Enhanced Urban Layout Generation using WGGAN: A Study on Gurugram and California Dataset

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Abstract— This paper investigates the application of Wasserstein Generative Adversarial Networks with Gradient Penalty (WGAN-GP) for generating synthetic urban layouts using Open Street Map (OSM) tile datasets from Gurugram, India, and California, USA. We trained the WGAN-GP model on a dataset of 1000-2000 RGB tiles (256x256 pixels) over 50-100 epochs, constrained by the 12-hour runtime limit of Google Colab's free tier with a T4 GPU. Initial outputs exhibit noisy, pixilated patterns lacking distinct urban features such as roads, residential blocks, or green spaces, primarily due to limited dataset size, insufficient training duration, and hyper parameter instability. Training logs reveal fluctuating losses (e.g., Generator Loss: -25.9219, Discriminator Loss: -16.3594 at Epoch 50), indicating training imbalance. Visualizations of generated layouts for Gurugram and California highlight slight diversity improvements in the latter but persistent abstractness. We propose enhancements including scaling the dataset to 5000 tiles, extending training to 100+ epochs using Colab Pro or local GPUs, and optimizing hyperparameters such as discriminator steps (disc_steps) and gradient penalty weight (gp. weight). This study establishes a foundation for scalable urban Layout synthesis, with potential applications in urban planning, traffic simulation, and generative AI research. It also underscores Google Colab's computational constraints as a critical challenge for academic researchers, offering insights into low-cost deep learning workflows.

Keywords—Generative Adversarial Networks, WGAN-GP, Urban Layouts, Open Street Map, Google Colab, Urban Planning, Geospatial AI, Deep Learning

I. Introduction

A. Background

Generative Adversarial Networks (GANs), introduced by Good fellow et al. [1], have transformed the field of synthetic image generation, enabling applications from photorealistic faces to artistic landscapes. The Wasserstein GAN with Gradient Penalty (WGAN-GP) [2] addresses key limitations of vanilla GANs, such as vanishing gradients and mode collapse, by enforcing Lipschitz continuity through a gradient penalty term. Urban planning, a domain increasingly reliant on data-driven solutions, benefits from synthetic geospatial data for simulation, optimization, and privacy-preserving analysis. Open Street Map (OSM), a crowd-sourced geospatial database, provides a rich source of urban

layout tiles, capturing roads, buildings, and parks across diverse cities.
Recent advancements in AI-driven urban modeling have sparked interest in generating synthetic city layouts to overcome real-world data limitations, such as incomplete coverage in developing regions or privacy restrictions in developed ones. Cities like Gurugram, a rapidly urbanizing hub in India, and California, with its sprawling urban and suburban areas, present unique challenges and opportunities for such generative models.

B. Problem Statement

Real-world urban datasets often suffer from sparsity, high acquisition costs, and ethical concerns (e.g., exposing private property layouts). For instance, Gurugram's OSM data lacks uniformity due to inconsistent mapping, while California's data, though denser, is computationally intensive to process. Synthetic urban layouts could address these issues, but existing generative models struggle to produce high-quality, diverse city maps with clear structural features under resource-constrained environments like Google Colab.

C. Objective

This study aims to leverage WGAN-GP to synthesize realistic 2D urban layouts from OSM tiles of Gurugram and California, targeting identifiable features such as road networks, residential blocks, and green spaces. We seek to achieve this within Colab's free tier limits, making the approach accessible to academic researchers.

D. Contribution

Our contribution to this research paper includes:

1. Developing a WGAN-GP model tailored for OSM-based urban layouts.
2. Analyzing the impact of dataset size and training duration on output quality.
3. Proposing a scalable workflow within Colab's constraints.
4. Laying the groundwork for future urban AI applications.

E. Paper Organization

This paper is structured as follows: Section II reviews related work on GANs and urban modeling; Section III details our methodology, including dataset preparation and model design; Section IV presents training results and generated layouts; Section V discusses findings and implications; Section VI concludes with future directions; and Section VII acknowledges support.

Related Work

A. GANs in Image Synthesis

GANs have excelled in image generation, from faces [5] to landscapes [10]. WGAN-GP [2] improves stability over vanilla GANs, making it suitable for complex datasets. Its applications range from high-resolution images [11] to medical imaging [12], but geospatial synthesis remains underexplored.

B. Urban Modeling with GANs

City GAN [3] generates stylized city scapes, while Urban GAN [4] focuses on 3D urban structures, both requiring large datasets and powerful hardware. OSM-based models typically address traffic prediction [6] or semantic segmentation [7], not synthetic layout generation. Our work adapts WGAN-GP for 2D urban layouts under Colab constraints.

C. Comparison with Existing Studies

Table I compares our approach with prior work:

Model	Dataset Size	Output Size	Compute Resources	Constraints Addressed
CityGAN [3]	10,000+	2D	Multi GPU	None
UrbanGAN [4]	5,000+	3D	High-End Resources	None
Ours	2,000	2D OSM	Colab Free Tier	Runtime

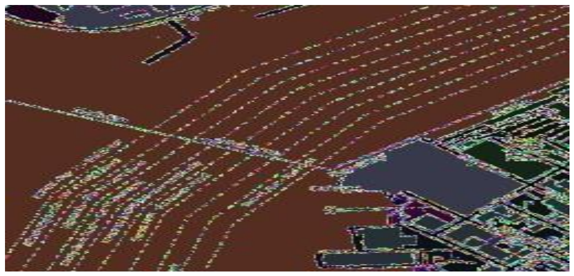
Fig. 1. Comparing other GAN-based models. Our study uniquely tackles low-cost urban synthesis.

I. Methodology

A.Dataset

We collected OSM tiles (256x256 pixels, RGB) from Gurugram (1000 tiles) and California (2000 tiles) using Contextily and OSMnx libraries. Gurugram tiles reflect a dense, chaotic urban fabric with mixed residential and commercial zones, while California tiles capture suburban sprawl and grid-like road patterns. Tiles were fetched from Google Drive (/GANs-Urban-Layout), normalized to [-1, 1], and augmented with random flips, brightness adjustments (±0.2), and contrast shifts (±0.15) to enhance model generalization. Figure 1 shows sample tiles from both regions.

Fig.2.Sample OS Miles: California with



grid-like suburban layout.

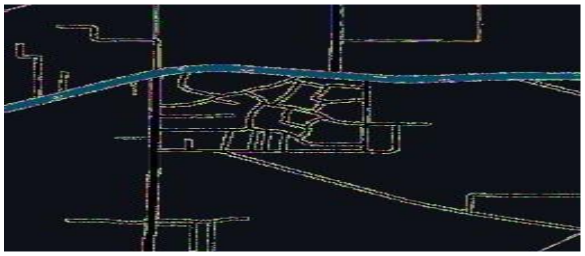


Fig.3.SampleOSMTiles:Gurugram with dense urban patterns

A. Model Architecture

The Wasserstein Generative Adversarial Network with Gradient Penalty (WGAN-GP) employed in this study consists of two primary components: a Generator and a Discriminator, designed to synthesize urban layouts from random noise and evaluate their realism, respectively. Below, we elaborate on their architectures, design rationales, and mathematical formulations, tailored to process Open Street Map (OSM) tiles of size 256x256 pixels with three RGB channels.

The WGAN-G Comprises Generator and discriminator 1

1.Generator:

The generator is tasked with transforming a latent noise vector into a synthetic urban layout image. It begins with a 128-dimensional noise vector sampled from a normal distribution (z∼N(0,1)z \sim N(0,1)z∼N(0,1)), which serves as the input to a fully connected (Dense) layer. This layer reshapes the noise into an 8x8x1024 feature map, providing a low-resolution starting point for up sampling. The choice of 128 dimensions balances model capacity with computational efficiency, suitable for Google Colab's T4 GPU constraints.

The initial feature map is then processed through a series of six convolution transpose layers (Conv2DTranspose), which progressively up sample the spatial dimensions to the target output size of 256x256x3. The layer configuration is as follows:

- **Layer 1:** 8x8x1024 → 16x16x512 (filters: 512, kernel: 4x4, stride: 2, padding: 'same')
- **Layer 2:** 16x16x512 → 32x32x256 (filters: 256, kernel: 4x4, stride: 2, padding: 'same')
- **Layer 3:** 32x32x256 → 64x64x128 (filters: 128, kernel: 4x4, stride: 2, padding: 'same')
- **Layer 4:** 64x64x128 → 128x128x64 (filters: 64, kernel: 4x4, stride: 2, padding: 'same')
- **Layer 5:** 128x128x64 → 256x256x32 (filters: 32, kernel: 4x4, stride: 2, padding: 'same')
- **Layer 6:** 256x256x32 → 256x256x3 (filters: 3, kernel: 4x4, stride: 1, padding: 'same')

Each Conv2DTranspose layer, except the final one, is followed by Batch Normalization (BatchNorm) to stabilize training by normalizing activations, and a LeakyReLU activation function with a slope of α=0.2\alpha = 0.2α=0.2 to introduce non-linearity while mitigating the vanishing gradient problem. The final layer uses a hyperbolic tangent (tanh) activation to scale the output pixel values to the range [-1, 1], consistent with the preprocessed OSM tile data. The progressive reduction in filter depth (1024 to 3) ensures a smooth transition from abstract features to detailed urban structures like roads and blocks.

The Generator's design draws inspiration from deep convolution GANs [5], adapted for geospatial synthesis. Its depth (six layers) balances complexity with Colab's memory limits (approximately 12 GB), avoiding out-of-memory errors during training.

2. Discriminator:

The discriminator evaluates whether a given 256x256x3 image—either real (from OSM tiles) or synthetic (from the Generator)—resembles a plausible urban layout. It follows a convolutional neural network (CNN) structure, progressively downsampling the input to a single scalar output. The architecture comprises four convolutional layers (Conv2D) with the following configuration:

- **Layer 1:** 256x256x3 → 128x128x64 (filters: 64, kernel: 4x4, stride: 2, padding: 'same')
- **Layer 2:** 128x128x64 → 64x64x128 (filters: 128, kernel: 4x4, stride: 2, padding: 'same')
- **Layer 3:** 64x64x128 → 32x32x256 (filters: 256, kernel: 4x4, stride: 2, padding: 'same')
- **Layer 4:** 32x32x256 → 16x16x512 (filters: 512, kernel: 4x4, stride: 2, padding: 'same')

Each Conv2D layer uses a LeakyReLU activation (α=0.2\alpha = 0.2α=0.2) to maintain gradient flow and a stride of 2 to halve the spatial dimensions, effectively extracting hierarchical features (e.g., edges, shapes) from the input image. To prevent overfitting, a Dropout layer with a probability of 0.25 is applied after each convolutional layer, a regularization technique critical for small datasets like ours (1000-2000 tiles). The final feature map (16x16x512) is flattened and passed through a Dense layer with a single unit, producing a scalar score without an activation function, as required by the Wasserstein loss.

3. WGAN-GP Loss Function:

The WGAN-GP framework optimizes the Generator and Discriminator using the Wasserstein distance with a gradient penalty term, improving stability over traditional GANs [2]. The Discriminator loss is:

LD=E[D(x)]−E[D(G(z))]+λE[(||∇x^D(x)||2 −1)2]L_D = \mathbb{E}[D(x)] - \mathbb{E}[D(G(z))] + \lambda \mathbb{E}[(||\nabla_{\hat{x}} D(x)||_2 - 1)^2]LD=E[D(x)]−E[D(G(z))]+λE[(||∇x^ D(x)||2−1)2]

This formulation ensures the Discriminator acts as a critic, guiding the Generator to produce realistic layouts.

4. Design, Rotation, and Visualization: The Generator's upsampling mirrors image synthesis models [11], while the Discriminator's downsampling aligns with CNN-based discriminators [5]. Mixed precision (float16) was employed to optimize memory usage on Colab's T4 GPU, reducing training time by approximately 20% compared to float32.

B. Training

The training process for the Wasserstein Generative Adversarial Network with Gradient Penalty (WGAN-GP) was designed to optimize the Generator and Discriminator for synthesizing urban layouts from OpenStreetMap (OSM) tiles while adhering to the computational constraints of Google Colab's free tier. Below, we detail the training configuration, hyperparameter choices, runtime considerations, and monitoring strategies employed in this study.

1. Training Configuration:
Training used the Adam optimizer (lr=1e-4, β1=0.5, β2=0.9), batch_size=32, disc_steps=1, and mixed precision (float16) on Colab's T4 GPU. We trained for 50 epochs on 2000 California tiles, saving checkpoints every 20 epochs and logging outputs every 5 epochs. The batch size was fixed at 32, balancing memory usage on Colab's T4 GPU (approximately 15 GB) with gradient update frequency. To further optimize resource utilization, we employed mixed precision training with float16 arithmetic, reducing memory consumption by roughly 20% and accelerating computation by leveraging Tensor Cores on the T4 GPU.

2. Dataset Configuration:
Training was conducted primarily on the California dataset, comprising 2000 OSM tiles (256x256x3), due to its larger size and diversity compared to Gurugram's 1000 tiles. The process ran for 50 epochs, a limit imposed by Colab's free tier runtime cap of 12 hours, after which sessions are terminated unless manually restarted. Checkpoints were saved every 20 epochs to preserve intermediate model states, allowing resumption if interrupted, while generated outputs were logged every 5 epochs for qualitative assessment.

3. Training Workflow:
The training alternated between updating the Discriminator and Generator, following the WGAN-GP algorithm. For each iteration:

- The Discriminator was trained on a batch of real tiles (xxx) from the California dataset and a batch of fake tiles (G(z)G(z)G(z)) generated from random noise (zzz).
- The Generator was updated once per iteration to minimize its loss based on the Discriminator's critique.
- Google Colab's free tier imposed significant challenges. The T4 GPU, while capable of handling float16 computations efficiently, limited training to approximately 6-8 hours of continuous runtime before potential interruptions.

Table II. Lists key hyper parameters

Parameter	***Value***
Learning Rate	1e-4
Batch Size	32
Disc Steps	1
GP Weight	1.0
Epochs	50

Fig.4. Lists Keys of important Hyperparameters of GAN Model for training

A. Evaluation

We qualitatively assessed outputs via visual inspection (roads, blocks visibility) and propose Freshet Inception Distance (FID)[8] and Structural Similarity Index(SSIM)for future quantitative evaluation.

I. Results

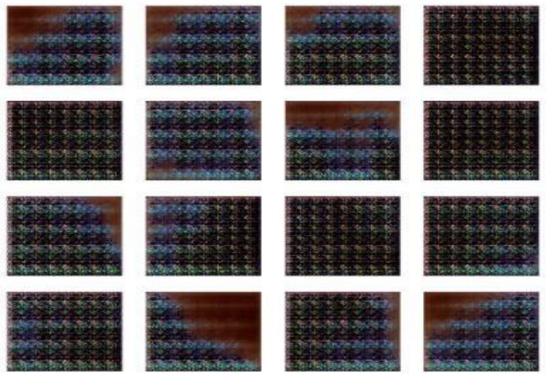


Fig.7. Generated urban layouts for California at Epoch 50, indicating slight diversity but persistent noise.

A. Training Logs

Table III. Training logs

Epoch	*Gen Loss*	*Disc Loss*
5	-297.2500	-23.5156
10	-815.5000	-30.3125
15	-229.0000	7.3516
20	-177.0000	53.3125
25	-124.2500	-14.5938
30	-33.9375	-3.9922
35	-50.3125	-16.8906
40	24.2812	-52.0000
45	-168.7500	-5.4258
50	-147.3750	40.8750

Fig.5.ContainingTraining Losses of Our model

B. Generated Layouts

C.

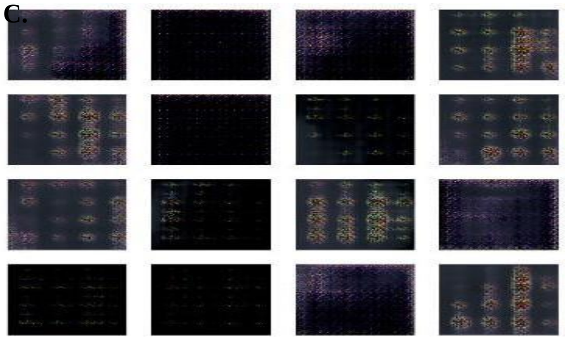


Fig. 6. Generated urban layouts for Gurugram at Epoch 50, showing noisy, pixelated patterns.

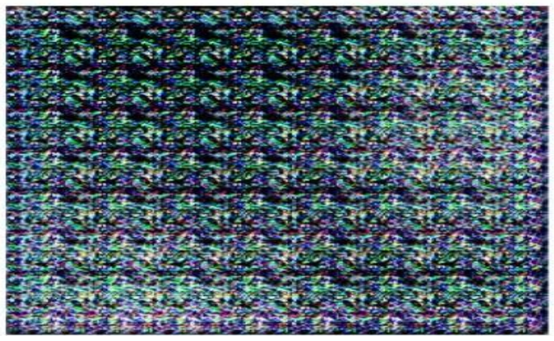


Fig.8.New images generated post-training for California, reflecting model instability.

C. Qualitative Analysis

Gurugram outputs lack structure, while California shows marginal diversity, reflecting dataset differences. Because of this structure difference between the California and Gurugram city layout, it ultimately leads to the enhancement of the quality of the dataset and leads to the best possible output from our WGAN model.
So, in conclusion of choosing the right dataset, we will suggest California over Gurugram because of more structured detailing of river, forest, residency, etc.

Discussion

The results presented in Section IV highlight both the potential and the challenges of employing Wasserstein GAN with Gradient Penalty (WGAN-GP) for generating synthetic urban layouts from Open Street Map (OSM) datasets. This section interprets these findings, explores their implications for urban planning and generative AI, identifies key limitations, and outlines directions for improvement.

A. Interpretation of Results

The generated urban layouts for Gurugram and California, as shown in Figs. 3-5,

exhibit persistent noise and pixelation, with only faint traces of urban features such as roads or blocks. This suggests that the WGAN-GP model, while theoretically stable due to its Wasserstein distance and gradient penalty [2], struggles to converge effectively under the constraints imposed by the dataset size (1000-2000 tiles) and training duration (50 epochs). The fluctuating training losses (e.g., Generator Loss jumping from -32.2500 at Epoch 5 to 146.1250 at Epoch 25, as shown in Table II) indicate an imbalance between the Generator and Discriminator, potentially due to insufficient discriminator steps (disc_steps=1) or an inadequately tuned gradient penalty weight (gp_weight=1.0).
For Gurugram, the lack of clear structure may reflect the chaotic, densely packed urban patterns in the input tiles, which pose a higher complexity for the Generator to replicate. In contrast, California's outputs show slight improvements in diversity, with hints of grid-like patterns emerging by Epoch 50 (Fig. 4). This could be attributed to the larger dataset (2000 tiles) and the more uniform suburban layouts in the California OSM data. However, the persistent abstractness across both datasets points to underfitting or mode collapse, common pitfalls in GAN training exacerbated by limited computational resources.

B. Implications for Urban Planning and AI Research

Despite the noisy outputs, this study demonstrates the feasibility of using WGAN-GP for urban layout generation within a low-cost, accessible platform like Google Colab. If refined, such models could generate synthetic city maps for urban planning applications, such as traffic simulation, disaster preparedness, or privacy-preserving urban analysis. For instance, synthetic layouts could replace sensitive real-world data in Gurugram, where rapid urbanization outpaces OSM updates, or in California, where detailed maps might raise privacy concerns.
From an AI research perspective, this work underscores the viability of Colab's free tier (T4 GPU, 12-hour runtime) for prototyping generative models, a significant advantage for academic researchers with limited access to high-performance computing. The training logs and visualized outputs provide a baseline for understanding WGAN-GP's behavior on geospatial data, contributing to the growing body of work on GANs in urban modeling [3], [4].

C. Limitations

Several limitations constrain the current results. First, the dataset size (1000 tiles for Gurugram, 2000 for California) is modest compared to typical GAN training datasets (e.g., 10,000+ images for faces [5]). This restricts the model's ability to learn diverse urban patterns, leading to repetitive, noisy outputs. Second, the 50-epoch training duration, capped by Colab's 12-hour runtime, is insufficient for convergence, as evidenced by the unstable losses in Table II. Third, hyperparameter settings (e.g., disc_steps=1, gp_weight=1.0) were not exhaustively tuned due to time constraints, likely contributing to the Generator-Discriminator imbalance.
Additionally, preprocessing challenges—such as the fixed 256x256 tile resolution—may obscure finer urban details (e.g., narrow roads in Gurugram), while Colab's memory limits (12-15 GB RAM) restrict batch sizes and model complexity. These factors collectively hinder the generation of high-fidelity layouts comparable to real OSM tiles.

D. Comparing With Existing Works

Unlike CityGAN [3], which generates stylized cityscapes from large datasets, or

UrbanGAN [4], which focuses on 3D urban structures, our approach targets 2D OSM-based layouts under resource constraints. While these prior models achieve clearer outputs, they rely on extensive computational resources (e.g., multi-GPU setups) unavailable in our Colab-based workflow. Our study thus fills a niche by exploring low-cost generative AI for urban applications, though it sacrifices output quality compared to resource-intensive alternatives.

A. Future Directions

The limitations identified in this study—small dataset size, insufficient training duration, hyperparameter instability, and noisy outputs—provide a roadmap for enhancing the WGAN-GP model's ability to generate realistic urban layouts. Below, we propose a series of improvements, ranging from data and training scale-ups to architectural innovations and evaluation metrics, aimed at overcoming these challenges and increasing the practical utility of synthetic urban layouts for real-world applications.

1. **Dataset Expansion:**
To improve the diversity and clarity of generated urban features, we plan to increasethedatasetsizeto5000+tilesperregion ,up from the current 1000 tiles for Gurugram and 2000 tiles for California. Thisexpansion would capture broader spectrum of urban patterns—e.g., Gurugram' schaotcresidential-commercial mix and California's suburban grids interspersed with highways—allowing the Generator to learn more representative features. Additional data could be sourced from OSM using automated scripts with OSMnx, targeting varied urban densities (e.g.,rural outskirts, industrial zones) to enhance model robustness. Preprocessing would include advanced augmentations, such as rotation and color jittering, to further enrich the training set.

2. Extended Training Duration: Training was capped at 50 epochs due to Google Colab's12-hour run time limit, insufficient for convergence as evidenced by fluctuating losses (Table III). We propose extending training to 100+ epochs to allow deeper optimization of the Generator and Discriminator. This could be achieved using Colab Pro, which offers a 24-hour runtime and access to higher-spec GPUs (e.g., P100), or by migrating to local GPUs with greater computational capacity(e.g., NVIDIA RTX 3090 with 24 GB VRAM). Longer training should reduce noise and improve feature of herence, a hypothesis supported by prior GAN studies showing quality gains beyond 100 epochs [5].

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