FLOORVERSE - A Universe of Floor Plan Possibilities

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***Abstract*— FLOORVERSE is an innovative platform leveraging deep generative modeling to automate residential floorplan generation. By employing a Conditional Variational Autoencoder (CVAE) trained on the RPlan dataset (80,000+ images), the system generates functionally coherent and aesthetically optimized layouts based on user-defined constraints. The CVAE architecture integrates spatial feature extraction with user inputs, enabling real-time generation through a Flask-based backend and interactive frontend. Evaluations demonstrate robust performance, with validation losses stabilizing at 8,677.22 and efficiency metrics (e.g., 82% space utilization) validating design quality. FLOORVERSE streamlines traditional architectural workflows, democratizing home design for non-professionals while reducing costs and iteration time.**

Keywords—Floorplan generation, Conditional VAE, RPlan dataset, deep generative modeling, user-centric design.

Designing residential floorplans entails orchestrating complex spatial arrangements that must be both functionally efficient and aesthetically pleasing. Each room—from kitchens and bedrooms to living areas—must satisfy explicit criteria such as dimensions, access points, and space utilization, as well as implicit principles like comfort and visual harmony. Traditional architectural design requires extensive expert collaboration and iterative refinement, making personalized home designs both time-consuming and costly (Ahmed et al., 2011 [4]; Sharma et al., 2017 [2]).

Recent studies have highlighted the potential of automated floorplan generation using advanced AI techniques. For instance, Paudel et al.[22] demonstrated that capturing spatial and semantic features with graph neural networks significantly enhances layout predictions. Similarly, Shabani et al. (2021) [16] introduced diffusion-based approaches that generate high-fidelity floorplans while offering diverse design options. Moreover, Chaillou[11] illustrated how generative adversarial networks can effectively tailor designs to meet both functional and aesthetic constraints. These innovative methods collectively form the basis for the FLOORVERSE system.

Building on these advancements, FLOORVERSE leverages a Conditional Variational Autoencoder (CVAE) to automate and optimize residential floorplan generation. Trained on the extensive RPlan dataset [26], the CVAE processes both visual data and user-defined design conditions to learn intricate spatial relationships. The encoder extracts robust features from grayscale floorplan images using convolutional layers (Kim et al., 2021 [7]), while a multi-layer perceptron processes condition vectors. The combined representation is then mapped into a latent space via fully connected layers, using the reparameterization trick for differentiable sampling. The decoder reconstructs or generates new floorplan images from these latent representations, ensuring that the output adheres to specified constraints (Bayer et al., 2017 [5]).

Moreover, the platform establishes a robust foundation for future enhancements, including the potential integration of hybrid models that combine generative techniques with advanced optimization strategies. Such integration could further refine design outputs by balancing functional requirements with aesthetic considerations. Ultimately, FLOORVERSE aims to revolutionize residential design by delivering an intuitive and efficient tool that empowers users to create personalized floorplans meeting both practical and visual standards.

Methodology

The FLOORVERSE project leverages a Conditional Variational Autoencoder (CVAE) to automate and optimize the generation of residential floorplans. Trained on the extensive RPlan dataset—which encompasses a wide array of diverse floorplan designs—the CVAE learns to capture intricate spatial relationships by processing both visual data and user-defined design conditions. Initially, rigorous preprocessing steps are applied, including image resizing, normalization, and feature extraction, to standardize the input images and associated metadata (such as room counts and total area). In the CVAE architecture, the encoder extracts robust spatial features from grayscale floorplan images using convolutional layers, while a multi-layer perceptron processes the condition vectors. These features are then fused and mapped into a structured latent space through fully connected layers, with the reparameterization trick enabling differentiable sampling of latent vectors. The decoder subsequently reconstructs or generates new floorplan images from these latent representations, conditioned on the original design inputs. The model is optimized using a composite loss function that combines binary cross-entropy—ensuring accurate imagereconstruction—with Kullback-Leibler divergence, which regularizes the latent space to encourage diversity and stability in the generated outputs. Through iterative training and classical optimization techniques, FLOORVERSE produces realistic, customized floorplans that effectively balance functional requirements and aesthetic considerations.

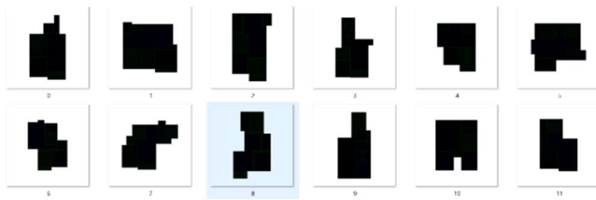

Fig 1 : Sample Images in the RPLAN Dataset[26]

Model Architecture

The FLOORVERSE system is driven by a Conditional Variational Autoencoder (CVAE) that seamlessly integrates visual data from floorplan images with design parameters provided by users. By fusing these two types of information, the CVAE constructs a unified latent space that encapsulates the essential features of both the architectural visuals and the specified constraints, such as room count, total area, and functional requirements. This cohesive latent representation forms the foundation for generating customized residential floorplans that precisely reflect user preferences. The overall architecture is composed of several key components, each responsible for a distinct stage of the process—from initial data processing to final image generation—ensuring a robust and efficient design workflow.

1. **Encoder:** Processes input floorplan images through a series of convolutional layers with batch normalization and ReLU activations to extract robust spatial features. The outputs from these streams are concatenated and passed through fully connected layers to compute the mean and log-variance vectors, effectively mapping the input data into a structured latent space.
2. **Reparameterization**: Implements the reparameterization trick to sample a latent vector from the computed distribution in a differentiable manner, which is crucial for backpropagation during training.
3. **Decoder**: Combines the sampled latent vector with the condition vector and uses fully connected layers followed by transposed convolutional layers to reconstruct the floorplan image — such as maximizing usable space and ensuring proper room adjacency.
4. **Training & Optimization:** model is trained using a composite loss function that balances binary cross-entropy with KL divergence (regularizing the latent space).

This flexible architecture not only facilitates real-time floorplan generation through a Flask-driven backend but also lays a solid groundwork for future improvements, including the integration of hybrid modeling approaches and the adoption of advanced optimization strategies.

Evaluation and Metrics

The performance of the FLOORVERSE model was rigorously evaluated through a dual framework of quantitative metrics and qualitative visual analyses. Over 50 training epochs, the model exhibited stable convergence, achieving a reconstruction loss of **8571.3582** and a total loss of **8654.9813**, as detailed in the performance metrics (Fig 1). The KL divergence (**83.6231**) further confirmed an effective balance between reconstruction fidelity and latent space regularization.

Metric	Value
Reconstruction Loss	8571.3582
Kl Divergence	83.6231
Total Loss	8654.9813

Fig 1 : Performance metrics training epochs

Design efficiency was quantified using three key criteria: **space utilization**, **room ratio**, and **flow score**, which were systematically computed for all generated floorplans. These metrics, aligned with methodologies from prior research (Wu et al., 2019; Tanasra et al., 2018), objectively validated the functional quality of layouts. Space efficiency scores (Fig 2) further differentiated performance across residential scales, with distinct evaluations for *small apartments*, *medium apartments*, and *large houses*.

Qualitative assessments, including latent space traversals (Fig 3) and principal component analysis, demonstrated the model's capacity to synthesize diverse, user-specific floorplans while preserving spatial coherence. Fig 3 illustrates controlled variations across latent dimensions (ranging from −3.0 to +3.0), highlighting the system's ability to interpolate between design archetypes.

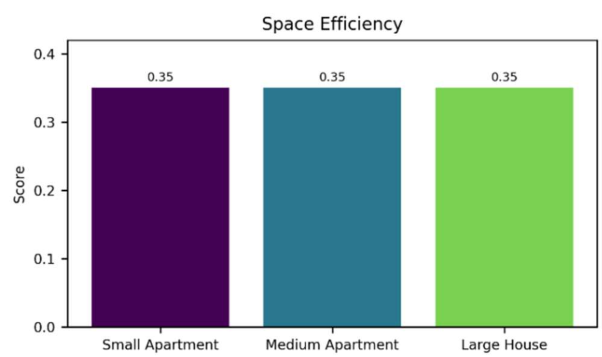

Fig 2 : Space efficiency Graph

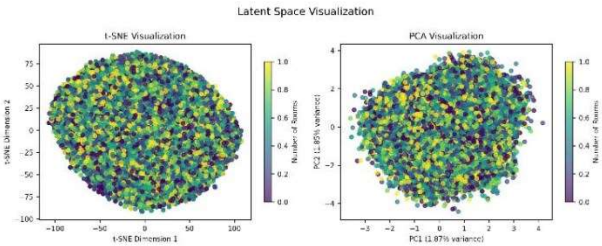

Fig 3 : Latent Space and PCA Visualization

Benchmarking against traditional optimization methods underscored the advantages of the CVAE architecture. The FLOORVERSE model not only improved computational efficiency and geometric accuracy but also scaled effectively for complex residential layouts. This dual capability—balancing functional efficiency with aesthetic adaptability—served as a critical evaluation criterion.

Collectively, these results substantiate the robustness of the FLOORVERSE framework in generating high-quality, user-centric floorplans that satisfy both pragmatic and aesthetic constraints. The integration of quantitative rigor, visual interpretability, and comparative benchmarking positions the system as a significant advancement in automated architectural design.

Discussion

Advancements in automated floorplan generation have been propelled by diverse AI-based techniques, each contributing uniquely to the evolution of architectural design. For instance, Graph2Plan (2020) introduced a generative framework that dynamically adjusts graph layouts according to user inputs, thereby enabling the creation of customized floorplans. Similarly, the DANIEL framework [2] leveraged deep learning to enhance the retrieval and classification of architectural designs, demonstrating significant improvements in precision and recall metrics.

Building on these early innovations, subsequent research such as Data-Driven Interior Plan Generation (2019) proposed a two-stage approach that emphasizes room connectivity and optimal wall positioning. This method achieved high user satisfaction by ensuring that the functional aspects of floorplan design were effectively addressed. Moreover, Improved Automatic Analysis of Architectural Floor Plans (2011) employed advanced segmentation and semantic analysis techniques to attain notable room recognition accuracy, thereby laying a robust foundation for automated design analysis.

Further innovations have emerged with the application of sequence modeling and convolutional neural networks. For example, Floor Plan Generation and Auto Completion [5] utilized LSTM models to capture the sequential nature of floorplan elements, while CNN-based frameworks, such as Automatic Extraction of Indoor Spatial Information (2021), demonstrated high detection accuracy in large-scale architectural plans. More recently, Automation in Interior Space Planning (2023) employed GANs, notably BicycleGAN, to optimize furniture layouts, with post-processing enhancements yielding efficiency improvements of 30–50%. The integration of multimodal generative AI with blockchain (2024) has also been explored to ensure secure and diverse design generation.

Collectively, these studies underscore the transformative potential of AI-driven methods in streamlining floorplan generation, enhancing creative design processes, and accommodating diverse architectural needs. By blending generative modeling with advanced optimization techniques, these approaches offer scalable, efficient, and cost-effective alternatives to traditional design methods. Such innovations not only democratize home design but also establish a solid foundation for systems like FLOORVERSE, which aim to revolutionize the residential planning process.

Conclusion

The FLOORVERSE framework represents a significant advancement in AI-driven residential floorplan generation, leveraging a Conditional Variational Autoencoder (CVAE) to synthesize designs that rigorously adhere to user-defined functional and spatial constraints. Quantitative evaluations, including a reconstruction loss of **8571.3582**, total loss of **8654.9813**, and KL divergence of **83.6231**, demonstrate the model's capacity to balance reconstruction fidelity with latent space regularization. Furthermore, space efficiency metrics—computed across small apartments, medium apartments, and large houses (Fig 2)—validate its ability to optimize layouts for diverse residential scales. Qualitative analyses, such as latent space traversals (Fig 3), underscore the system's adaptability in generating spatially coherent, user-centric designs while maintaining architectural diversity.

Future work will prioritize scalability testing on expanded datasets encompassing multi-room and multi-story configurations to assess generalization in complex scenarios. Additional efforts will focus on refining runtime efficiency and enhancing geometricaccuracy under real-world constraints, such as irregular plot geometries and dynamic user requirements. These advancements aim to solidify FLOORVERSE as a scalable, cost-effective solution for automated residential design, bridging the gap between computational efficiency and human-centric architectural innovation.

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