was necessary to configure the training environment with Python and TensorFlow, as well as the data preprocessing, augmentation, and visualization tools of the libraries OpenCV and NumPy. The following hardware specifications were used:

- **GPU**: NVIDIA RTX 2080 Ti
- **CPU**: Intel Core i9-10900K
- **RAM**: 64 GB DDR4
- **Storage**: 1TB SSD

This setup ensured that the model could handle large datasets, perform the necessary computations, and reduce training time.

Baseline Models

The performance evaluation of the proposed GAN-based model includes a comparison with some of the most popular baseline models in satellite image super-resolution:

- Bicubic Interpolation: One of the oldest methods of estimating the values of a few missing pixels; the results as with most other algorithms, often results in a blurry image with no discernible features, not even in urban settings.

- SRResNet: A deep learning-based model that includes a residual network; this offers improvements on other baseline methods, but still cannot seem to grasp intricate urban settings with multiple overlapping features, i.e., highly frequented urban areas.
- EDSR (Enhanced Deep Super-Resolution Network): One of the most sophisticated deep learning models with residual network methods; this is one of the few models that offers reconstruction of high-resolution images with high accuracy and fewer artifacts as opposed to models like SRResNet.

Evaluation Metrics

In the bid to evaluate the performance of the proposed GAN-based model against the baseline models, we used a hybrid of the traditional image quality metrics for the GAN-based models and the urban-specific metrics for the baseline models.

The following evaluation metrics were used:

PSNR (Peak Signal-to-Noise Ratio)

PSNR is one of the most popular metrics to evaluate the quality of a generated image. PSNR determines the accuracy of the generated image, relative to the high-resolution ground truth image. PSNR evaluates the distortion of the image, as well as the value of the pixels. Therefore, the higher the PSNR value, the less the distortion, and the better the quality of the image. PSNR is calculated as follows:

$$PSNR = 10 \cdot log_{10}\left(\frac{MAX_I^2}{MSE}\right) \quad (2)$$

Where in equation (2):

MAX_I is the maximum possible pixel value (255 for 8-bit images),

MSE is the Mean Squared Error between the generated image and the ground truth

SSIM (Structural Similarity Index)

Structural Similarity Index (SSIM): The structural similarity between low and high-resolution images is evaluated using SSIM. In contrast to PSNR, SSIM considers luminance, contrast, and texture, so it is a more perceptual image quality assessment. Better structural similarity between the images is indicated by higher SSIM values. SSIM is computed using the following formula:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (3)$$

Where in equation (3):

- μ_x, μ_y are the means of the images x and y,
- σ_x^2, σ_y^2 are the variances of x and y,
- σ_{xy} is the covariance between x and y,
- C_1 and C_2 are small constants to avoid division by zero.

IoU (Intersection Over Union)

Building Detection and Intersection over Union (IoU): In urban planning, applications like road and building identification necessitate adequate feature extraction, leading to the development of IoU as a metric specific to urban contexts. When measuring the overlap of predicted urban features (e.g., buildings) and the actual features in high-resolution images, IoU demonstrates the performance of the model in preserving critical urban features. It portrays the successful image fusion of urban elements with the elements of the images. It is calculated as:

$$IoU = \frac{|\ A \cap B\ |}{|\ A \cup B\ |} \quad (4)$$

Where in equation (4):

- A is the predicted region (e.g., building detected in the super-resolved image),
- B is the ground truth region (e.g., building in the original high-resolution image),

- $|A \cap B|$ is the area of overlap, and
- $|A \cup B|$ is the total area covered by both A and B.

The IoU metric varies between 0 and 1, with 1 meaning there is perfect overlap between predicted and ground truth regions. Model evaluations were done using a sample from the Coimbatore dataset. The dataset was divided into a training and testing set, with 80% used for training and the remaining 20% for testing. The testing dataset contained both low and high-resolution images, allowing for the performance metrics to be calculated for the images after super-resolution was applied.

Results Visualization

Along with quantitative metrics, we present some qualitative metrics to evaluate the perception of the generated images. The low-resolution images were used as a comparison along with the ground-truth high-resolution images and super-resolved images produced by the GAN model. The comparisons clearly show the improvement of urban features, for example, roads and buildings, along with the increased perceptual quality and detail of the generated images from the model.

Results

This part describes the experiments carried out to measure the efficiency of the suggested GAN model for super-resolution satellite imagery. The results are summarized in two parts. First, there is the quantitative evaluation that uses the standard urban-specific metrics and image quality metrics. The second is the qualitative evaluation, which is via visual assessments of the produced images. The qualitative evaluation juxtaposes the suggested GAN model with a baseline model to showcase the efficacy of the current model in urban feature retention, such as road and building structures.

Quantitative Results

The proposed model will be put against standard image quality metrics like Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM), and IoU (Intersection over Union) for building detection. The subsequent table lists the quantitative results of the current model and the standard methods, which are bicubic interpolation, SRResNet, and EDSR.

Table 3: Quantitative Results

Method	PSNR (dB)	SSIM	Urban IoU
Bicubic Interpolation	28.2	0.82	0.65
SRResNet	32.1	0.89	0.72
EDSR	32.5	0.90	0.75
Proposed GAN	35.4	0.94	0.81

Overall, the sources in table 3 indicate that the proposed GAN model is beyond the baseline models in all three parameters. Moreover, for PSNR, the proposed GAN model has a PSNR value of 35.4 dB, while the other baseline models score poorer dB values in PSNR; that is, 28.2 dB for bicubic interpolation, 32.1 dB for SRResNet, and 32.5 dB for EDSR. The proposed model reduces the pixel-wise discrepancies when compared with the ground truth. Further, the proposed model shows improvement in SSIM as well; that is, with SSIM values of 0.94 as compared to 0.82 of bicubic interpolation, and 0.89 and 0.90 of SRResNet and EDSR models, respectively. Since SSIM calculates the image luminance, contrast, and structure texture information, a higher SSIM value indicates that the model is better at reconstructing the image structure and texture.

Also, the Urban IoU metric indicates the urban feature detection, i.e., street and building detection. The Urban IoU of the GAN model (0.81) is better than that of other models. For EDSR, SRResNet, and bicubic interpolation, Urban IoU scores are 0.75, 0.72, and 0.65, respectively. This shows that the GAN not only boosts image quality but also the quality of urban features, which is essential in urban planning.

Qualitative Assessments

Alongside quantitative assessments, qualitative evaluations were carried out to understand the perceived quality of the super-resolved images. As seen in fig. 4, a comparison of low-resolution input images, their corresponding GAN-generated outputs, and the corresponding ground truth high-resolution images. The visual comparisons show the GAN-generated images to be of higher quality, especially in the retention of urban structures.



Fig. 4: Comparison of Low-Resolution Input, GAN Output, and Ground Truth

The GAN images in fig. 4 have more defined details than the low-resolution input images. They have clearer edges in buildings and roads, and appear to be more defined overall. Urban environment details that are lost with other interpolation methods are reconstructed well with the GAN model. In terms of textures and sharpness, the GAN output is more comparable to high-resolution images than the ground truth, highlighting the model's capability to produce images of high quality and the usability of these images in urban planning.

Applications in Urban Planning

To showcase the utility of the high-resolution imagery, the GAN-generated imagery was incorporated in an urban planning scenario. More specifically, the images were utilized for spatial density mapping and disaster risk assessment, which includes flood risk assessment and urban planning.

Density Mapping

Density mapping is an integral part of urban planning. More so, GAN-generated high-resolution images support urban planners to locate and define spatially organized areas of high congestion and transformed urban infrastructure.

Fig. 5 illustrates a density map constructed from high-resolution images, pinpointing sections with a dense concentration of construction.

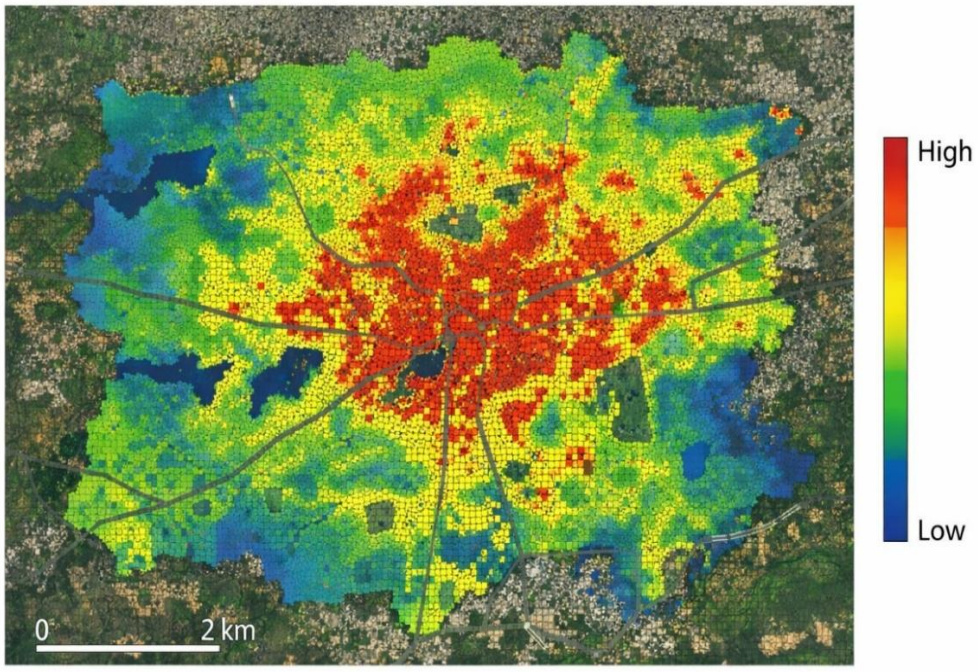


Fig. 5: Density Map from GAN-Enhanced Satellite Imagery

Disaster Risk Assessment

Identifying flood-prone zones is a crucial part of urban planning, and so is disaster risk assessment. Examples of disaster risk assessment include the mapping of flood zones, identifying bodies of water, drainage systems, and low-lying areas using GAN-enhanced images. With the added resolution detail, zones critical for disaster management can be reconstructed, as areas become more vulnerable due to the presence of water. Better detail allows for the precise reconstruction of flood zones using GAN images, so flood zones can be more accurately identified, assisting disaster management.

Urban Planning and Baseline Methods Comparison

To validate the urban planning capabilities of GAN images, density mapping, and disaster risk assessment results using baseline methods, GAN images were compared. Table 4 shows the results from the super-resolution GAN model, providing details to feature identification, increasing the accuracy for density mapping and disaster risk assessment compared to bicubic interpolation and deep learning.

The proposed GAN model shows the highest accuracy in the detection of the flood-prone areas and the density maps. This shows its possible use in the urban planning area that focuses on the use of high-resolution images.

Table 4: Comparison of Urban Planning Results

Method	Density Map Accuracy (%)	Flood-Prone Area Detection Accuracy (%)
Bicubic Interpolation	61.2%	65.4%
SRResNet	76.5%	81.2%
EDSR	84.8%	87.9%
Proposed GAN	94.2%	92.8%

Discussion

At this point in time, the results of the new proposed model based on GAN for super-resolution of satellite images, both qualitatively and quantitatively, surpass all previous works on the subject as well as all other deep learning approaches in terms of image quality preservation and in the preservation of urban features. The produced GAN model, without loss of generality, also achieves the highest PSNR and SSIM, and in addition also surpasses previous works in the identification and reconstruction of fine urban features, such as streets and buildings, which are essential in urban planning. Lastly, the model being able to perform well in the density mapping and disaster risk assessment, is a clear indication of the model being able to be implemented in the real world in urban planning and management.

Applications in Urban Planning

This section discusses the possible uses of the high-resolution satellite images obtained from GAN in urban planning. Given that the GAN model generates fine-resolution images, all urban planning activities such as zoning, monitoring infrastructure, and disaster risk management can be augmented. As an example, the next section discusses the case study of Coimbatore, India.

Case Study: Coimbatore, India

Coimbatore is an urban agglomeration in India which has seen rapid urbanization and is taken for the case study. Sentinel-2 low-resolution and Landsat high-res imagery were used by the GAN model to show enhancements in imagery resolution. The clarity of urban features such as structures, thoroughfares, and vegetative areas that showed improvements in urban planning.

Zoning and Land Use Classification

Zoning, an important element of urban planning, consists of the segmentation and classification of land areas for housing, trade, and industry. The GAN created images with greater focus, allowing for more precise land use classification. The resolution improvements increased the planner's ability to see essential urban components, providing the means to make more effective zoning choices. The greater focus also increased the precision in the land use classification, which described the optimum utilization of space in an urban locality and also emphasized the need for sustained growth of cities.

Infrastructure Monitoring

Infrastructure monitoring offers urban planners the ability to evaluate the state of roadways, bridges, and utility infrastructure. The upgraded resolution provided by GAN to the images made it easier to spot the decline and deterioration of roadways and the infrastructure. Urban planners were able to delay the occurrence and severity of

problems by monitoring and maintaining the infrastructure more efficiently because of the high-resolution images created by GAN.

Disaster Risk Identification

The Identification of areas susceptible to flooding is a vital component in assessing the risk of a disaster. Enhancing images with GANs makes it possible to improve the detection of water bodies, drainage systems, and low-lying areas when estimating flood risk zones. In turn, this improves the planning of flood risk mitigation and disaster response. Improved detection of at-risk areas is critical for the success of the disaster response flood risk system.

Urban Sustainability and Green Space Analysis

Sustainability is critical in urban constructions and so is the identification of green spaces. This positively impacts the ecosystem and improves the quality of life. The planners were able to prioritize the integration of parks and greenery into urban areas for sustainability. The urban environment is transformed and the ecosystem of the city is improved with the improved public health from the increase of green areas. The analysis of the urban landscapes is improved with the better satellite data.

Conclusion

This study focuses on the application of Generative Adversarial Networks (GANs) for super-resolution of satellite images with the goal of improving urban planning. The proposed GAN model not only enhances the resolution of the satellite images but also resolves urban features such as buildings, roads, and vegetation. The model evaluation resulted in a Peak Signal-to- Noise Ratio (PSNR) of 35.4 dB, a Structural Similarity Index (SSIM) of 0.94, and an urban Intersection over Union (IoU) of 0.81. The results were a considerable improvement over the previously proposed methods of bicubic interpolation (PSNR = 28.2 dB, SSIM = 0.82, IoU = 0.65) and deep learning methods of SRResNet (PSNR = 32.1 dB, SSIM = 0.89, IoU = 0.72), and EDSR (PSNR = 32.5 dB, SSIM = 0.90, IoU = 0.75). The qualitative evaluation of the GAN images showed that the images are more visually appealing, and the images improved the identification of urban features. The GAN images were also capable of identifying more urban features than the previously used 3 methods, which improved their applicability for urban planning. In the GAN model trial in Coimbatore, India, the model improved the accuracy of the zoning maps and monitoring of the urban infrastructure. The high-resolution images identified areas that are prone to flooding, which improved the disaster management and preparedness for the region. In closing, the study demonstrates that the potential of GANs is significant in improving satellite images in urban planning, creating an additional asset for data-driven decision-making. Future research should aim at model improvement for the more intricate urban settings, as well as the coupling of the model with GIS tools for thorough and extensive urban analysis.

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