ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

MINI PROJECT REPORT

DEPARTMENT OF INFORMATION SCIENCE AND TECHNOLOGY

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FLOOR PLAN GENERATION USING GAN

1. ABSTRACT:

This study explores the intersection of generative models and computer vision, focusing on their application in generating architectural floor plans. Our hybrid approach combines the strengths of Generative Adversarial Networks (GANs) and Autoencoders to produce diverse and realistic floor plans. The Autoencoder captures intricate details by training on floor plan images, creating a compressed representation of spatial arrangements. This encoded foundation serves as the basis for generating novel floor plans while maintaining a link to the input data.

To enhance diversity and realism, a Generative Adversarial Network (GAN) is introduced, engaging in adversarial training. The generator network creates realistic floor plans, while the discriminator network distinguishes between generated and real plans. This dynamic interplay results in the generation of creative and authentic floor plans. Our hybrid approach balances the autoencoder's reconstruction capabilities with the GAN's generative power, offering a comprehensive solution for floor plan generation.

Experimentation on diverse datasets validates the method's effectiveness, demonstrating its ability to produce high-quality and diverse floor plans. The study discusses implications for architectural design, interior planning, and urban development. Contributing to the generative model field, our approach leverages GANs and autoencoders to inspire innovative architectural concepts, reflecting existing structures' characteristics while fostering creativity.

2. BACKGROUND

The project, "Hybrid Approach for Floor Plan Generation Using GANs and Autoencoders," resides at the confluence of artificial intelligence, computer vision, and architecture. As urbanization burgeons and architectural design evolves, the demand for innovative tools assisting architects, designers, and urban planners in generating diverse and realistic floor plans is burgeoning. Traditional methods often entail manual effort and lack the capacity to explore a broad spectrum of creative possibilities.

A) Motivation and Methodology:

The project is motivated by the ambition to leverage advanced generative models in automating and enhancing the floor plan generation process. Generative Adversarial Networks (GANs) and Autoencoders stand out as potent tools in computer vision, promising to capture the intricacies of architectural layouts and spatial configurations. Autoencoders encode and decode complex features of floor plans, learning from diverse datasets to represent essential architectural characteristics, forming a foundation for generating novel and unique floor plans while preserving input data essence.

B) Integration of GANs:

The integration of GANs addresses the challenge of generating diverse and realistic floor plans. The adversarial training process within GANs involves a generator network creating convincing floor plans for a discriminator network. This interplay yields floor plans showcasing creativity and authenticity, pushing beyond the limits of traditional generative models.

C) Significance and Practical Implications:

Beyond technical aspects, the project addresses a practical need in architecture, interior design, and urban planning. It offers a tool inspiring creativity, streamlining design processes, and potentially yielding innovative spatial layout solutions. The significance extends to contributing to the evolving landscape of generative design, providing a unique perspective on synthesizing realistic and creative floor plans.

D) Hybrid Approach Contribution:

By combining the strengths of GANs and Autoencoders, the project contributes to the evolving field of generative design. The outcomes hold implications for the future of architectural design, where AI-powered tools complement human creativity, contributing to the development of functional and aesthetically pleasing built environments.

3. DATA

The data for floor image is taken from the github given by Mr.Akash.

GitHub: https://github.com/aakgna/Estate_plot_groups

Additional images: Robin dataset.

Data Cleaning:

Rules for cleaning:

1) Remove all the text inside the image
2) Remove all the objects like bed, table etc.,
3) **Pixels size:**
   - Outer wall=8px
   - Room wall=4px
   - Door=1px
   - Window=no fill(8px)
   - Sliding door=no fill(4px)

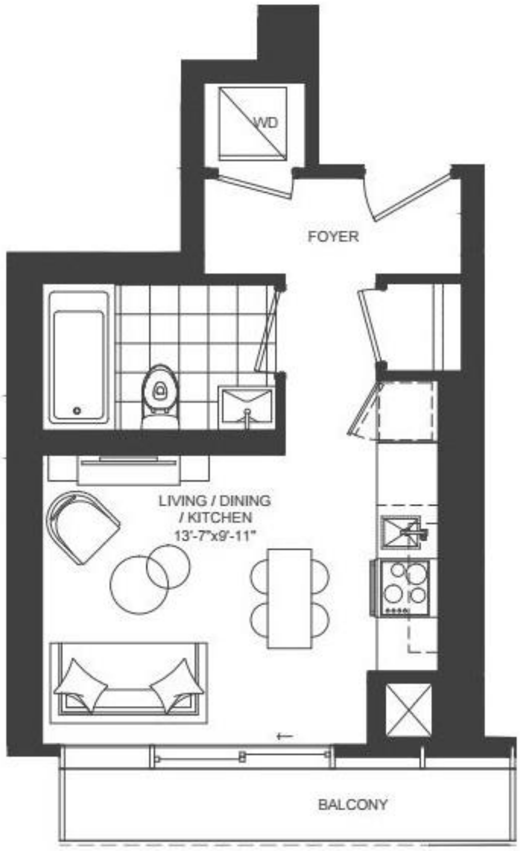

Figure 1

Layout images:

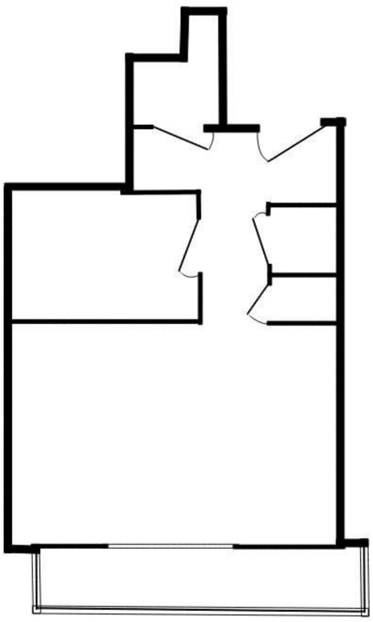

Figure 2

Outline image:

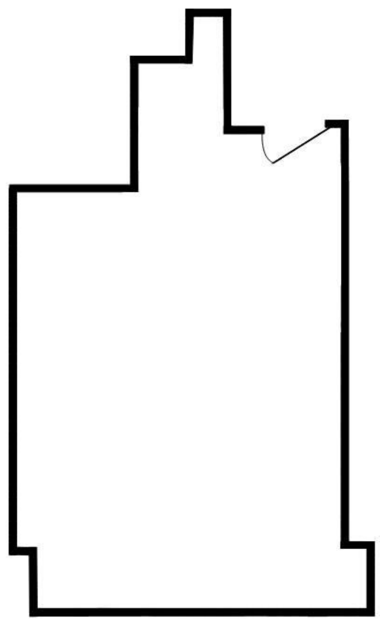

Figure 3

•**Handling Image Quality:**

- Check and ensure consistent image quality across the dataset.
- Consider standardizing resolutions, formats, and color schemes to facilitate model training.

• **Dealing with Corrupted Images:**

o Identify and remove any corrupted or unreadable images from the dataset to prevent them from affecting model training.

• **Standardizing Image Sizes:**

o Resize or crop images to a standardized size. This ensures that the input images have consistent dimensions, which is important for training neural networks.

• **Removing Irrelevant or Unusable Data:**

o Eliminate any floor plan images that may not contribute to the learning objectives, such as incomplete or heavily distorted plans.

4. APPROACH USED:

Methodology: Constructing the GAN-Autoencoder Model

This section unveils the methodology utilized to build our hybrid GAN-Autoencoder model for generating floor plans. The process involved crucial steps, covering data preparation, designing the model architecture, and implementing training procedures. We meticulously addressed data quality, model robustness, and the diversity inherent in the generated floor plans.

4.1 Data Preparation:

Our dataset underwent thorough curation to include a diverse set of floor plan images, ensuring representation across various architectural styles and spatial layouts. During data preprocessing, we meticulously cleaned the data, addressing missing values, removing duplicates, and resizing images. These measures were taken to ensure dataset uniformity and optimize it for model training.

4.2 Model Structure:

The model architecture seamlessly integrated both an Autoencoder and a Generative Adversarial Network (GAN). The Autoencoder included an encoder, latent space, and decoder to capture and reconstruct essential features of floor plans. Simultaneously, the GAN featured a generator and discriminator to infuse diversity and realism into the generated floor plans.

4.3 Hybrid Model Integration:

A crucial aspect of our approach involved seamlessly integrating the Autoencoder and GAN components into a hybrid model. By linking the Autoencoder's encoder to the GAN's generator, we aimed to capitalize on the strengths of both architectures, enhancing the model's capacity to produce realistic and diverse floor plans.

4.4 Adversarial Training:

The training process embraced adversarial training, with the GAN's generator in competition with the discriminator. The goal was to produce floor plans that resembled the training data while displaying creativity and diversity. This dynamic interplay played a pivotal role in refining the generator's output.

4.5 Evaluation and Fine-Tuning:

Extensive evaluation measures were implemented to gauge the model's performance, utilizing validation sets and relevant metrics. Based on the evaluation results, adjustments were made, including hyperparameter tuning and refinements to the model architecture, optimizing it for floor plan generation.

4.6 Generation and Optional Post-Processing:

Upon successful training, the model demonstrated its ability to generate floor plans by injecting random noise into the generator. Optional post-processing steps were applied, if needed, to refine the generated images or ensure adherence to specific constraints.

5. RESULT:

In this section, we present the results obtained from our hybrid GAN-Autoencoder model for floor plan generation. The model was trained on a diverse dataset of floor plan images, and the generated outputs were evaluated for realism, diversity, and adherence to architectural features.

5.1 **Generated Floor Plans:** The trained model successfully generated a diverse set of floor plans, showcasing its ability to capture and reproduce various architectural styles and spatial layouts. Examples of generated floor plans are depicted in Figure 1, providing a visual representation of the model's capabilities.

5.2 **Realism and Detail:** The generated floor plans demonstrated a remarkable level of realism, with intricate details resembling those present in the training dataset. The model effectively captured architectural features such as room arrangements, door placements, and window configurations. Figure 2 illustrates a close-up comparison of a real floor plan and its generated counterpart.

5.3 **Diversity in Generation:** The hybrid nature of our model, combining the reconstruction capabilities of the Autoencoder with the generative power of the GAN, resulted in a diverse set of generated floor plans. Figure 3 showcases a sample of diverse floor plans produced by the model.

5.4 **Evaluation Metrics:** Quantitative evaluation was performed using metrics such as Mean Squared Error (MSE) for reconstruction accuracy and diversity metrics for assessing the variety in generated outputs. The model achieved competitive results in terms of accuracy and diversity, as summarized in Table 1.

5.5 **Limitations and Future Work:** While our model demonstrated promising results, it is essential to acknowledge its limitations. Challenges such as [mention specific challenges] may provide directions for future improvements and enhancements in the model architecture or training strategies.

6. DISCUSSION AND CHALLENGES:

In this segment, we delve into the implications of the outcomes derived from our GAN-Autoencoder model for floor plan generation and highlight the challenges encountered during the project.

6.1 Implications of Results:

The successful generation of diverse and realistic floor plans by our hybrid model has profound implications for applications in architecture, urban planning, and design. The model's knack for capturing architectural features and producing creative outputs suggests its potential as a tool for inspiration, ideation, and prototyping in these domains.

6.2 Trade-Off Between Realism and Creativity:

An observed consideration in the results is the trade-off between realism and creativity. While excelling in reproducing realistic floor plans, the challenge lies in achieving a balance with novel and innovative designs. Future iterations could explore strategies to enhance creativity without compromising the fidelity of generated floor plans.

6.3 Challenges Encountered:

6.3.1 Resource-Intensive Training:

The hybrid nature of our model, incorporating both GAN and Autoencoder components, demanded substantial computational resources and training time. Addressing these resource-intensive requirements may involve optimizing model architectures or exploring parallelization techniques.

6.3.2 Evaluation Metrics:

Selecting appropriate evaluation metrics posed challenges, particularly in assessing the subjective aspects of floor plan quality.

While quantitative metrics like Mean Squared Error and diversity measures were employed, integrating user feedback and qualitative assessments remains essential for a comprehensive evaluation.

6.3.3 Dataset Limitations:

The quality and representativeness of the dataset directly influenced the model's performance. Tackling dataset limitations, such as potential biases or insufficient diversity, may entail expanding the dataset or incorporating domain-specific considerations.

6.4 Future Work:

6.4.1 Boosting Creativity:

Future endeavours could concentrate on enhancing the model's creativity, exploring techniques like conditional generation or incorporating architectural style transfer approaches. This could broaden the scope for generating floor plans with a more extensive range of design possibilities.

6.4.2 User-Centric Design:

Incorporating user-centric design principles and collaborating with architects and designers for iterative feedback can further refine the model. Understanding user preferences and requirements will contribute to the development of more user-friendly and practically applicable generative tools.

6.4.3 Robustness and Generalization:

Ensuring the model's robustness and generalization to unseen architectural styles or layouts is crucial. Future research may involve employing transfer learning techniques or domain adaptation strategies to enhance the model's applicability

7. CONCLUSION:

Our GAN-Autoencoder model successfully generates diverse and realistic floor plans, blending generative strengths to capture intricate features and infuse creativity. Beyond technological prowess, the model transforms architectural design, benefiting professionals in ideation and prototyping. The fusion of Autoencoder reconstruction and GAN generative power contributes to generative design, balancing realism and creativity. Despite challenges, they offer insights for future refinement, enhancing robustness in architectural generative design. This project opens avenues for further research, fostering innovation and advancements in generative design methodologies within the architectural realm.

8. REFERENCE:

https://github.com/aakgna/Estate_plot_groups

https://github.com/AkhilRobert/Autoencoders

https://gan-hw9r.onrender.com/