VISVESVARAYA TECHNOLOGICAL UNIVERSITY
JNANA SANGAMA, BELAGAVI - 590018

A Project Report on

VIRTUAL INTERIOR DESIGN COMPANION-HARNESSING THE POWER OF GANs

Submitted in partial fulfilment of the requirements for the award of the degree of

Bachelor of Engineering
in
Electronics and Communication Engineering
for the **Academic Year: 2023-24**

Submitted by

Aditya Kumar	**(1NT20EC007)**
Yash Mathur	**(1NT20EC175)**
Shubham Sharma	**(1NT20EC178)**

Under the Guidance of

Dr. Rekha Phadke
Associate Professor
Dept. of Electronics and Communication Engineering

NITTE EDUCATION TRUST
NITTE MEENAKSHI INSTITUTE OF TECHNOLOGY

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

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BENGALURU- 560 064

Certificate

Certified that the project work titled **"Virtual Interior Design Companion-Harnessing the Power of GANs"** is carried out by **Aditya Kumar (1NT20EC007)**, **Yash Mathur (1NT20EC175)** and **Shubham Sharma (1NT20EC178)**, bonafide students of Nitte Meenakshi Institute of Technology in partial fulfilment for the award of Bachelor of Engineering in Electronics and Communication Engineering of Visvesvaraya Technological University, Belagavi during the academic year 2023-2024. The project report has been approved as it satisfies the academic requirement in respect of the project work prescribed as per the autonomous scheme of Nitte Meenakshi Institute of Technology for the said degree.

Signature of the Guide	Signature of the HoD	Signature of the Principal
Dr. Rekha Phadke Associate Professor Dept of ECE, NMIT	**Dr. Parameshachari B.D.** HoD Dept of ECE, NMIT	**Dr. H C Nagaraj** Principal NMIT

External Viva-Voce

Name of Examiners	Signature with Date
1.	
2.	

Abstract

It is always a costly affair to prepare suitable interior design. Automatic interior design generation with suitable interiors will have an enormous effect on the trillion-dollar real-estate/construction industry. The impact of deep neural networks has made a leap forward where state-of-the-art algorithms utilize Generative Adversarial Networks (GANs). AI-driven innovation with GANs has many applications in creative industries such as design, be it architectural design, landscape design or interior design, the possibilities are endless. Such generated designs have the potential to drive rapid growth and profits in the design industry. The goal of this work was to generate realistic new interior room designs by training a GAN network on the IKEA Interior Design Dataset. This work faced challenges in distinguishing a good design from a poor design along with training the GAN. The goal was to overcome these challenges by incorporating human feedback and using various evaluation methods to ensure the generated designs are of high quality. The project has the potential to provide valuable solutions for the interior design industry, by generating new designs quickly and efficiently. DCGAN generated satisfactory images for 21800 epochs and FID score of 237 but had mode collapse and vanishing gradient issues. While Style3GAN outperformed by generating high resolution images with 2500 epochs and FID score of 105.

Acknowledgement

The successful execution of our project gives us an opportunity to convey our gratitude to each one who have been instrumental in paving path to our continuation of this project. Whatever we have done is due to such guidance and help and we would not forget to thank them all.

We would like to thank and seek the blessings from **Dr. N R Shetty,** Advisor, **Nitte Meenakshi Institute of Technology**, for his thrust on project-based learning and constructivist principles in our institution.

We would like to express our gratitude to the **Nitte Meenakshi Institute of Technology** and our beloved Principal **Dr. H C Nagaraj** for providing us with the support, facilities, and motivation to carry out our project.

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We whole heartedly thank our guide **Dr. Rekha Phadke,** Associate Professor, Department of Electronics and Communication Engineering, for his support and guidance anytime we required.

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Place: Bengaluru
Date:

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List Of Acronyms

GANs	Generative Adversarial Networks
AI	Artificial Intelligence
UI	User Interface
UX	User Experience
API	Application Programming Interface
ML	Machine Learning
NLP	Natural Language Processing
CV	Computer Vision
IoT	Internet of Things
VR	Virtual Reality
AR	Augmented Reality

Chapter 1 Introduction

The research conducted explores the transformative impact of integrating Generative Adversarial Networks (GANs) into the field of interior design, particularly focusing on how these AI algorithms revolutionize the automated generation of space aesthetics. GANs, being sophisticated AI models, have the ability to autonomously generate a diverse range of design proposals, addressing challenges related to creativity and efficiency in the field.

One of the key strengths of GANs lies in their training on a diverse dataset, enabling them to excel in producing visually appealing design concepts that go beyond conventional norms. The research suggests that GANs have the potential to surpass human limitations in creativity and contribute innovative and avant-garde ideas to interior design.

Moreover, the integration of user preferences into the GAN model is highlighted as a crucial aspect. This adaptability allows for the creation of personalized design solutions tailored to individual tastes and spatial requirements. This not only increases the practicality of the designs but also enhances their relevance to the end users, ultimately leading to a more satisfying and user-centric design process.

The study emphasizes the collaborative potential between AI and human designers, positioning GANs as tools that can inspire and complement human creativity rather than replace it. By leveraging the strengths of both AI and human designers, the research suggests a symbiotic relationship that results in more innovative and efficient design processes.

Ethical considerations are woven into the fabric of the research, emphasizing responsible AI use in design. The importance of human oversight is underlined, acknowledging the need for ethical guidelines and ensuring that AI is employed in ways that align with cultural values and societal norms. Preservation of cultural values is highlighted as a significant aspect, ensuring that the integration of AI into interior design respects and contributes to the preservation of diverse cultural aesthetics.

In conclusion, the research positions GANs as transformative tools in reshaping the landscape of interior design. The innovative paradigm presented involves a harmonious collaboration between AI and human designers, with a strong emphasis on ethical considerations and the preservation of human input in the creative process. The study contributes to the discourse on the responsible integration of AI into creative fields, offering insights into the potential benefits and challenges while stressing the importance of maintaining a balance between technological advancements and human values.

1.1 Motivation

The project is motivated by challenges in interior design creativity and efficiency. GANs, as AI algorithms, offer a solution by autonomously generating diverse design proposals, overcoming creative blocks and streamlining processes. The focus is on personalization, aligning with user preferences for more user-centric designs. The research aims to establish a collaborative relationship between GANs and human designers, emphasizing GANs as tools to inspire human creativity rather than replace it. Ethical considerations, including responsible AI use and cultural value preservation, are integral to the project. Overall, the research seeks to transform interior design paradigms by integrating GANs in an innovative, ethical, and collaborative manner.

1.2 Organization of the project

Organizing a project for a GAN-based virtual interior design system involves defining project goals, researching market trends, and identifying the target audience. Selecting an appropriate technology stack and collecting a diverse dataset for GAN training are crucial steps. Designing an intuitive UI, integrating GAN models with the backend, and implementing features like style transfer and color customization follow suit. Rigorous testing, including user testing, ensures the system's quality. Deployment on a stable platform and continuous monitoring are essential. Documentation, marketing strategies, user support, and a maintenance plan for updates and improvements complete the comprehensive approach. Regular communication within the team and with stakeholders ensures alignment with project goals.

Chapter 2 Literature Survey

2.1 Background Work

1. The article discusses how AI has been utilised in various industries to address complex problems and increase efficiency. However, the integration of AI in the architecture field is still in its early stages. The article focuses on the first step of the architectural design process, the Conceptual Design Stage, which is currently a manual process that limits the number of design iterations due to cost, time constraints, and human limitations. This leads to potentially subpar final building designs that may have negative economic, functional, performance, or psychological effects. **[Michael Hasey, 2019, GAN_Itecture]**
2. Generative adversarial networks are a kind of artificial intelligence algorithm designed to solve the generative modelling problem. The goal of a generative model is to study a collection of training examples and learn the probability distribution that generated them. Generative Adversarial Networks (GANs) are then able to generate more examples from the estimated probability distribution. Generative models based on deep learning are common, but GANs are among the most successful generative models (especially in terms of their ability to generate realistic high-resolution images). GANs have been successfully applied to a wide variety of tasks (mostly in research settings) but continue to present unique challenges and research opportunities because they are based on game theory while most other approaches to generative modelling are based on optimization**. [Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron C. Courville, and Yoshua Bengio. 2020. Generative Adversarial Networks. NIPS 27(2020).]**
3. This paper reviews the state-of-the-art video Generative Adversarial Networks (GANs) models, which are increasingly used in various fields for content creation. It categorises GANs review papers into general, image, Dept. of Electronics and Communication Engineering, Nitte Meenakshi Institute of Technology, Bengaluru 3 and special field GANs review papers. GANs consist of a generator and a discriminator network that are trained in an adversarial manner to generate new data points that conform to the distribution of the training dataset. The goal is to reach the Nash equilibrium where the discriminator is unable to differentiate between real and fake samples. The paper demonstrates an upward trend in publications on GANs since the mid-2010s. **[Nuha Aldausari, Arcot Sowmya, Nadine Marcus, and Gelareh Mohammadi. 2020. Video Generative Adversarial Networks: A Review. arXiv preprint arXiv:2011.02250(2020).]**

4. From this reference we got to know the basic principles of GANs, including the adversarial process and the roles of the generator and discriminator networks. The discriminator network's objective is to determine whether a sample belongs to a real or fake distribution, while the generator network's objective is to deceive the discriminator by generating a fake sample distribution. The GAN architecture consists of the generator and discriminator networks, which are updated iteratively during the training process. The generator network uses random noise to generate images, while the discriminator network determines whether an image is real or fake. **[Hamed Alqahtani, Manolya Kavakli-Thorne, and Gulshan Kumar. 2019. Applications of generative adversarial networks (gans): An updated review. Archives of Computational Methods in Engineering (2019), 1–28.]**
5. In this paper, we reviewed some basics of GANs and described some applications in the field of image synthesis based on GANs. The pros and cons of these GANs applications are also provided. Besides, we summarised the methods used in GANs applications which improved the performance of generated images. Although the research on GANs is becoming more and more mature, GANs are still faced with some challenges, such as unstable training and hard to evaluate. **[Lei Wang, Wei Chen, Wenjia Yang, Fangming Bi, and Fei Richard Yu. 2020. Review on Image Synthesis With Generative Adversarial Networks. IEEE Access 8(2020), 63514–63537]**
6. The article discusses the emergence of Deepfakes, a manipulation technique that allows swapping identities in videos. To address this threat, the authors have created the largest publicly available face swap video dataset, called the DeepFake Detection Challenge (DFDC) dataset, with over 100,000 clips sourced from 3,426 actors. The article describes the methods used to construct the dataset and provides an analysis of the top submissions from the accompanying Kaggle competition. The authors demonstrate that a Deepfake detection model trained on the DFDC dataset can generalise to real-world Deepfake videos and can be a useful tool in analysing potentially manipulated videos. **[Brian Dolhansky, Joanna Bitton, Ben Pflaum, Jikuo Lu, Russ Howes, Menglin Wang, and Cristian Canton Ferrer. 2020. The deepfake detection challenge dataset. arXiv preprint arXiv:2006.07397(2020)]**
7. The article discusses how AAL (Ambient Assisted Living) in Smart Homes is not limited to tracking indoor location but also includes analysing user behaviour and activity patterns to improve their quality of life. It goes on to review recent AAL technologies that focus on activity recognition and analysis in Smart Homes. **[Nirmalya Thakur and Chia Y Han.**

2021. Multimodal Approaches for Indoor Localization for Ambient Assisted Living in Smart Homes. Information 12, 3 (2021), 114.]

8. The dataset was collected from IKEA.com website for the purpose of building Style Search Engine (note: only for non-commercial use). It consists of: 2193 object (product) photos, 298 context (room scene) photos in which those objects appear, text descriptions for products, ground truth information on which items appear in which rooms. **[Tautkute et al., 2017, ACICS, IKEA: Interior Design Dataset]**

9. In our research, we propose an innovative method named GlyphGAN for generating fonts with style consistency using Generative Adversarial Networks (GANs). GANs operate through a dual-network system where one network generates synthetic images from random input vectors, while the other network distinguishes between these synthetic images and real ones. Our primary goal is to leverage the capabilities of GANs to create diverse fonts while ensuring a consistent style across all characters.

GlyphGAN introduces a distinctive input vector for the generator network, composed of two components: a character class vector and a style vector. The character class vector is created through one-hot encoding, associating it with the character class of each sample image during the training process. On the other hand, the style vector is a randomly generated vector without any supervised information. This design choice empowers GlyphGAN to produce an extensive variety of fonts, offering independent control over both the character and style aspects of the generated fonts.In our experiments, we observed that fonts generated by GlyphGAN exhibit a unique combination of style consistency and diversity. Importantly, this diversity is distinct from the fonts present in the training dataset, showcasing GlyphGAN's ability to create novel and diverse fonts without sacrificing legibility.The significance of GlyphGAN lies in its potential to revolutionize font design by providing a tool for designers to effortlessly generate fonts with desired styles while maintaining consistency across different characters. The results of our experiments demonstrate the effectiveness of GlyphGAN in achieving this delicate balance between style diversity and consistency, highlighting the promising applications of GANs in the creative domain of font generation.**[Hideaki Hayashi, Kohtaro Abe, and Seiichi Uchida. 2019. GlyphGAN: Style-consistent font generation based on generative adversarial networks. Knowledge-Based Systems 186 (2019), 104927.Google ScholarDigital Library]**

10. We study the problem of 3D object generation. We propose a novel framework, namely 3D Generative Adversarial Network (3D-GAN), which generates 3D objects from a probabilistic space by leveraging recent advances in volumetric convolutional networks and generative adversarial nets. The benefits of our model are three-fold: first, the use of an adversarial criterion, instead of traditional heuristic criteria, enables the generator to capture object structure implicitly and to synthesize high-quality 3D objects; second, the generator establishes a mapping from a low-dimensional probabilistic space to the space of 3D objects, so that we can sample objects without a reference image or CAD models, and explore the 3D object manifold; third, the adversarial discriminator provides a powerful 3D shape descriptor which, learned without supervision, has wide applications in 3D object recognition. Experiments demonstrate that our method generates high-quality 3D objects, and our unsupervisedly learned features achieve impressive performance on 3D object recognition, comparable with those of supervised learning methods. **[Jiajun Wu, Chengkai Zhang, Tianfan Xue, Bill Freeman, and Josh Tenenbaum. 2016. Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling. NIPS (2016), 82–90.Google Scholar]**

11. We introduce the TL-embedding network, a novel architecture for an object's vector representation. This representation is both generative in 3D, allowing the creation of new objects, and predictable from 2D images for interpretation. The network integrates an autoencoder for generativity, ensuring the representation's ability to generate diverse 3D objects. Additionally, a convolutional network guarantees predictability from 2D images. The TL-embedding network excels in tasks like voxel prediction from 2D images and 3D model retrieval, showcasing its versatility. Extensive experiments validate its effectiveness, marking a significant advancement in achieving a comprehensive vector representation for objects in 3D generative modeling and 2D-to-3D interpretation. **[Rohit Girdhar, David F. Fouhey, Mikel Rodriguez, and Abhinav Gupta. 2016. Learning a Predictable and Generative Vector Representation for Objects.]**

12. In this paper, we introduced the large ONSF database which includes various changes in pose, expressions and focus. We also created another INF database in the laboratory environment to test the performance of near infrared facial recognition. We propose a novel near infrared facial recognition method in an end-to-end deep architecture which includes face detection and alignment, NIR-VIS image translation and a face embedding module. This is the first time that it has been proposed to apply the image-image translation method to enhance the performance of a near-infrared facial image recognition. This is achieved by synthesizing a virtual sample from an input near infrared face image. Using this approach, we reduce the intra-personal difference caused by the completely different illumination. Therefore, we can achieve much better recognition results by applying the existing pre-trained VLD deep neural network face recognition model. The proposed method was tested on the INF database and the CSIST dataset, with promising results. **[Fangyu Wu, Weihang You, Jeremy S.Smith, Wenjin Lu and Bailing Zhang, "Image-Image translation to enhance Near Infrared Face Recognition,",2020.]**

13. The paper focuses on facial diagnosis and how using deep transfer learning can be helpful. It starts by explaining why facial diagnosis is important and introduces the idea of using deep transfer learning in this area. The beginning of the paper outlines what problem the research is trying to solve and what goals it has. The paper then reviews existing information on deep learning, face recognition, and facial diagnosis, finding places where transfer learning could be useful. In the methodology section, it explains in detail how deep transfer learning was used, including information about the datasets and steps taken to prepare the facial data. The paper also talks about the design of the model and how transfer learning was applied from face recognition to facial diagnosis. The experiments section gives details about how the tests were set up, what metrics were used to measure success, and the results, including comparisons with other methods. In the discussion part, the paper talks about what these results mean, the impact of using transfer learning in facial diagnosis, and what could be improved. The conclusion summarizes the main discoveries, emphasizes the contribution of the research, and suggests areas for future exploration. The paper ends with a carefully crafted list of references, citing studies that influenced the research. **[Bo Jin, Leandro Cruz and Nuno Goncalves, "Deep Facial Diagnosis: Deep Transfer Learning From Face Recognition to Facial Diagnosis,",2020.]**

14. Face Recognition (FR) applications in the open world or adapted domain incur an undesirable downtime due to retraining or finetuning of FR models. Resorting to low-cost O(1) , threshold setting methods like σ values may not achieve optimal performance. Using such fixed threshold values also compromises the security of an FR application. Hence this paper proposed an adaptive threshold using a dynamic ROI-based threshold adapter algorithm. The proposed method narrows the search space of the optimal threshold and makes it 12 times faster than conventional methods. Making real-time threshold setting feasible. We demonstrated on two evaluation datasets that the proposed algorithm significantly improved five state-of-the-art deep FR models, yielding the best performance. Additionally, the positive pairs are minimal in the open world FR application. Hence, consideration of the F1-score is vital. The proposed method suggests that taking accuracy at the highest reported F1-scores is a better metric for performance benchmarking in the open world FR applications. **[Ahmed Rimaz Faizabadi, "Efficient Region of Interest Based**

Metric Learning for Effective Open World Deep Face Recognition Applications,”,2022.]

15. In this paper, we propose a new face alignment method, called APA, which can be used for data processing in face recognition or face analysis tasks to improve performance. The APA method can not only reduce intra-class variability (increasing intra-class similarity) but also correct the noise caused by alignment process. Furthermore, we also propose a simple, yet effective feature normalization method. It can be used by combining with the APA method to generate more discriminative feature representation of a face or template. Experiments on LFW, CPLFW, IJB-A, and IJB-C datasets show that the proposed methods provide significant and consistent improvements and achieve state-of-the-art results. In conclusion, the APA is an effective data processing method for pose-invariant face recognition. **[Zhanfu An, Weihong Deng, Jian Hu, Yaoyao Zhong and Yuying Zhao, “APA: Adaptive Pose Alignment for Pose-Invariant Face Recognition,”,2020.]**

2.2 Problem Definition

Interior design involves creating visually attractive and functional spaces

There is a growing demand for customized and unique interior designs

Tools are needed to generate a large number of design options that meet the client's specifications2.3 Objectives

The following are the proposed objectives of the project based on the research gaps:

- A demonstration of how GAN’s can be used in the field of interior design and how it can improve the design process.
- To evaluate the GAN architecture performance on the interior design based on the performance and error metrics.
- Working with GAN might help interior designers gain the exposure they need. As a result, people benefit from technology and expand their knowledge base.

2.3 Objectives

- A demonstration of how GAN’s can be used in the field of interior design and how it can improve the design process.
- To evaluate the GAN architecture performance on the interior design based on the performance and error metrics.
- Working with GAN might help interior designers gain the exposure they need. As a result, people benefit from technology and expand their knowledge base.

2.4 Scope of Work

The project will involve the design and implementation of a GAN-based virtual interior design platform, including the development of the GAN model, user interface, and backend infrastructure. The platform should support the creation, visualization, and customization of virtual interiors, providing an immersive and realistic experience for both designers and clients. The scope also includes testing, refining, and potentially scaling the platform for wider adoption in the interior design industry. rephrase in bullet point.

Chapter 3 Design Approach and Methodology

3.1 Introduction

GAN is a machine learning model for unsupervised learning with two neural networks - generator and discriminator.

Generator takes random noise as input and produces images, while discriminator detects fake or real images.

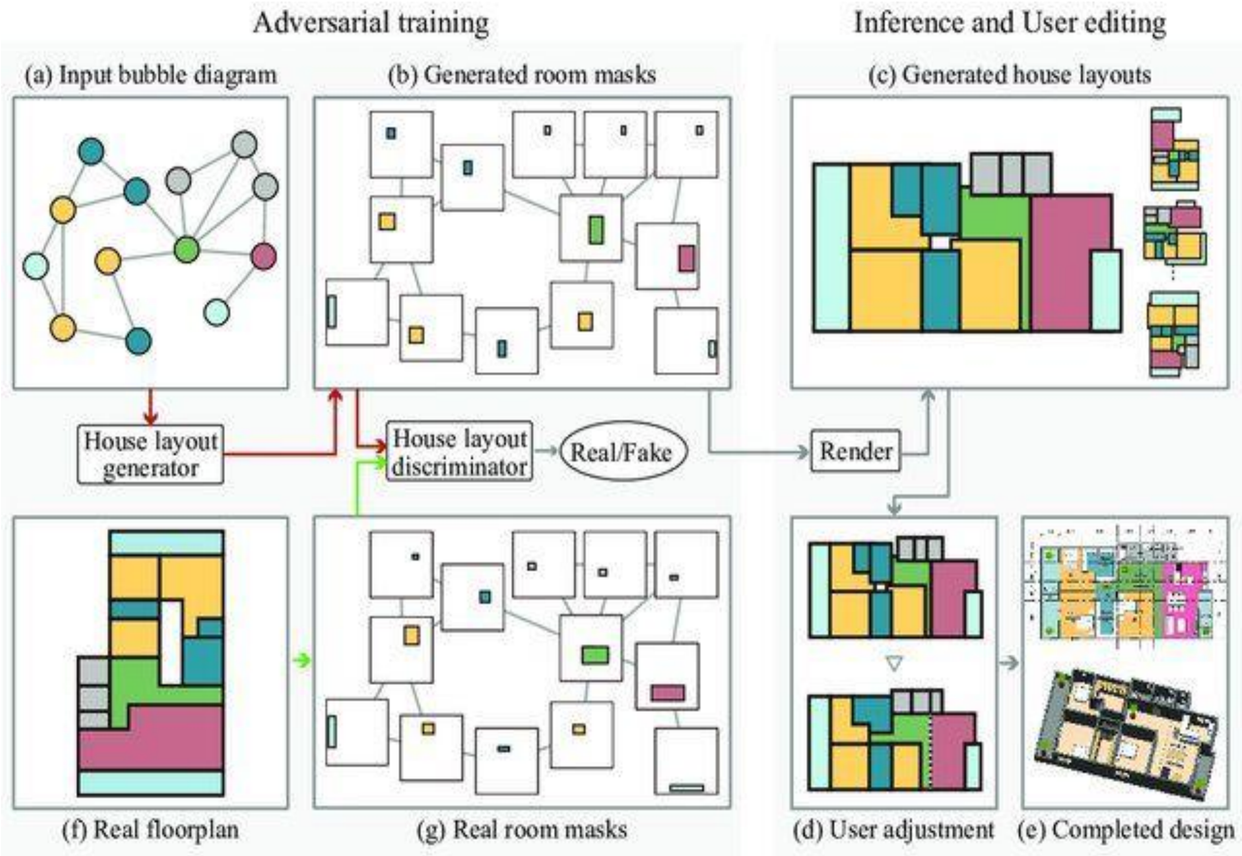

Fig 1 : Working architecture of GAN

The above image shows a house layout generator that uses Generative Adversarial Networks (GANs) to generate realistic floor plans. The workflow consists of the following steps:

1. Input bubble diagram: The user provides a bubble diagram, which is a rough sketch of the desired layout, including the location and size of each room.
2. Generated room masks: The GAN generates a set of room masks, which are binary images that indicate the presence or absence of a room at each pixel.
3. Generated house layouts: The GAN generates a set of house layouts, which are graphs that represent the connectivity between the different rooms.
4. User adjustment: The user selects a house layout that they like and makes any necessary adjustments.
5. Completed design: The GAN renders a realistic image of the completed design.

GAN-based interior design can be used to elaborate the picture in the following ways:

- Generate more realistic and varied floor plans: GANs can generate a wide variety of floor plans, including those with complex shapes and layouts. This allows users to explore more creative design options.
- Incorporate additional design elements: GANs can be trained to generate floor plans that incorporate additional design elements, such as furniture, windows, and doors. This allows users to get a better sense of the overall look and feel of the design.
- Generate 3D renderings: GANs can be used to generate 3D renderings of the completed design. This allows users to visualize the design from multiple angles and get a more realistic sense of how it would look in real life.

Here are some specific examples of how GAN-based interior design can be used to elaborate the picture:

- The GAN could be used to generate a variety of floor plans for the same bubble diagram, with different room arrangements and sizes. This would allow the user to compare different design options and choose the one that they like best.
- The GAN could be used to generate a floor plan that incorporates additional design elements, such as furniture, windows, and doors. This would give the user a better sense of the overall look and feel of the design.
- The GAN could be used to generate a 3D rendering of the completed design. This would allow the user to visualize the design from multiple angles and get a more realistic sense of how it would look in real life.

Overall, GAN-based interior design can be used to elaborate the picture in a number of ways by generating more realistic and varied floor plans, incorporating additional design elements, and generating 3D renderings.

3.2 GAN Framework

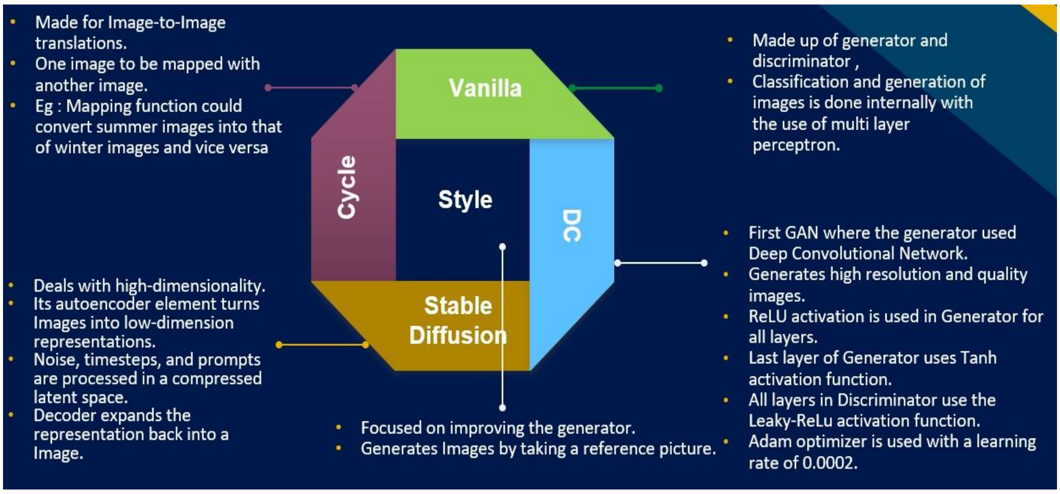

Fig 2 : GAN - At a glance

Vanilla GAN

The term "Vanilla GAN" refers to the original and basic form of the Generative Adversarial Network (GAN) introduced by Ian Goodfellow and his colleagues in their 2014 paper titled "Generative Adversarial Nets." In the context of GANs, "vanilla" is often used to denote the simplest and most fundamental version of a model, without any additional enhancements or modifications.

Here are the key components and concepts associated with Vanilla GAN:

1. Generator and Discriminator:

- **Generator:** The generator network takes random noise as input and generates synthetic data (e.g., images).

- **Discriminator:** The discriminator network tries to distinguish between real data (from the true distribution) and fake data produced by the generator.

2. Adversarial Training:

- The generator and discriminator are trained simultaneously through adversarial training. The generator aims to produce data that is indistinguishable from real data, while the discriminator aims to correctly classify between real and generated data.

3. Loss Function:

- The training process involves minimizing a specific loss function, often referred to as the adversarial loss. It is based on the idea of a minimax game, where the generator and discriminator are in constant competition.

4. Stochastic Gradient Descent (SGD):

- Vanilla GANs typically use stochastic gradient descent or related optimization algorithms to update the parameters of the generator and discriminator networks during training.

Despite its simplicity, Vanilla GANs can be challenging to train and are sensitive to hyperparameters. Issues such as mode collapse (where the generator produces limited diversity in its output) and training instability can occur. Over the years, researchers have proposed various improvements and modifications to address these challenges, leading to the development of different GAN variants, such as DCGAN (Deep Convolutional GAN), WGAN (Wasserstein GAN), and others.

While Vanilla GANs serve as the foundation for GAN research and applications, many advanced architectures and techniques have been introduced to enhance stability, scalability, and the quality of generated samples.

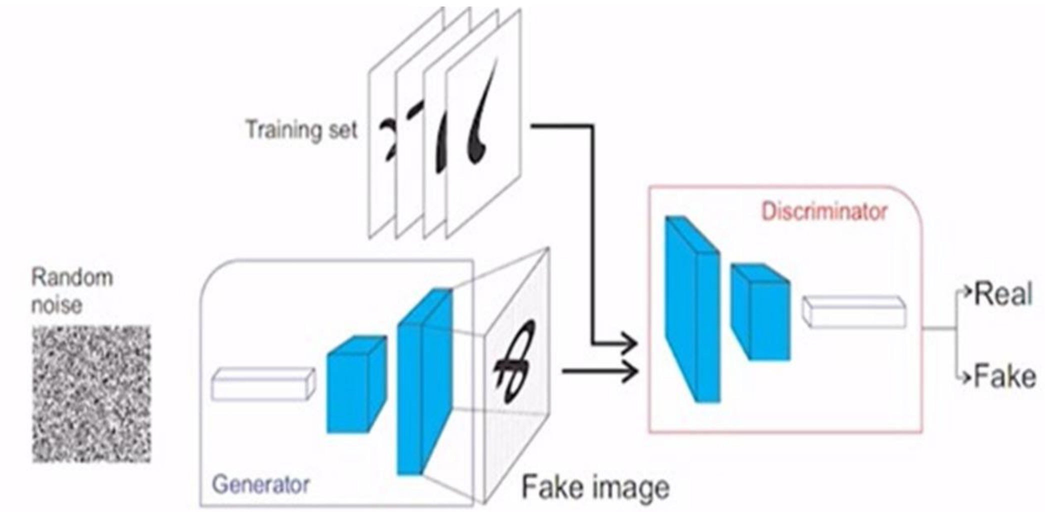

Fig 3 : A General GAN Architecture

DCGAN (Deep Convolutional GAN)

1. Description:

DCGAN, short for Deep Convolutional Generative Adversarial Network, is a type of GAN architecture designed specifically for image generation tasks. It was introduced to address the limitations of the original GAN architecture in generating high-resolution and visually realistic images.

2. Key Features:

- **Convolutional Layers:** DCGAN incorporates convolutional layers in both the generator and discriminator networks. This allows the networks to effectively capture spatial hierarchies and learn image features at different scales.

- Strided Convolutions and Transposed Convolutions: DCGAN uses strided convolutions in the discriminator to downsample the input image and transposed convolutions in the generator to upsample the noise into a full-sized image.

- Batch Normalization: Batch normalization is applied in both the generator and discriminator networks. It helps stabilize and accelerate the training process by normalizing the input of each layer.

- No Fully Connected Layers: DCGAN avoids the use of fully connected layers in the convolutional parts of the network, relying on convolutional and transposed convolutional layers for all operations.

3. Applications:

DCGAN has been successfully applied to various image generation tasks, including the generation of realistic faces, objects, and scenes. Its architecture has become a standard baseline for many image synthesis tasks within the GAN framework.

4. Advantages:

DCGAN's architecture promotes stable training and facilitates the generation of high-quality images with more intricate details. It has become a widely adopted architecture for many computer vision and image generation tasks.

DCGAN has played a significant role in the development of GANs, providing a foundation for subsequent improvements and variations in the architecture. It has proven effective in generating diverse and realistic images across different domains.

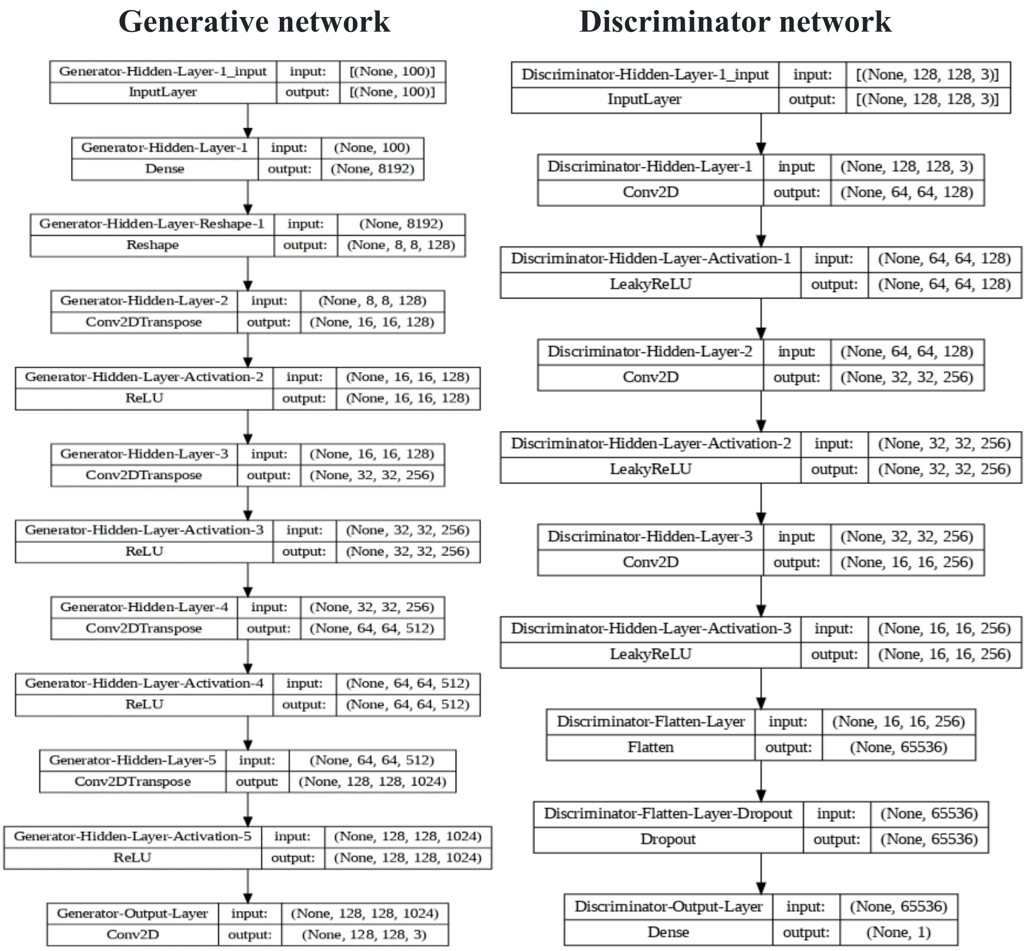

Fig 4: Workflow of DC GAN

Style GAN

1. Description:

StyleGAN is an advanced variant of the Generative Adversarial Network (GAN) architecture that was introduced by NVIDIA researchers in a paper titled "A Style-Based Generator Architecture for Generative Adversarial Networks" in 2018. StyleGAN aims to overcome limitations in controlling the style and diversity of generated images.

2. Key Features:

Style-Based Generator:

The key innovation in StyleGAN is the introduction of a style-based generator, which disentangles the latent space into a content space and a style space. This allows for independent control over the high-level features (content) and the low-level details (style) of generated images.

Mapping Network:

StyleGAN includes a mapping network that transforms a latent code into style information. This helps in controlling features like pose, facial expression, and more in a more structured manner.

Noise Injection:

StyleGAN incorporates controlled noise injection at different resolutions, allowing for the generation of more diverse and realistic details in the images.

Progressive Growing:

While not exclusive to StyleGAN, the use of a progressive growing approach is common in training GANs. It involves gradually increasing the resolution of generated images during training, starting from low resolution to high resolution.

3. Applications:

StyleGAN has been widely adopted for various image synthesis applications, particularly in generating highly realistic and diverse human faces. Its ability to control the style of generated images makes it suitable for tasks where fine-grained control over visual attributes is crucial.

4. Fine-Grained Control:

StyleGAN allows for the manipulation of specific visual attributes such as age, gender, and facial expressions by manipulating the corresponding style vectors. This makes it a powerful tool for image synthesis with detailed control.

5. Training Stability:

StyleGAN is designed to be more stable during training compared to earlier GAN architectures. The progressive growing approach and style-based generator contribute to a more reliable training process.

6. StyleGAN2:

Subsequently, StyleGAN2 was introduced as an improvement to the original StyleGAN, enhancing the quality of generated images and addressing certain artifacts.StyleGAN and its variants have become instrumental in the generation of high-quality, diverse images with fine-grained control over various visual aspects. They have found applications in art, design, and entertainment, showcasing the capabilities of generative models in creating realistic and customizable content.

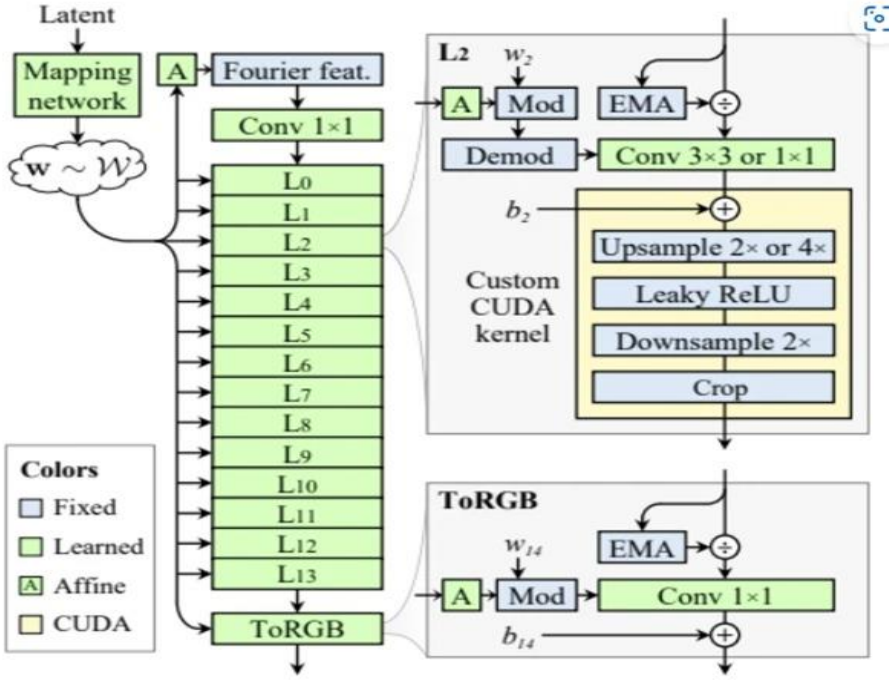

Fig 5: Style GAN Workflow

3.3 Flow Of Work

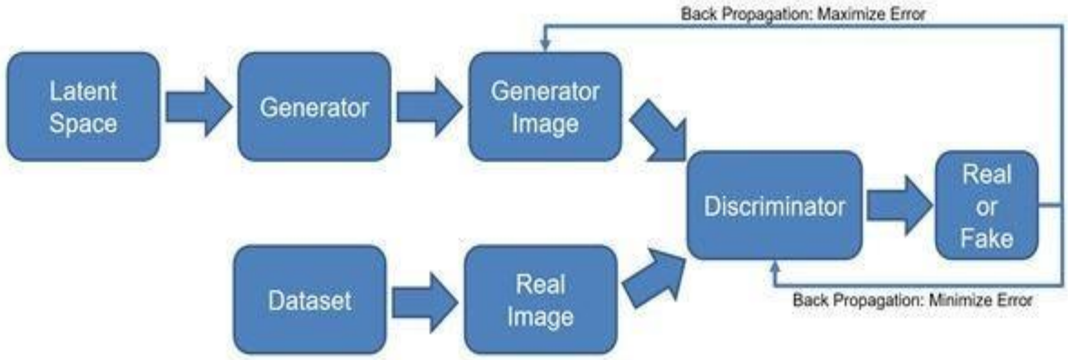

Fig 6: Flow Chart of working of GAN

The first step is to collect a large dataset of high-quality interior design images. This dataset should represent a variety of styles, layouts, and functionalities.

GAN Model Training: Once you have your dataset, you can start training your GAN model. A GAN model is made up of two parts: a generator and a discriminator. The generator takes in random noise as input and tries to generate realistic images of interior designs. The discriminator takes in both real images and images generated by the generator and tries to tell the difference between them. The two networks are trained together in an adversarial process, where the generator is trying to get better at fooling the discriminator, and the discriminator is trying to get better at telling real images from fake images.

User Input and Design Generation: Once your GAN model is trained, you can use it to generate interior design ideas based on user input. Users can specify their preferences for things like style, color palette, furniture, and layout. The GAN model will then generate a number of different design options that meet the user's criteria.

Refinement and Iteration: The user can then choose their favorite design option and make further refinements. They can change the furniture, the colors, or the layout. The GAN model can then be used to generate new versions of the design that incorporate the user's changes.

Final Design and Output: Once the user is happy with their design, they can finalize it and output it in a variety of formats, such as a 3D model, a virtual reality experience, or a set of blueprints.

Chapter 4 Implementation Details

4.1 Software tools used – Google Collab

Software Tools for StyleGAN3 with Google Collab and other specifications:

Considering your preferences for Google Collab, StyleGAN3, DCGAN, 25GB RAM, CUDA 11.3, Tesla GPU, and Visual Studio integration, here are some potential software tools in brief:

Free and Open-Source Options:

NVIDIA StyleGAN2-ADA Implementation: Official implementation of StyleGAN2-ADA by NVIDIA, which can be adapted for StyleGAN3 with adjustments. Supports Colab, CUDA 11.3, and Tesla GPUs, but requires integration with Visual Studio through TensorFlow or PyTorch plugins.

StarGAN2: Offers style transfer and image-to-image translation capabilities along with StyleGAN2 architecture. Supports Collab, CUDA 11.3, and Tesla GPUs, and can be integrated with Visual Studio through Python APIs.

StyleGAN2-pytorch: PyTorch implementation of StyleGAN2 with potential adaptation for StyleGAN3. Supports Collab, CUDA 11.3, and Tesla GPUs, but requires manual Visual Studio integration through Python environment configurations.

Paid Options:

Artbreeder: Cloud-based platform offering user-friendly tools for exploring and manipulating StyleGAN models, including StyleGAN3. Provides pre-trained models and allows training custom models, but lacks direct Visual Studio integration.

Topaz Labs' Gigapixel AI: Software for upscaling images with StyleGAN technology. It includes StyleGAN3 models and offers some creative control, but functions as a standalone application separate from Visual Studio.

Style2D: Closed-source tool specifically designed for 2D StyleGAN training and manipulation. Offers advanced features and integrates with existing libraries like PyTorch, potentially allowing Visual Studio integration through scripting.

Additional Notes:

RAM requirement: 25GB RAM might be sufficient for smaller StyleGAN3 models but could be limiting for larger models or extensive training. Consider cloud instances with higher RAM allocation if needed.

Visual Studio integration: Most options require scripting or plugin integrations to connect with Visual Studio. Consider your preferred development environment and scripting skills when choosing a tool.

4.2 About Dataset Used

The dataset utilized in this study was sourced from the IKEA.com website, specifically gathered to construct a Style Search Engine for non-commercial use. It encompasses a comprehensive collection, including 2193 photos of individual objects or products, offering a diverse representation of items available on the IKEA platform. Additionally, the dataset comprises 298 context photos, providing room scenes where these objects naturally appear. Accompanying the visual data are textual descriptions for the products, offering insights into features, dimensions, and other relevant details. A notable aspect of the dataset is the inclusion of ground truth information, delineating which objects are present in specific rooms. This annotation is invaluable for training and validating algorithms, ensuring the accuracy and effectiveness of the envisioned Style Search Engine. It is important to highlight that the dataset is expressly intended for non-commercial use, aligning with the project's focus on developing a Style Search Engine. Such datasets serve as foundational resources for advancing research in computer vision, image recognition, and related fields, fostering innovation in applications and tools.

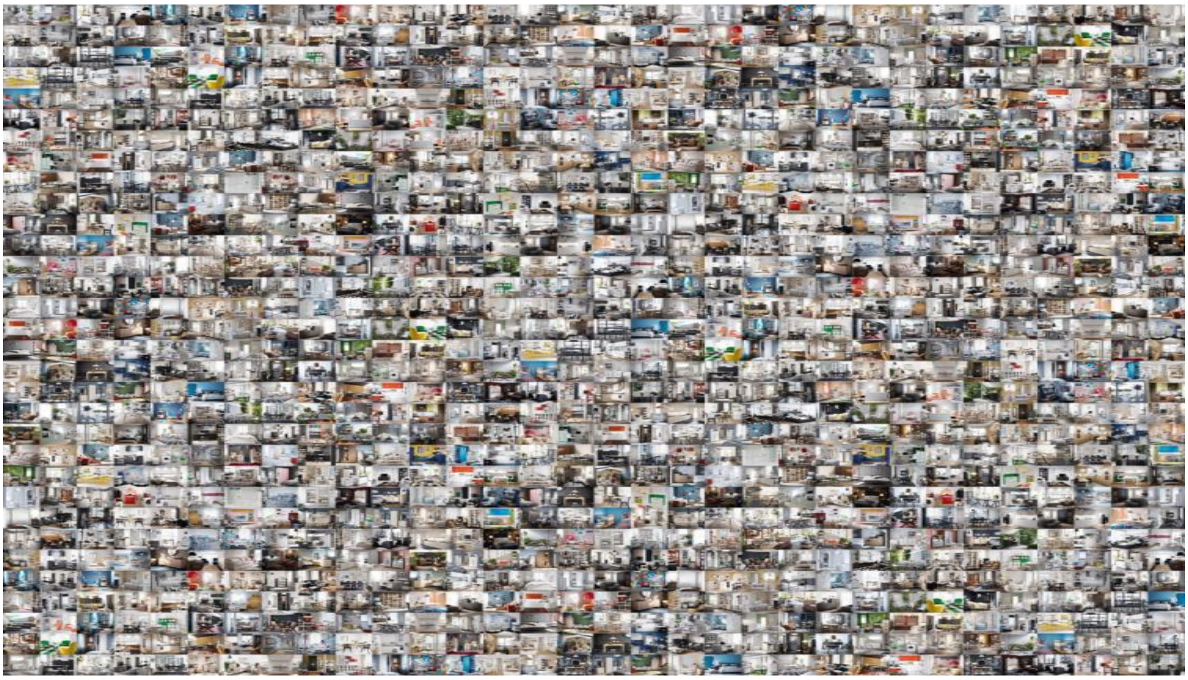

Fig 7: Datasets Samples

Key Features of the IKEA:

The dataset sourced from the IKEA.com website for constructing a Style Search Engine exhibits several key features:

1. Size and Composition:

- The dataset is substantial, comprising 2193 photos of individual objects and 298 context photos capturing room scenes. This diversity ensures a comprehensive representation of IKEA products in various settings.

2. Purpose and Usage:

- The dataset is explicitly collected for the purpose of building a Style Search Engine, emphasizing its application in enhancing visual search and design-related algorithms.

3. Non-commercial Use Restriction:

- Notably, the dataset is intended solely for non-commercial use, aligning with the specified purpose of creating a Style Search Engine and adhering to usage guidelines set by IKEA.com.

4. Textual Descriptions:

- Alongside visual content, the dataset includes textual descriptions for the products, providing additional information about features, dimensions, and other relevant details.

5. Ground Truth Information:

- The dataset includes ground truth information detailing which objects are present in specific rooms, serving as a valuable annotation for training and validating algorithms.

6. Context Photos:

- The inclusion of 298 context photos depicting room scenes enhances the dataset's realism and practicality for applications related to interior design and visual search.

7. Support for Style Search Engine:

- The dataset is specifically curated to support the development of a Style Search Engine, highlighting its utility for advancing research and innovation in the field of computer vision and image recognition.

Benefits of using the IKEA:

- Realistic Representation of Furniture
- Variety in Styles and Designs
- Practicality and Feasibility
- Widely Recognized Brand
- Large and Diverse Dataset
- Potential for Personalization

4.3 Dataset Processing

Images in JPG or PNG format can be processed in Google Colab for a virtual interior design project using GAN architecture:

1.Loading Images:

Images in JPG or PNG format can be loaded using the Python Imaging Library (PIL) or its fork, Pillow. In Google Colab, you can use the Image module from PIL to open and load images from file paths.

2.Preprocessing:

Preprocessing involves transforming the raw image data into a format suitable for the GAN model. This may include resizing the images to a consistent size, normalizing pixel values to a specific range (e.g., [0, 1]), and handling any other transformations required by the GAN architecture.

3.Visualization:

Visualization is an essential step to inspect the original and processed images. Matplotlib can be employed for displaying images in the Colab environment. Visualization aids in understanding the impact of preprocessing and ensures the images are prepared appropriately for input to the GAN.

4.GAN Inference:

The preprocessed image can be fed into the GAN architecture for inference. GANs, being generative models, can take an input image and generate new, realistic images based on the learned patterns from the training data.

5. Generated Image Display:

Displaying the generated images allows for an assessment of the GAN's performance in creating virtual interior designs. This step involves using Matplotlib or similar tools to showcase the generated content to the user or designer.

6.Iterative Refinement:

The process is often iterative, with adjustments made to preprocessing and GAN parameters to enhance the quality of generated interior designs. This may involve experimenting with different architectures, training strategies, and hyperparameters.

7.User Interaction:

In the context of virtual interior design, the processed and generated images can be presented to users through a user interface. Users may interact with the GAN-generated designs, providing feedback or making customization requests.

8.Testing and Scaling:

The platform should undergo extensive testing to ensure its reliability and functionality. If successful, considerations for scaling the platform for wider adoption in the interior design industry may be explored, involving optimizations for performance and usability.

In summary, the process involves loading, preprocessing, visualizing, and utilizing GANs to generate virtual interior designs from input images. The iterative nature of refining the GAN model and its parameters is crucial for achieving high-quality results. User interaction and testing play pivotal roles in ensuring the effectiveness of the virtual interior design platform.

Chapter 5 Results and Analysis

The Fréchet Inception Distance (FID) serves as a crucial performance metric by quantifying the difference between the feature vectors of genuine images and those generated artificially by the generator. A reduced FID score indicates higher quality in the generated images, closely resembling real ones, as it relies on comparing the feature vectors of images. The Inception score, while useful, has limitations in evaluating the similarity between synthetic and real images. Thus, the introduction of the FID score aims to assess the fidelity of synthetic images by comparing their statistical properties with those of real images in the desired domain. Lower FID scores correspond to better-generated images, as depicted in the FID Graph, which illustrates the proximity of images concerning their distribution, as shown in figure 8.

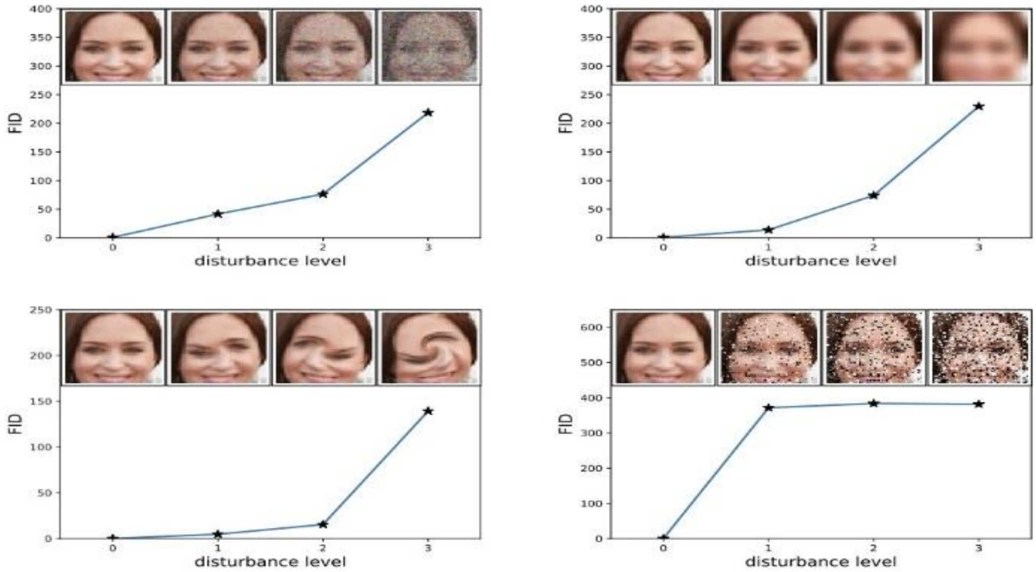

Fig 8: FID score plot

The generator of the DCGAN network needed around 21000 epochs to generate good quality images as in figure 10. The major issues with DCGAN network were its mode collapse as in figure 11 and Vanishing Gradient as in figure 12. The performance metric of DCGAN is tabulated in table 1

Table 1 : DCGAN Network Performance Metrics

Epoch#	stats	FID Score
21000	Discriminator Loss: 0.0006483550532720983 Generator Loss: 13.37311553955078	237
19000	Discriminator Loss: 0.009213417768478394 Generator Loss: 18.83767318725586	355
16000	Discriminator Loss: 8.113920126062713e-12 Generator Loss: 26.006271362304688	382
13000	Discriminator Loss: 8.237818411352566e-12 Generator Loss: 25.84298324584961	419
10000	Discriminator Loss: 6.662484366287691e-12 Generator Loss: 25.632919311523438	439

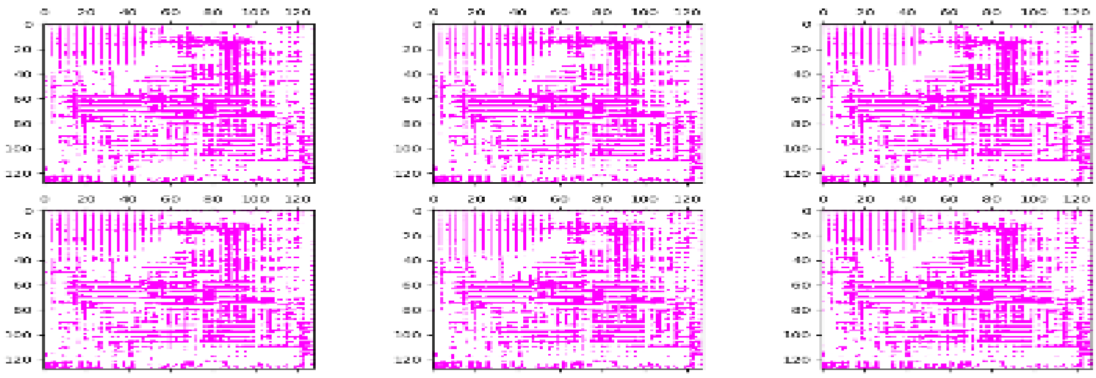

Fig 9 : Image Transition 1

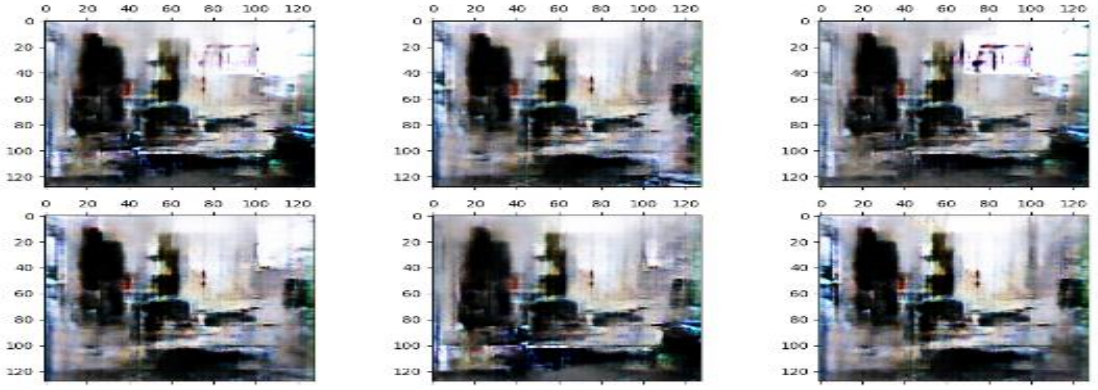

Fig 10 : Image Transition 2

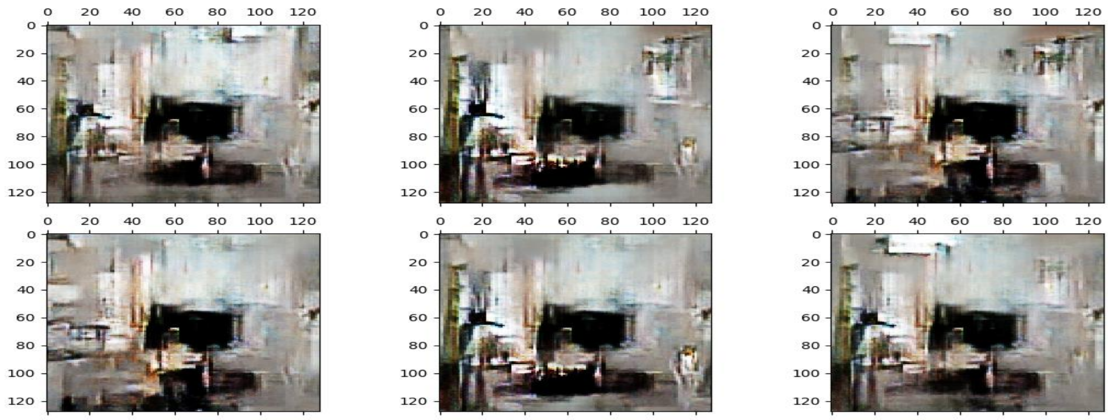

Fig 11 : Image Transition 3

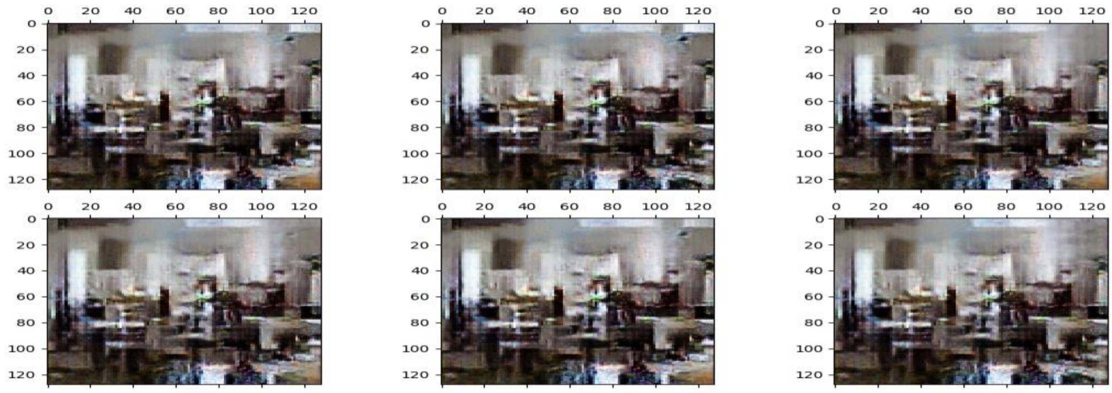

Fig 12 : Image Transition 4

The generator of StyleGAN3 needed around 2500 epoch to generate high quality images. Its performance metrics are tabulated in table 2 and figure 13.

Table 2 : Epoch vs FID score of StyleGAN3

Ticks	FID SCORE	Ticks	FID SCORE
100	483.9971	1000	144.2901
200	366.1188	1100	122.8043
400	296.1188	1300	111.9371
500	202.7571	1600	111.361
600	202.2473	2000	107.368
700	185.1233	2200	106.9345
800	152.2309	2500	105.6143

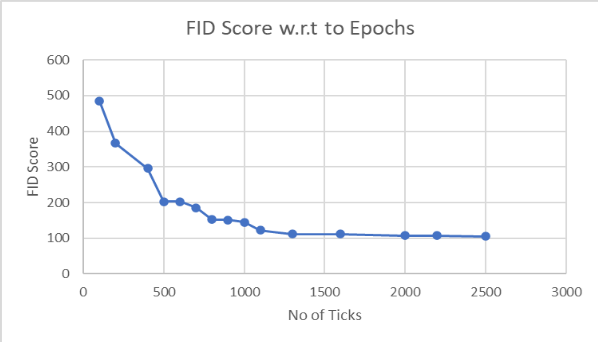

Fig 13 : Epochs vs FID score of StyleGAN3 Network

Some good quality images can be seen after training for 2500 ticks as in figure 14. Images are still blurry and needs more training to get expected good outcome.

Fig 14 : Good Quality Images Generated by StyleGAN

Table 3 : Comparative analysis of DCGAN vs STYLE3GAN

	Epochs(Final value)	FID SCORE (performance Metrics)
DCGAN	21000	237
Style3GAN	2500	105

From Table 3 we can conclude that the DCGAN offers higher loss values alongside FID scores across epochs, indicating a focus on training progress and finding the optimal balance between the generator and discriminator. The StyleGAN captures FID scores more frequently (possibly) and lacks loss details, suggesting a focus on monitoring overall image quality over time. This aligns with StyleGAN's reputation for superior image generation, while DCGAN might provide more insights into the training process itself.

Table 4 compares the different state-of-the-art GAN architecture that are well suited for image classification, object detection, high resolution image generation, image analysis and natural language processing.

Table 4 : State of the art comparison

GAN Architecture	Loss function	Training Performance	Suitable for tasks
Cycle GAN	GAN	Can be computationally sensitive, hyperparameter sensitive	Unpaired image-image translation, style transfer, domain adaptation
DCGAN	GAN	Simple to implement, Good quality, robust to overfitting	Image classification, object detection, image segmentation
Style GAN	GAN	Can be computationally sensitive, hyperparameter sensitive	High resolution image generation, photo editing image inpainting

Analysis

Analysing the results of a DCGAN for virtual interior design with a high FID score involves evaluating various aspects:

1. FID Score: A lower FID score indicates better image quality and diversity, while a high score suggests a gap between real and generated images.
2. Image Quality: Assess clarity, sharpness, and overall visual quality, addressing any issues in resolution, detail, and fidelity.
3. Diversity of Designs: Ensure a broad spectrum of styles, color schemes, and layouts to avoid generating similar or repetitive designs.

4. Realism and Plausibility: Examine if generated interiors align with real-world expectations in terms of furniture placement, lighting, and aesthetics.
5. Colour Consistency: Check the consistency and appropriateness of color schemes to avoid unrealistic combinations.
6. Texture and Detail: Enhance intricate details, such as texture variations and realistic lighting effects, to improve overall realism.
7. User Satisfaction: Collect user feedback to ensure virtual interiors are aesthetically pleasing, engaging, and reflective of desired design styles.
8. Training Data Quality: Ensure the training dataset is representative and diverse, addressing any mismatches between data and desired output.
9. Fine-Tuning and Iterative Training: Consider adjustments like fine-tuning and additional training iterations to improve the model's ability to generate high-fidelity designs.
10. Comparison with Baseline: Compare FID scores with baselines or previous iterations to track progress and identify areas for further refinement.

In summary, the analysis involves a comprehensive assessment of image quality, diversity, realism, color consistency, texture/detail, user satisfaction, training data quality, and iterative adjustments to enhance the model's performance.

Chapter 6 Conclusion and Future scope

The IKEA dataset, combined with GAN technology, holds immense potential for revolutionizing interior design through accessible, personalized virtual assistants. With the ability to generate diverse and realistic room scenes based on individual preferences, this technology can empower users to visualize their dream spaces and make informed design decisions.

The challenges faced in our proposed work are System limitations, vanishing gradient issue, mode collapse, Unavailability of pre-trained models, Uncategorized dataset, small amount of data to train. If these challenges are overcome, then this model can be extended to be used for generating new interior designs. With more data, this model can be fine-tuned further to generate the expected high-quality images. Tuning the hyperparameters such as Latent Space and seed can give improved results. More training is required to get more diverse designs. Also, other GAN models can be tried with add on features such as generate designs from sketch, text to design, transform uploaded room image to a new design, addressing issues like mode collapse. In developing an interior design assistant, DCGANs enable the generation of realistic room scenes with detailed features, facilitating informed decision-making and creative exploration in interior design through their stability and capacity for diverse outputs.

Key benefits of this GAN-based approach can be used in future to include:

Visualizing diverse style options: Users can experiment with different colors, furniture arrangements, and design themes before committing to real-world purchases.

Overcoming spatial limitations: The virtual assistant can generate stunning interior designs even for small or irregularly shaped spaces, helping users maximize their available space.

Personalized recommendations: By incorporating user preferences and existing room features, the assistant can recommend specific furniture pieces and decorative elements, creating a cohesive and harmonious design.

Democratizing design expertise: This technology democratizes access to professional-looking designs, making it easier for everyone to achieve a beautiful and functional living space.

Looking ahead, the future scope of this technology is vast

Incorporating 3D room scans: By integrating with 3D scanning technology, the assistant can generate even more realistic and accurate representations of existing spaces, further enhancing design visualization.

Interactive furniture manipulation: Users could directly interact with virtual furniture within the generated scenes, adjusting placement, size, and even customizing finishes in real-time.

Augmented reality integration: Overlaying virtual design elements onto real-world spaces using augmented reality could provide an even more immersive and interactive experience.

Expanding beyond IKEA: While the initial focus might be on IKEA products, the technology can be adapted to incorporate furniture and decor from other brands and styles, offering users a wider range of design possibilities.

In conclusion, the GAN-based Virtual Interior Design Assistant built on the IKEA dataset has the potential to fundamentally transform the way we design and decorate our homes. By offering accessible, personalized, and visually stunning design solutions, this technology can empower individuals to create spaces that reflect their unique styles and bring their design dreams to life.

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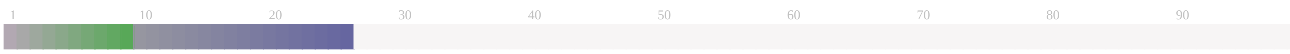

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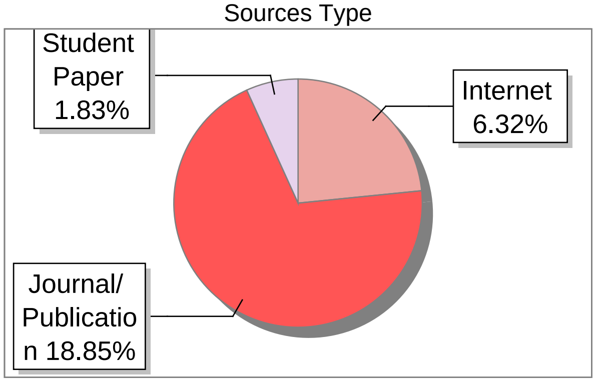

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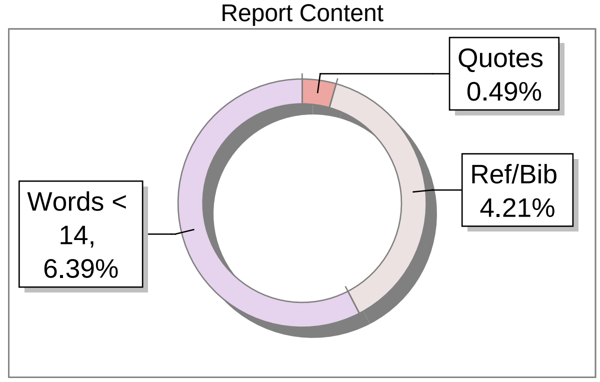

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78	www.researchgate.net	<1	Internet Data
79	IEEE 2016 XVIII Symposium on Virtual and Augmented Reality (SVR) - G	<1	Publication

VISVESVARAYA TECHNOLOGICAL UNIVERSITY
JNANA SANGAMA, BELAGAVI - 590018

A Project Report on

IMPLEMENTATION OF FACE FEATURE ALGORITHMS FOR AUTHENTICATION OF A PERSON

Submitted in partial fulfilment of the requirements for the award of the degree of

Bachelor of Engineering
in
Electronics and Communication Engineering
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Submitted by

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Abstract

It is always a costly affair to prepare suitable interior design. Automatic interior design generation with suitable interiors will have an enormous effect on the trillion-dollar real-estate/construction industry. The impact of deep neural networks has made a leap forward where state-of-the-art algorithms utilize Generative Adversarial Networks (GANs). AI-driven innovation with GANs has many applications in creative industries such as design, be it architectural design, landscape design or interior design, the possibilities are endless. Such generated designs have the potential to drive rapid growth and profits in the design industry. The goal of this work was to generate realistic new interior room designs by training a GAN network on the IKEA Interior Design Dataset. This work faced challenges in distinguishing a good design from a poor design along with training the GAN. The goal was to overcome these challenges by incorporating human feedback and using various evaluation methods to ensure the generated designs are of high quality. The project has the potential to provide valuable solutions for the interior design industry, by generating new designs quickly and efficiently. DCGAN generated satisfactory images for 21800 epochs and FID score of 237 but had mode collapse and vanishing gradient issues. While Style3GAN outperformed by generating high resolution images with 2500 epochs and FID score of 105.

Acknowledgement

The successful execution of our project gives us an opportunity to convey our gratitude to each one who have been instrumental in paving path to our continuation of this project. Whatever we have done is due to such guidance and help and we would not forget to thank them all.

We would like to thank and seek the blessings from **Dr. N R Shetty,** Advisor, **Nitte Meenakshi Institute of Technology**, for his thrust on project-based learning and constructivist principles in our institution.

We would like to express our gratitude to the **Nitte Meenakshi Institute of Technology** and our beloved Principal **Dr. H C Nagaraj** for providing us with the support, facilities, and motivation to carry out our project.

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We whole heartedly thank our guide **Dr. Rekha Phadke,** Associate Professor, Department of Electronics and Communication Engineering, for his support and guidance anytime we required.

We also thank and share this moment of happiness with our parents who rendered us enormous support during the whole tenure of our studies at Nitte Meenakshi Institute of Technology, Bengaluru.

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List Of Acronyms

GANs	Generative Adversarial Networks
AI	Artificial Intelligence
UI	User Interface
UX	User Experience
API	Application Programming Interface
ML	Machine Learning
NLP	Natural Language Processing
CV	Computer Vision
IoT	Internet of Things
VR	Virtual Reality
AR	Augmented Reality

Chapter 1 Introduction

The research conducted explores the transformative impact of integrating Generative Adversarial Networks (GANs) into the field of interior design, particularly focusing on how these AI algorithms revolutionize the automated generation of space aesthetics. GANs, being sophisticated AI models, have the ability to autonomously generate a diverse range of design proposals, addressing challenges related to creativity and efficiency in the field.

One of the key strengths of GANs lies in their training on a diverse dataset, enabling them to excel in producing visually appealing design concepts that go beyond conventional norms. The research suggests that GANs have the potential to surpass human limitations in creativity and contribute innovative and avant-garde ideas to interior design.

Moreover, the integration of user preferences into the GAN model is highlighted as a crucial aspect. This adaptability allows for the creation of personalized design solutions tailored to individual tastes and spatial requirements. This not only increases the practicality of the designs but also enhances their relevance to the end users, ultimately leading to a more satisfying and user-centric design process.

The study emphasizes the collaborative potential between AI and human designers, positioning GANs as tools that can inspire and complement human creativity rather than replace it. By leveraging the strengths of both AI and human designers, the research suggests a symbiotic relationship that results in more innovative and efficient design processes.

Ethical considerations are woven into the fabric of the research, emphasizing responsible AI use in design. The importance of human oversight is underlined, acknowledging the need for ethical guidelines and ensuring that AI is employed in ways that align with cultural values and societal norms. Preservation of cultural values is highlighted as a significant aspect, ensuring that the integration of AI into interior design respects and contributes to the preservation of diverse cultural aesthetics.

In conclusion, the research positions GANs as transformative tools in reshaping the landscape of interior design. The innovative paradigm presented involves a harmonious collaboration between AI and human designers, with a strong emphasis on ethical considerations and the preservation of human input in the creative process. The study contributes to the discourse on the responsible integration of AI into creative fields, offering insights into the potential benefits and challenges while stressing the importance of maintaining a balance between technological advancements and human values.

1.1 Motivation

The project is motivated by challenges in interior design creativity and efficiency. GANs, as AI algorithms, offer a solution by autonomously generating diverse design proposals, overcoming creative blocks and streamlining processes. The focus is on personalization, aligning with user preferences for more user-centric designs. The research aims to establish a collaborative relationship between GANs and human designers, emphasizing GANs as tools to inspire human creativity rather than replace it. Ethical considerations, including responsible AI use and cultural value preservation, are integral to the project. Overall, the research seeks to transform interior design paradigms by integrating GANs in an innovative, ethical, and collaborative manner.

1.2 Organization of the project

Organizing a project for a GAN-based virtual interior design system involves defining project goals, researching market trends, and identifying the target audience. Selecting an appropriate technology stack and collecting a diverse dataset for GAN training are crucial steps. Designing an intuitive UI, integrating GAN models with the backend, and implementing features like style transfer and color customization follow suit. Rigorous testing, including user testing, ensures the system's quality. Deployment on a stable platform and continuous monitoring are essential. Documentation, marketing strategies, user support, and a maintenance plan for updates and improvements complete the comprehensive approach. Regular communication within the team and with stakeholders ensures alignment with project goals.

Chapter 2 Literature Survey

2.1 Background Work

1. The article discusses how AI has been utilised in various industries to address complex problems and increase efficiency. However, the integration of AI in the architecture field is still in its early stages. The article focuses on the first step of the architectural design process, the Conceptual Design Stage, which is currently a manual process that limits the number of design iterations due to cost, time constraints, and human limitations. This leads to potentially subpar final building designs that may have negative economic, functional, performance, or psychological effects. **[Michael Hasey, 2019, GAN_Itecture]**
2. Generative adversarial networks are a kind of artificial intelligence algorithm designed to solve the generative modelling problem. The goal of a generative model is to study a collection of training examples and learn the probability distribution that generated them. Generative Adversarial Networks (GANs) are then able to generate more examples from the estimated probability distribution. Generative models based on deep learning are common, but GANs are among the most successful generative models (especially in terms of their ability to generate realistic high-resolution images). GANs have been successfully applied to a wide variety of tasks (mostly in research settings) but continue to present unique challenges and research opportunities because they are based on game theory while most other approaches to generative modelling are based on optimization. **[Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron C. Courville, and Yoshua Bengio. 2020. Generative Adversarial Networks. NIPS 27(2020).]**
3. This paper reviews the state-of-the-art video Generative Adversarial Networks (GANs) models, which are increasingly used in various fields for content creation. It categorises GANs review papers into general, image, Dept. of Electronics and Communication Engineering, Nitte Meenakshi Institute of Technology, Bengaluru 3 and special field GANs review papers. GANs consist of a generator and a discriminator network that are trained in an adversarial manner to generate new data points that conform to the distribution of the training dataset. The goal is to reach the Nash equilibrium where the discriminator is unable to differentiate between real and fake samples. The paper demonstrates an upward trend in publications on GANs since the mid-2010s. **[Nuha Aldausari, Arcot Sowmya, Nadine Marcus, and Gelareh Mohammadi. 2020. Video Generative Adversarial Networks: A Review. arXiv preprint arXiv:2011.02250(2020).]**

4. From this reference we got to know the basic principles of GANs, including the adversarial process and the roles of the generator and discriminator networks. The discriminator network's objective is to determine whether a sample belongs to a real or fake distribution, while the generator network's objective is to deceive the discriminator by generating a fake sample distribution. The GAN architecture consists of the generator and discriminator networks, which are updated iteratively during the training process. The generator network uses random noise to generate images, while the discriminator network determines whether an image is real or fake. **[Hamed Alqahtani, Manolya Kavakli-Thorne, and Gulshan Kumar. 2019. Applications of generative adversarial networks (gans): An updated review. Archives of Computational Methods in Engineering (2019), 1–28.]**
5. In this paper, we reviewed some basics of GANs and described some applications in the field of image synthesis based on GANs. The pros and cons of these GANs applications are also provided. Besides, we summarised the methods used in GANs applications which improved the performance of generated images. Although the research on GANs is becoming more and more mature, GANs are still faced with some challenges, such as unstable training and hard to evaluate. **[Lei Wang, Wei Chen, Wenjia Yang, Fangming Bi, and Fei Richard Yu. 2020. Review on Image Synthesis With Generative Adversarial Networks. IEEE Access 8(2020), 63514–63537]**
6. The article discusses the emergence of Deepfakes, a manipulation technique that allows swapping identities in videos. To address this threat, the authors have created the largest publicly available face swap video dataset, called the DeepFake Detection Challenge (DFDC) dataset, with over 100,000 clips sourced from 3,426 actors. The article describes the methods used to construct the dataset and provides an analysis of the top submissions from the accompanying Kaggle competition. The authors demonstrate that a Deepfake detection model trained on the DFDC dataset can generalise to real-world Deepfake videos and can be a useful tool in analysing potentially manipulated videos. **[Brian Dolhansky, Joanna Bitton, Ben Pflaum, Jikuo Lu, Russ Howes, Menglin Wang, and Cristian Canton Ferrer. 2020. The deepfake detection challenge dataset. arXiv preprint arXiv:2006.07397(2020)]**
7. The article discusses how AAL (Ambient Assisted Living) in Smart Homes is not limited to tracking indoor location but also includes analysing user behaviour and activity patterns to improve their quality of life. It goes on to review recent AAL technologies that focus on activity recognition and analysis in Smart Homes. **[Nirmalya Thakur and Chia Y Han.**

2021. Multimodal Approaches for Indoor Localization for Ambient Assisted Living in Smart Homes. Information 12, 3 (2021), 114.]

8. The dataset was collected from IKEA.com website for the purpose of building Style Search Engine (note: only for non-commercial use). It consists of: 2193 object (product) photos, 298 context (room scene) photos in which those objects appear, text descriptions for products, ground truth information on which items appear in which rooms. **[Tautkute et al., 2017, ACICS, IKEA: Interior Design Dataset]**

9. In our research, we propose an innovative method named GlyphGAN for generating fonts with style consistency using Generative Adversarial Networks (GANs). GANs operate through a dual-network system where one network generates synthetic images from random input vectors, while the other network distinguishes between these synthetic images and real ones. Our primary goal is to leverage the capabilities of GANs to create diverse fonts while ensuring a consistent style across all characters.

GlyphGAN introduces a distinctive input vector for the generator network, composed of two components: a character class vector and a style vector. The character class vector is created through one-hot encoding, associating it with the character class of each sample image during the training process. On the other hand, the style vector is a randomly generated vector without any supervised information. This design choice empowers GlyphGAN to produce an extensive variety of fonts, offering independent control over both the character and style aspects of the generated fonts.In our experiments, we observed that fonts generated by GlyphGAN exhibit a unique combination of style consistency and diversity. Importantly, this diversity is distinct from the fonts present in the training dataset, showcasing GlyphGAN's ability to create novel and diverse fonts without sacrificing legibility.The significance of GlyphGAN lies in its potential to revolutionize font design by providing a tool for designers to effortlessly generate fonts with desired styles while maintaining consistency across different characters. The results of our experiments demonstrate the effectiveness of GlyphGAN in achieving this delicate balance between style diversity and consistency, highlighting the promising applications of GANs in the creative domain of font generation.**[Hideaki Hayashi, Kohtaro Abe, and Seiichi Uchida. 2019. GlyphGAN: Style-consistent font generation based on generative adversarial networks. Knowledge-Based Systems 186 (2019), 104927.Google ScholarDigital Library]**

10. We study the problem of 3D object generation. We propose a novel framework, namely 3D Generative Adversarial Network (3D-GAN), which generates 3D objects from a probabilistic space by leveraging recent advances in volumetric convolutional networks and generative adversarial nets. The benefits of our model are three-fold: first, the use of an adversarial criterion, instead of traditional heuristic criteria, enables the generator to capture object structure implicitly and to synthesize high-quality 3D objects; second, the generator establishes a mapping from a low-dimensional probabilistic space to the space of 3D objects, so that we can sample objects without a reference image or CAD models, and explore the 3D object manifold; third, the adversarial discriminator provides a powerful 3D shape descriptor which, learned without supervision, has wide applications in 3D object recognition. Experiments demonstrate that our method generates high-quality 3D objects, and our unsupervisedly learned features achieve impressive performance on 3D object recognition, comparable with those of supervised learning methods. **[Jiajun Wu, Chengkai Zhang, Tianfan Xue, Bill Freeman, and Josh Tenenbaum. 2016. Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling. NIPS (2016), 82–90.Google Scholar]**

11. We introduce the TL-embedding network, a novel architecture for an object's vector representation. This representation is both generative in 3D, allowing the creation of new objects, and predictable from 2D images for interpretation. The network integrates an autoencoder for generativity, ensuring the representation's ability to generate diverse 3D objects. Additionally, a convolutional network guarantees predictability from 2D images. The TL-embedding network excels in tasks like voxel prediction from 2D images and 3D model retrieval, showcasing its versatility. Extensive experiments validate its effectiveness, marking a significant advancement in achieving a comprehensive vector representation for objects in 3D generative modeling and 2D-to-3D interpretation. **[Rohit Girdhar, David F. Fouhey, Mikel Rodriguez, and Abhinav Gupta. 2016. Learning a Predictable and Generative Vector Representation for Objects.]**

12. In this paper, we introduced the large ONSF database which includes various changes in pose, expressions and focus. We also created another INF database in the laboratory environment to test the performance of near infrared facial recognition. We propose a novel near infrared facial recognition method in an end-to-end deep architecture which includes face detection and alignment, NIR-VIS image translation and a face embedding module. This is the first time that it has been proposed to apply the image-image translation method to enhance the performance of a near-infrared facial image recognition. This is achieved by synthesizing a virtual sample from an input near infrared face image. Using this approach, we reduce the intra-personal difference caused by the completely different illumination. Therefore, we can achieve much better recognition results by applying the existing pre-trained VLD deep neural network face recognition model. The proposed method was tested on the INF database and the CSIST dataset, with promising results. **[Fangyu Wu, Weihang You, Jeremy S.Smith, Wenjin Lu and Bailing Zhang, "Image-Image translation to enhance Near Infrared Face Recognition,",2020.]**

13. The paper focuses on facial diagnosis and how using deep transfer learning can be helpful. It starts by explaining why facial diagnosis is important and introduces the idea of using deep transfer learning in this area. The beginning of the paper outlines what problem the research is trying to solve and what goals it has. The paper then reviews existing information on deep learning, face recognition, and facial diagnosis, finding places where transfer learning could be useful. In the methodology section, it explains in detail how deep transfer learning was used, including information about the datasets and steps taken to prepare the facial data. The paper also talks about the design of the model and how transfer learning was applied from face recognition to facial diagnosis. The experiments section gives details about how the tests were set up, what metrics were used to measure success, and the results, including comparisons with other methods. In the discussion part, the paper talks about what these results mean, the impact of using transfer learning in facial diagnosis, and what could be improved. The conclusion summarizes the main discoveries, emphasizes the contribution of the research, and suggests areas for future exploration. The paper ends with a carefully crafted list of references, citing studies that influenced the research. **[Bo Jin, Leandro Cruz and Nuno Goncalves, "Deep Facial Diagnosis: Deep Transfer Learning From Face Recognition to Facial Diagnosis,",2020.]**

14. Face Recognition (FR) applications in the open world or adapted domain incur an undesirable downtime due to retraining or finetuning of FR models. Resorting to low-cost O(1) , threshold setting methods like σ values may not achieve optimal performance. Using such fixed threshold values also compromises the security of an FR application. Hence this paper proposed an adaptive threshold using a dynamic ROI-based threshold adapter algorithm. The proposed method narrows the search space of the optimal threshold and makes it 12 times faster than conventional methods. Making real-time threshold setting feasible. We demonstrated on two evaluation datasets that the proposed algorithm significantly improved five state-of-the-art deep FR models, yielding the best performance. Additionally, the positive pairs are minimal in the open world FR application. Hence, consideration of the F1-score is vital. The proposed method suggests that taking accuracy at the highest reported F1-scores is a better metric for performance benchmarking in the open world FR applications. **[Ahmed Rimaz Faizabadi, "Efficient Region of Interest Based**

Metric Learning for Effective Open World Deep Face Recognition Applications,",2022.]

15. In this paper, we propose a new face alignment method, called APA, which can be used for data processing in face recognition or face analysis tasks to improve performance. The APA method can not only reduce intra-class variability (increasing intra-class similarity) but also correct the noise caused by alignment process. Furthermore, we also propose a simple, yet effective feature normalization method. It can be used by combining with the APA method to generate more discriminative feature representation of a face or template. Experiments on LFW, CPLFW, IJB-A, and IJB-C datasets show that the proposed methods provide significant and consistent improvements and achieve state-of-the-art results. In conclusion, the APA is an effective data processing method for pose-invariant face recognition. **[Zhanfu An, Weihong Deng, Jian Hu, Yaoyao Zhong and Yuying Zhao, "APA: Adaptive Pose Alignment for Pose-Invariant Face Recognition,",2020.]**

2.2 Problem Definition

Interior design involves creating visually attractive and functional spaces

There is a growing demand for customized and unique interior designs

Tools are needed to generate a large number of design options that meet the client's specifications2.3 Objectives

The following are the proposed objectives of the project based on the research gaps:

- A demonstration of how GAN's can be used in the field of interior design and how it can improve the design process.
- To evaluate the GAN architecture performance on the interior design based on the performance and error metrics.
- Working with GAN might help interior designers gain the exposure they need. As a result, people benefit from technology and expand their knowledge base.

2.3 Objectives

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2.4 Scope of Work

The project will involve the design and implementation of a GAN-based virtual interior design platform, including the development of the GAN model, user interface, and backend infrastructure. The platform should support the creation, visualization, and customization of virtual interiors, providing an immersive and realistic experience for both designers and clients. The scope also includes testing, refining, and potentially scaling the platform for wider adoption in the interior design industry. rephrase in bullet point.

Chapter 3 Design Approach and Methodology

3.1 Introduction

GAN is a machine learning model for unsupervised learning with two neural networks - generator and discriminator.

Generator takes random noise as input and produces images, while discriminator detects fake or real images.

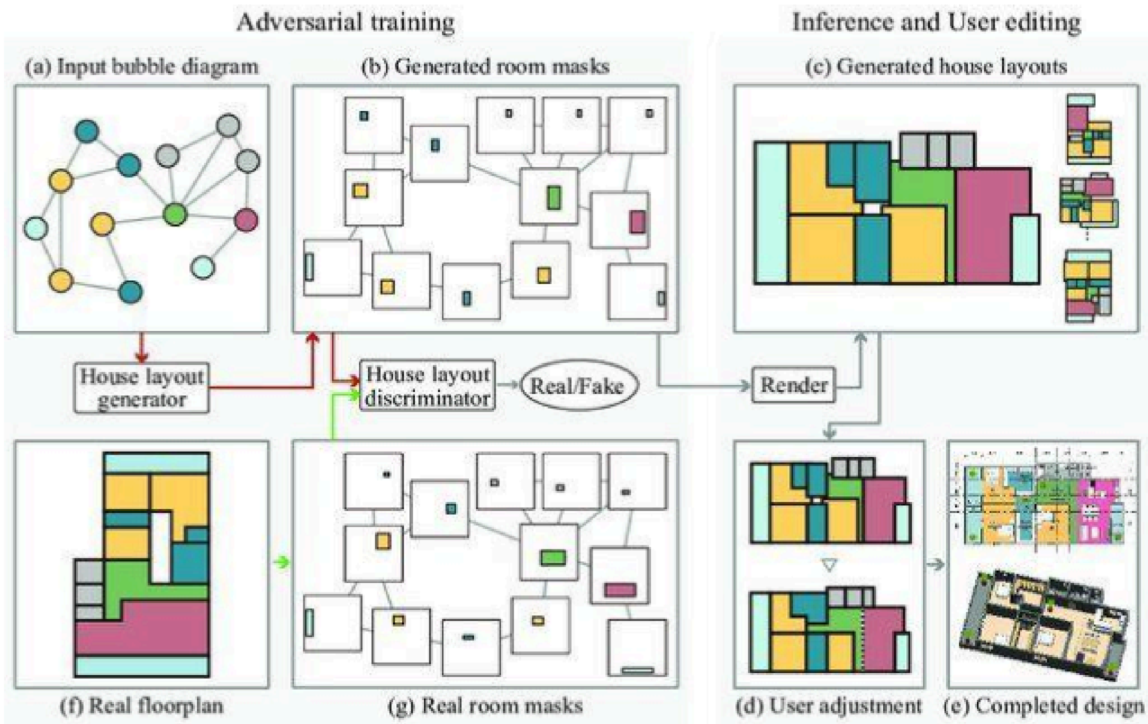

Fig 1 : Working architecture of GAN

The above image shows a house layout generator that uses Generative Adversarial Networks (GANs) to generate realistic floor plans. The workflow consists of the following steps:

1. Input bubble diagram: The user provides a bubble diagram, which is a rough sketch of the desired layout, including the location and size of each room.
2. Generated room masks: The GAN generates a set of room masks, which are binary images that indicate the presence or absence of a room at each pixel.
3. Generated house layouts: The GAN generates a set of house layouts, which are graphs that represent the connectivity between the different rooms.
4. User adjustment: The user selects a house layout that they like and makes any necessary adjustments.
5. Completed design: The GAN renders a realistic image of the completed design.

GAN-based interior design can be used to elaborate the picture in the following ways:

- Generate more realistic and varied floor plans: GANs can generate a wide variety of floor plans, including those with complex shapes and layouts. This allows users to explore more creative design options.
- Incorporate additional design elements: GANs can be trained to generate floor plans that incorporate additional design elements, such as furniture, windows, and doors. This allows users to get a better sense of the overall look and feel of the design.
- Generate 3D renderings: GANs can be used to generate 3D renderings of the completed design. This allows users to visualize the design from multiple angles and get a more realistic sense of how it would look in real life.

30 Here are some specific examples of how GAN-based interior design can be used to elaborate the picture:

- The GAN 14 could be used to generate a variety of floor plans for the same bubble diagram, with different room arrangements and sizes. This would allow the user to compare different design options and choose the one that they like best.
- The GAN could be used to generate a floor plan that incorporates additional design elements, such as furniture, windows, and doors. This would give the user a better sense of the overall look and feel of the design.
- The GAN could be used to generate a 3D rendering of the completed design. This would allow the user to visualize the design from multiple angles and get a more realistic sense of how it would look in real life.

Overall, GAN-based interior design can be used to elaborate the picture 6 in a number of ways by generating more realistic and varied floor plans, incorporating additional design elements, and generating 3D renderings.

3.2 GAN Framework

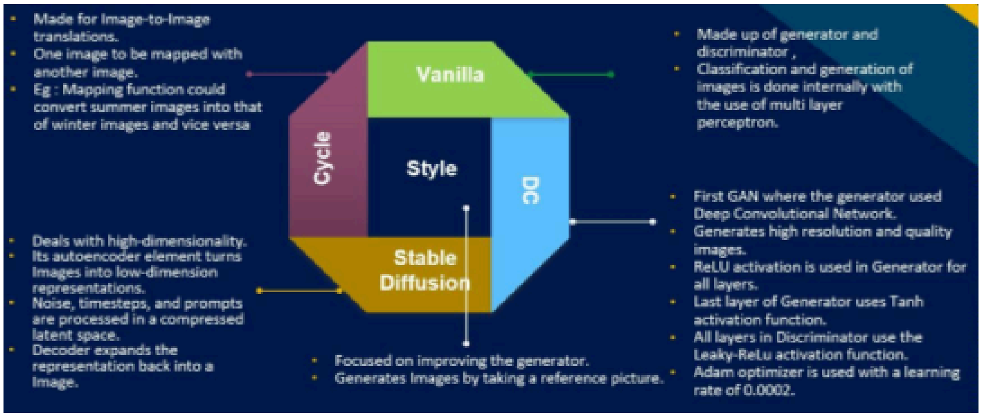

Fig 2 : GAN - At a glance

Vanilla GAN

The term "Vanilla GAN" refers to the original and basic form of the Generative Adversarial Network (GAN) introduced by Ian Goodfellow and his colleagues in their 2014 paper titled "Generative Adversarial Nets." In the context of GANs, "vanilla" is often used to denote the simplest and most fundamental version of a model, without any additional enhancements or modifications.

Here are the key components and concepts associated with Vanilla GAN:

1. Generator and Discriminator:

- **Generator:** The generator network takes random noise as input and generates synthetic data (e.g., images).

- **Discriminator:** The discriminator network tries to distinguish between real data (from the true distribution) and fake data produced by the generator.

2. Adversarial Training:

- The generator and discriminator are trained simultaneously through adversarial training. The generator aims to produce data that is indistinguishable from real data, while the discriminator aims to correctly classify between real and generated data.

3. Loss Function:

- The training process involves minimizing a specific loss function, often referred to as the adversarial loss. It is based on the idea of a minimax game, where the generator and discriminator are in constant competition.

4. Stochastic Gradient Descent (SGD):

- Vanilla GANs typically use stochastic gradient descent or related optimization algorithms to update the parameters of the generator and discriminator networks during training.

Despite its simplicity, Vanilla GANs can be challenging to train and are sensitive to hyperparameters. Issues such as mode collapse (where the generator produces limited diversity in its output) and training instability can occur. Over the years, researchers have proposed various improvements and modifications to address these challenges, leading to the development of different GAN variants, such as DCGAN (Deep Convolutional GAN), WGAN (Wasserstein GAN), and others.

While Vanilla GANs serve as the foundation for GAN research and applications, many advanced architectures and techniques have been introduced to enhance stability, scalability, and the quality of generated samples.

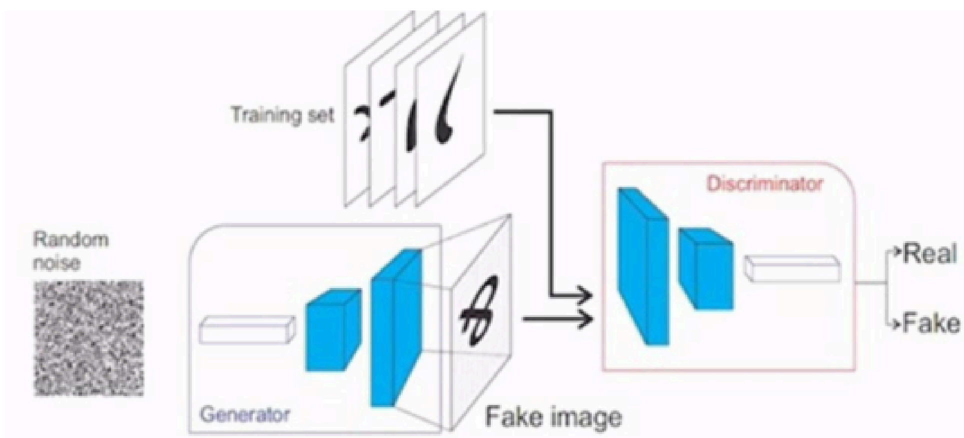

Fig 3 : A General GAN Architecture

DCGAN (Deep Convolutional GAN)

1. Description:

DCGAN, short for Deep Convolutional Generative Adversarial Network, is a type of GAN architecture designed specifically for image generation tasks. It was introduced to address the limitations of the original GAN architecture in generating high-resolution and visually realistic images.

2. Key Features:

- Convolutional Layers: DCGAN incorporates convolutional layers in both the generator and discriminator networks. This allows the networks to effectively capture spatial hierarchies and learn image features at different scales.

- Strided Convolutions and Transposed Convolutions: DCGAN uses strided convolutions in the discriminator to downsample the input image and transposed convolutions in the generator to upsample the noise into a full-sized image.

- Batch Normalization: Batch normalization is applied in both the generator and discriminator networks. It helps stabilize and accelerate the training process by normalizing the input of each layer.

- No Fully Connected Layers: DCGAN avoids the use of fully connected layers in the convolutional parts of the network, relying on convolutional and transposed convolutional layers for all operations.

3. Applications:

DCGAN has been successfully applied to various image generation tasks, including the generation of realistic faces, objects, and scenes. Its architecture has become a standard baseline for many image synthesis tasks within the GAN framework.

4. Advantages:

DCGAN's architecture promotes stable training and facilitates the generation of high-quality images with more intricate details. It has become a widely adopted architecture for many computer vision and image generation tasks.

DCGAN has played a significant role in the development of GANs, providing a foundation for subsequent improvements and variations in the architecture. It has proven effective in generating diverse and realistic images across different domains.

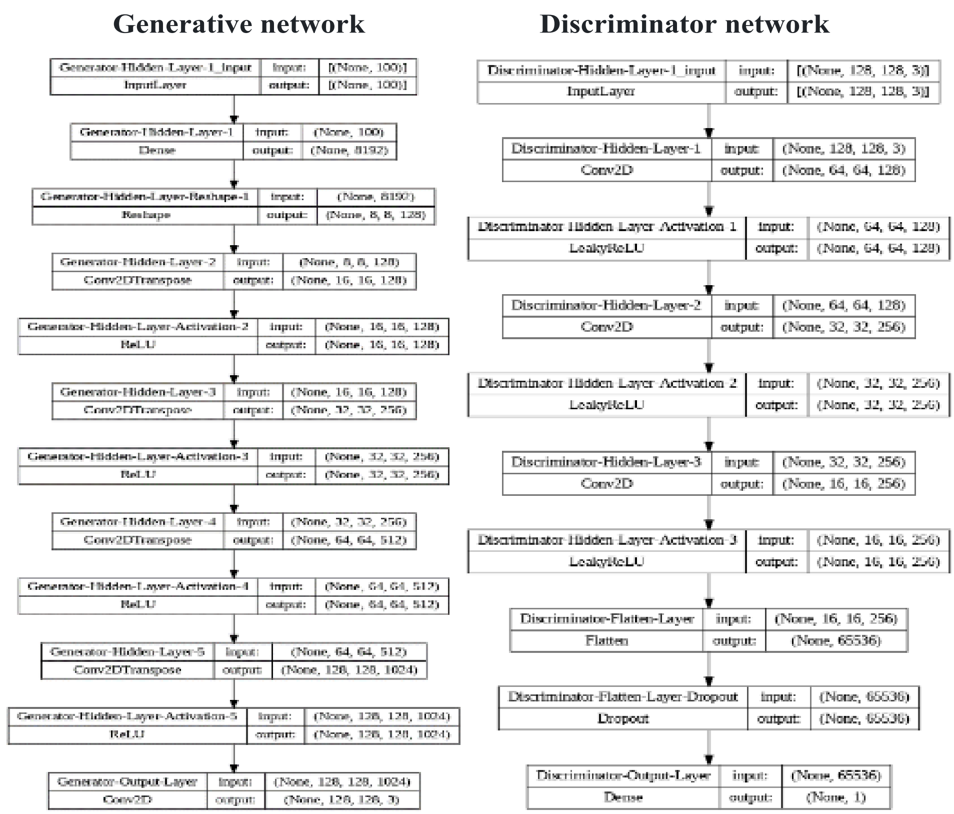

Fig 4: Workflow of DC GAN

Style GAN

1. Description:

StyleGAN is an advanced variant of the Generative Adversarial Network (GAN) architecture that was introduced by NVIDIA researchers in a paper titled "A Style-Based Generator Architecture for Generative Adversarial Networks" in 2018. StyleGAN aims to overcome limitations in controlling the style and diversity of generated images.

2. Key Features:

Style-Based Generator:

The key innovation in StyleGAN is the introduction of a style-based generator, which disentangles the latent space into a content space and a style space. This allows for independent control over the high-level features (content) and the low-level details (style) of generated images.

Mapping Network:

StyleGAN includes a mapping network that transforms a latent code into style information. This helps in controlling features like pose, facial expression, and more in a more structured manner.

Noise Injection:

StyleGAN incorporates controlled noise injection at different resolutions, allowing for the generation of more diverse and realistic details in the images.

Progressive Growing:

While not exclusive to StyleGAN, the use of a progressive growing approach is common in training GANs. It involves gradually increasing the resolution of generated images during training, starting from low resolution to high resolution.

3. Applications:

StyleGAN has been widely adopted for various image synthesis applications, particularly in generating highly realistic and diverse human faces. Its ability to control the style of generated images makes it suitable for tasks where fine-grained control over visual attributes is crucial.

4. Fine-Grained Control:

StyleGAN allows for the manipulation of specific visual attributes such as age, gender, and facial expressions by manipulating the corresponding style vectors. This makes it a powerful tool for image synthesis with detailed control.

5. Training Stability:

StyleGAN is designed to be more stable during training compared to earlier GAN architectures. The progressive growing approach and style-based generator contribute to a more reliable training process.

6. StyleGAN2:

Subsequently, StyleGAN2 was introduced as an improvement to the original StyleGAN, enhancing the quality of generated images and addressing certain artifacts.StyleGAN and its variants have become instrumental in the generation of high-quality, diverse images with fine-grained control over various visual aspects. They have found applications in art, design, and entertainment, showcasing the capabilities of generative models in creating realistic and customizable content.

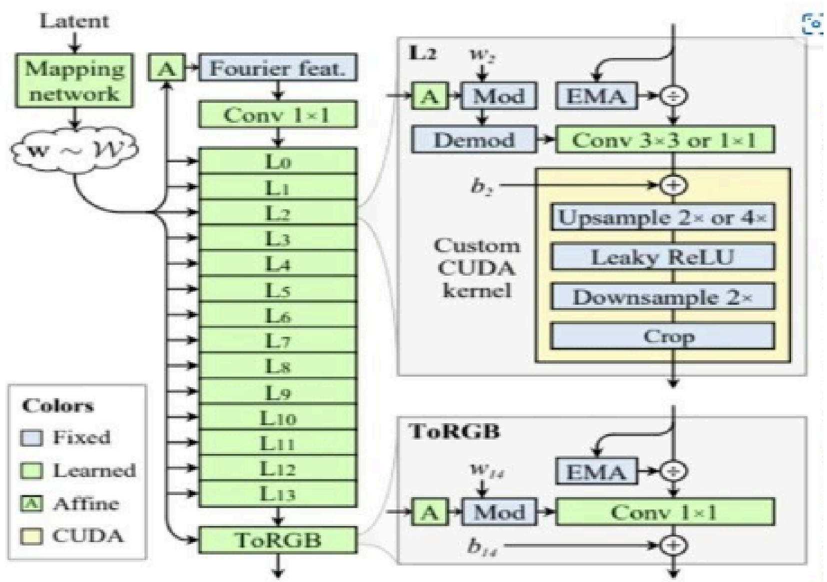

Fig 5: Style GAN Workflow

3.3 Flow Of Work

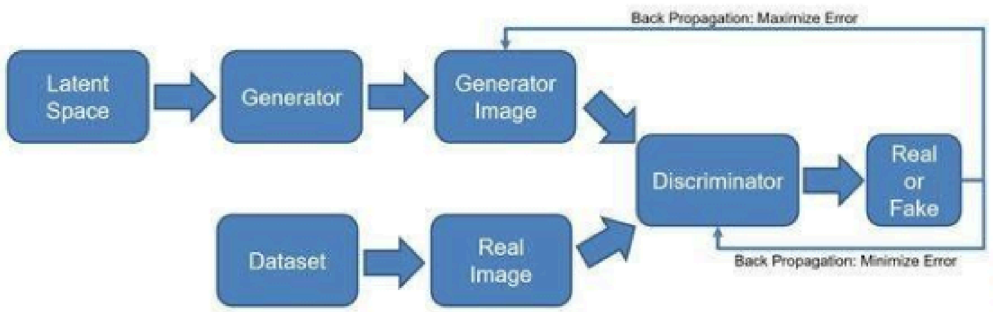

Fig 6: Flow Chart of working of GAN

The first step is to collect a large dataset of high-quality interior design images. This dataset should represent a variety of styles, layouts, and functionalities.

GAN Model Training: Once you have your dataset, you can start training your GAN model. A GAN model is made up of two parts: a generator and a discriminator. The generator takes in random noise as input and tries to generate realistic images of interior designs. The discriminator takes in both real images and images generated by the generator and tries to tell the difference between them. The two networks are trained together in an adversarial process, where the generator is trying to get better at fooling the discriminator, and the discriminator is trying to get better at telling real images from fake images.

User Input and Design Generation: Once your GAN model is trained, you can use it to generate interior design ideas based on user input. Users can specify their preferences for things like style, color palette, furniture, and layout. The GAN model will then generate a number of different design options that meet the user's criteria.

Refinement and Iteration: The user can then choose their favorite design option and make further refinements. They can change the furniture, the colors, or the layout. The GAN model can then be used to generate new versions of the design that incorporate the user's changes.

Final Design and Output: Once the user is happy with their design, they can finalize it and output it in a variety of formats, such as a 3D model, a virtual reality experience, or a set of blueprints.

Chapter 4 Implementation Details

4.1 Software tools used – Google Collab

Software Tools for StyleGAN3 with Google Collab and other specifications:

Considering your preferences for Google Collab, StyleGAN3, DCGAN, 25GB RAM, CUDA 11.3, Tesla GPU, and Visual Studio integration, here are some potential software tools in brief:

Free and Open-Source Options:

NVIDIA StyleGAN2-ADA Implementation: Official implementation of StyleGAN2-ADA by NVIDIA, which can be adapted for StyleGAN3 with adjustments. Supports Colab, CUDA 11.3, and Tesla GPUs, but requires integration with Visual Studio through TensorFlow or PyTorch plugins.

StarGAN2: Offers style transfer and image-to-image translation capabilities along with StyleGAN2 architecture. Supports Collab, CUDA 11.3, and Tesla GPUs, and can be integrated with Visual Studio through Python APIs.

StyleGAN2-pytorch: PyTorch implementation of StyleGAN2 with potential adaptation for StyleGAN3. Supports Collab, CUDA 11.3, and Tesla GPUs, but requires manual Visual Studio integration through Python environment configurations.

Paid Options:

Artbreeder: Cloud-based platform offering user-friendly tools for exploring and manipulating StyleGAN models, including StyleGAN3. Provides pre-trained models and allows training custom models, but lacks direct Visual Studio integration.

Topaz Labs' Gigapixel AI: Software for upscaling images with StyleGAN technology. It includes StyleGAN3 models and offers some creative control, but functions as a standalone application separate from Visual Studio.

Style2D: Closed-source tool specifically designed for 2D StyleGAN training and manipulation. Offers advanced features and integrates with existing libraries like PyTorch, potentially allowing Visual Studio integration through scripting.

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VIRTUAL INTERIOR DESIGN COMPANION-HARNESSING THE POWER OF GANs Dept of Electronics and Communication Engineering, Nitte Meenakshi Institute of Technology 27 Additional Notes: RAM requirement: 25GB RAM might be sufficient for smaller StyleGAN3 models but could be limiting for larger models or extensive training. Consider cloud instances with higher RAM allocation if needed. Visual Studio integration: Most options require scripting or plugin integrations to connect with Visual Studio. Consider your preferred development environment and scripting skills when choosing a tool. 4.2 About Dataset Used The dataset utilized 42 in this study was sourced from the IKEA.com website, specifically gathered to construct a Style Search Engine for non-commercial use. It encompasses a comprehensive collection, including 2193 photos of individual objects or products, offering a diverse representation of items available on the IKEA platform. Additionally, the dataset comprises 298 context photos, providing room scenes where these objects naturally appear. Accompanying the visual data are textual descriptions for the products, offering insights into features, dimensions, and other relevant details. A notable aspect of the dataset is the inclusion of ground truth information, delineating which objects are present in specific rooms. This annotation is invaluable for training and validating algorithms, ensuring the accuracy and effectiveness of the envisioned Style Search Engine. It is important to highlight that the dataset is expressly intended for non-commercial use, aligning with the project's focus on developing a Style Search Engine. Such datasets serve as foundational resources for advancing research in computer vision, image recognition, and related fields, fostering innovation in applications and tools. Fig 7: Datasets Samples

Key Features of the IKEA:

The dataset sourced from the IKEA.com website for constructing a Style Search Engine exhibits several key features:

1. Size and Composition:

• The dataset is substantial, comprising 2193 photos of individual objects and 298 context photos capturing room scenes. This diversity ensures a comprehensive representation of IKEA products in various settings.

2. Purpose and Usage:

• The dataset is explicitly collected for the purpose of building a Style Search Engine, emphasizing its application in enhancing visual search and design-related algorithms.

3. Non-commercial Use Restriction:

• Notably, the dataset is intended solely for non-commercial use, aligning with the specified purpose of creating a Style Search Engine and adhering to usage guidelines set by IKEA.com.

4. Textual Descriptions:

• Alongside visual content, the dataset includes textual descriptions for the products, providing additional information about features, dimensions, and other relevant details.

5. Ground Truth Information:

• The dataset includes ground truth information detailing which objects are present in specific rooms, serving as a valuable annotation for training and validating algorithms.

6. Context Photos:

• The inclusion of 298 context photos depicting room scenes enhances the dataset's realism and practicality for applications related to interior design and visual search.

7. Support for Style Search Engine:

• The dataset is specifically curated to support the development of a Style Search Engine, highlighting 38 its utility for advancing research and innovation in the field of computer vision and image recognition.

Benefits of using the IKEA:

- Realistic Representation of Furniture
- Variety in Styles and Designs
- Practicality and Feasibility
- Widely Recognized Brand
- Large and Diverse Dataset
- Potential for Personalization

4.3 Dataset Processing

Images in JPG or PNG format can be processed in Google Colab for a virtual interior design project using GAN architecture:

1.Loading Images:

Images in JPG or PNG format can be loaded using the Python Imaging Library (PIL) or its fork, Pillow. In Google Colab, you can use the Image module from PIL to open and load images from file paths.

2.Preprocessing:

Preprocessing involves transforming the raw image data into a format suitable for the GAN model. This may include resizing the images to a consistent size, normalizing pixel values to a specific range (e.g., [0, 1]), and handling any other transformations required by the GAN architecture.

3.Visualization:

Visualization is an essential step to inspect the original and processed images. Matplotlib can be employed for displaying images in the Colab environment. Visualization aids in understanding the impact of preprocessing and ensures the images are prepared appropriately for input to the GAN.

4.GAN Inference:

The preprocessed image can be fed into the GAN architecture for inference. GANs, being generative models, can take an input image and generate new, realistic images based on the learned patterns from the training data.

5. Generated Image Display:

Displaying the generated images allows for an assessment of the GAN's performance in creating virtual interior designs. This step involves using Matplotlib or similar tools to showcase the generated content to the user or designer.

6.Iterative Refinement:

The process is often iterative, with adjustments made to preprocessing and GAN parameters to enhance the quality of generated interior designs. This may involve experimenting with different architectures, training strategies, and hyperparameters.

7.User Interaction:

In the context of virtual interior design, the processed and generated images can be presented to users through a user interface. Users may interact with the GAN-generated designs, providing feedback or making customization requests.

8.Testing and Scaling:

The platform should undergo extensive testing to ensure its reliability and functionality. If successful, considerations for scaling the platform for wider adoption in the interior design industry may be explored, involving optimizations for performance and usability.

In summary, the process involves loading, preprocessing, visualizing, and utilizing GANs to generate virtual interior designs from input images. The iterative nature of refining the GAN model and its parameters is crucial for achieving high-quality results. User interaction and testing play pivotal roles in ensuring the effectiveness of the virtual interior design platform.

Chapter 5 Results and Analysis

The Fréchet Inception Distance (FID) serves as a crucial performance metric by quantifying the difference between the feature vectors of genuine images and those generated artificially by the generator. A reduced FID score indicates higher quality in the generated images, closely resembling real ones, as it relies on comparing the feature vectors of images. The Inception score, while useful, has limitations in evaluating the similarity between synthetic and real images. Thus, the introduction of the FID score aims to assess the fidelity of synthetic images by comparing their statistical properties with those of real images in the desired domain. Lower FID scores correspond to better-generated images, as depicted in the FID Graph, which illustrates the proximity of images concerning their distribution, as shown in figure 8.

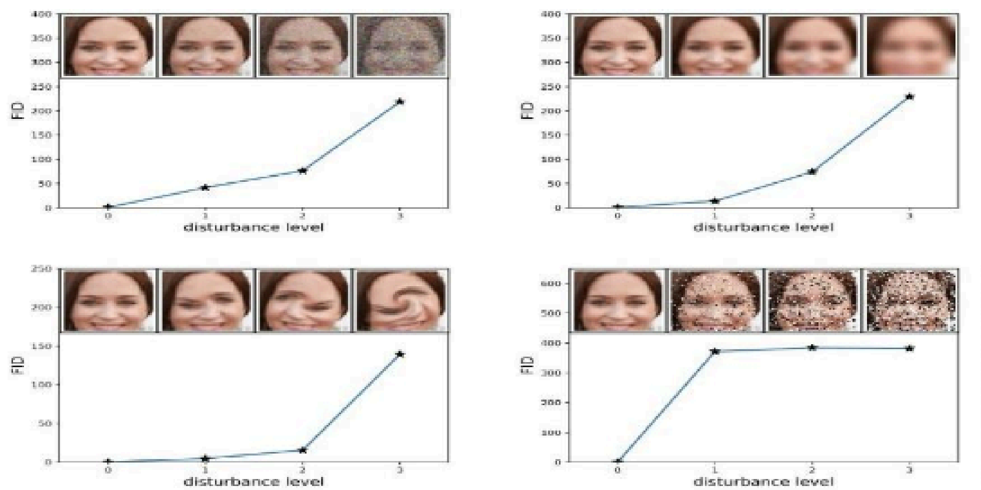

Fig 8: FID score plot

The generator of the DCGAN network needed around 21000 epochs to generate good quality images as in figure 10. The major issues with DCGAN network were its mode collapse as in figure 11 and Vanishing Gradient as in figure 12. The performance metric of DCGAN is tabulated in table 1

Table 1 : DCGAN Network Performance Metrics

Epoch#	stats	FID Score
21000	Discriminator Loss: 0.0006483550532720983 Generator Loss: 13.37311553955078	237
19000	Discriminator Loss: 0.009213417768478394 Generator Loss: 18.83767318725586	355
16000	Discriminator Loss: 8.113920126062713e-12 Generator Loss: 26.006271362304688	382
13000	Discriminator Loss: 8.237818411352566e-12 Generator Loss: 25.84298324584961	419
10000	Discriminator Loss: 6.662484366287691e-12 Generator Loss: 25.632919311523438	439

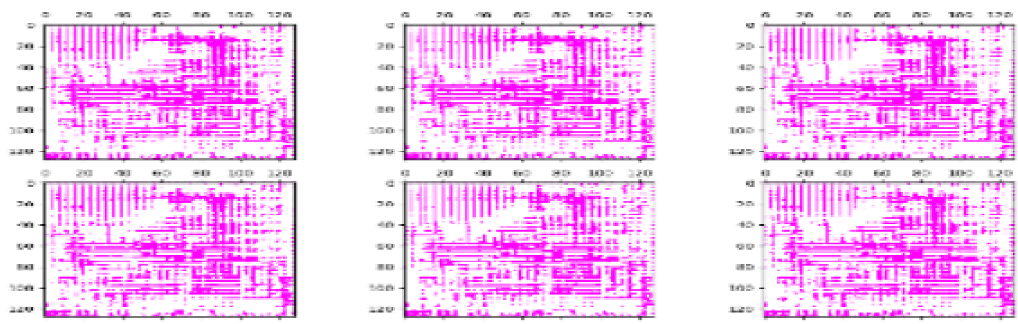

Fig 9 : Image Transition 1

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VIRTUAL INTERIOR DESIGN COMPANION-HARNESSING THE POWER OF GANs Dept of Electronics and Communication Engineering, Nitte Meenakshi Institute of Technology 33 Fig 10 : Image Transition 2 Fig 11 : Image Transition 3 Fig 12 : Image Transition 4 The generator of StyleGAN3 needed around 2500 epoch to generate high quality images. Its performance metrics are tabulated in table 2 and figure 13.

Table 2 : Epoch vs FID score of StyleGAN3

Ticks	FID SCORE	Ticks	FID SCORE
100	483.9971	1000	144.2901
200	366.1188	1100	122.8043
400	296.1188	1300	111.9371
500	202.7571	1600	111.361
600	202.2473	2000	107.368
700	185.1233	2200	106.9345
800	152.2309	2500	105.6143

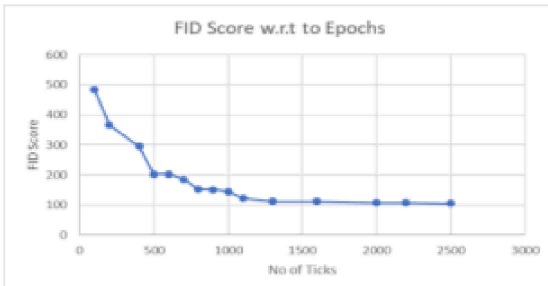

Fig 13 : Epochs vs FID score of StyleGAN3 Network

Some good quality images can be seen after training for 2500 ticks as in figure 14. Images are still blurry and needs more training to get expected good outcome.

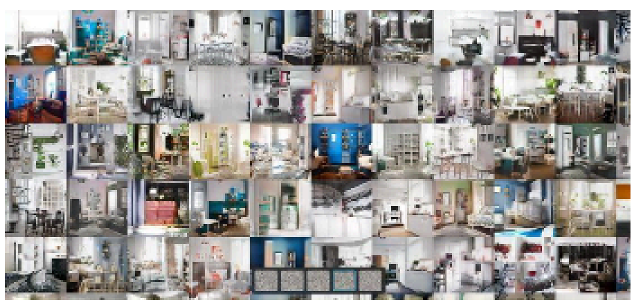

Fig 14 : Good Quality Images Generated by StyleGAN

Table 3 : Comparative analysis of DCGAN vs STYLE3GAN

	Epochs(Final value)	FID SCORE (performance Metrics)
DCGAN	21000	237
Style3GAN	2500	105

From Table 3 we can conclude that the DCGAN offers higher loss values alongside FID scores across epochs, indicating a focus on training progress and finding the optimal balance between the generator and discriminator. The StyleGAN captures FID scores more frequently (possibly) and lacks loss details, suggesting a focus on monitoring overall image quality over time. This aligns with StyleGAN's reputation for superior image generation, while DCGAN might provide more insights into the training process itself.

Table 4 compares the different state-of-the-art GAN architecture that are well suited for image classification, object detection, high resolution image generation, image analysis and natural language processing.

Table 4 : State of the art comparison

GAN Architecture	Loss functio n	Training Performance	Suitable for tasks
Cycle GAN	GAN	Can be computational ly sensitive, hyperparamet er sensitive	Unpaired image-image translation, style transfer, domain adaptation
DCGAN	GAN	Simple to implement, Good quality, robust to overfitting	Image classification, object detection, image segmentation
Style GAN	GAN	Can be computational ly sensitive, hyperparamet er sensitive	High resolution image generation, photo editing image inpainting

Analysis

Analysing the results of a DCGAN for virtual interior design with a high FID score involves evaluating various aspects:

1. FID Score: A lower FID score indicates better image quality and diversity, while a high score suggests a gap between real and generated images.
2. Image Quality: Assess clarity, sharpness, and overall visual quality, addressing any issues in resolution, detail, and fidelity.
3. Diversity of Designs: Ensure a broad spectrum of styles, color schemes, and layouts to avoid generating similar or repetitive designs.

4. Realism and Plausibility: Examine if generated interiors align with real-world expectations in terms of furniture placement, lighting, and aesthetics.
5. Colour Consistency: Check the consistency and appropriateness of color schemes to avoid unrealistic combinations.
6. Texture and Detail: Enhance intricate details, such as texture variations and realistic lighting effects, to improve overall realism.
7. User Satisfaction: Collect user feedback to ensure virtual interiors are aesthetically pleasing, engaging, and reflective of desired design styles.
8. Training Data Quality: Ensure the training dataset is representative and diverse, addressing any mismatches between data and desired output.
9. Fine-Tuning and Iterative Training: Consider adjustments like fine-tuning and additional training iterations to improve the model's ability to generate high-fidelity designs.
10. Comparison with Baseline: Compare FID scores with baselines or previous iterations to track progress and identify areas for further refinement.

In summary, the analysis involves a comprehensive assessment of image quality, diversity, realism, color consistency, texture/detail, user satisfaction, training data quality, and iterative adjustments to enhance the model's performance.

Chapter 6 Conclusion and Future scope

The IKEA dataset, combined with GAN technology, holds immense potential for revolutionizing interior design through accessible, personalized virtual assistants. With the ability to generate diverse and realistic room scenes based on individual preferences, this technology can empower users to visualize their dream spaces and make informed design decisions.

The challenges faced in our proposed work are System limitations, vanishing gradient issue, mode collapse, Unavailability of pre-trained models, Uncategorized dataset, small amount of data to train. If these challenges are overcome, then this model can be extended to be used for generating new interior designs. With more data, this model can be fine-tuned further to generate the expected high-quality images. Tuning the hyperparameters such as Latent Space and seed can give improved results. More training is required to get more diverse designs. Also, other GAN models can be tried with add on features such as generate designs from sketch, text to design, transform uploaded room image to a new design, addressing issues like mode collapse. In developing an interior design assistant, DCGANs enable the generation of realistic room scenes with detailed features, facilitating informed decision-making and creative exploration in interior design through their stability and capacity for diverse outputs.

Key benefits of this GAN-based approach can be used in future to include:

Visualizing diverse style options: Users can experiment with different colors, furniture arrangements, and design themes before committing to real-world purchases.

Overcoming spatial limitations: The virtual assistant can generate stunning interior designs even for small or irregularly shaped spaces, helping users maximize their available space.

Personalized recommendations: By incorporating user preferences and existing room features, the assistant can recommend specific furniture pieces and decorative elements, creating a cohesive and harmonious design.

Democratizing design expertise: This technology democratizes access to professional-looking designs, making it easier for everyone to achieve a beautiful and functional living space.

Looking ahead, the future scope of this technology is vast

Incorporating 3D room scans: By integrating with 3D scanning technology, the assistant can generate even more realistic and accurate representations of existing spaces, further enhancing design visualization.

Interactive furniture manipulation: Users could directly interact with virtual furniture within the generated scenes, adjusting placement, size, and even customizing finishes in real-time.

Augmented reality integration: Overlaying virtual design elements onto real-world spaces using augmented reality could provide an even more immersive and interactive experience.

Expanding beyond IKEA: While the initial focus might be on IKEA products, the technology can be adapted to incorporate furniture and decor from other brands and styles, offering users a wider range of design possibilities.

In conclusion, the GAN-based Virtual Interior Design Assistant built on the IKEA dataset has the potential to fundamentally transform the way we design and decorate our homes. By offering accessible, personalized, and visually stunning design solutions, this technology can empower individuals to create spaces that reflect their unique styles and bring their design dreams to life.

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VIRTUAL INTERIOR DESIGN COMPANION-HARNESSING THE POWER OF GANs

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***Abstract*— It is always a costly affair to prepare suitable interior design. Automatic interior design generation with suitable interiors will have an enormous effect on the trillion-dollar real-estate/construction industry. The impact of deep neural networks has made a leap forward where state-of-the-art algorithms utilize Generative Adversarial Networks (GANs). AI-driven innovation with GANs has many applications in creative industries such as design, be it architectural design, landscape design or interior design, the possibilities are endless. Such generated designs have the potential to drive rapid growth and profits in the design industry. The goal of this work was to generate realistic new interior room designs by training a GAN network on the IKEA Interior Design Dataset. This work faced challenges in distinguishing a good design from a poor design along with training the GAN. The goal was to overcome these challenges by incorporating human feedback and using various evaluation methods to ensure the generated designs are of high quality. The project has the potential to provide valuable solutions for the interior design industry, by generating new designs quickly and efficiently. DCGAN generated satisfactory images for 21800 epochs with FID score of 237 but had mode collapse and vanishing gradient issues. While Style3GAN outperformed by generating high resolution images for 2500 epochs with FID score of 105.**

Keywords— ***gesture recognition, resolution, algorithm, training, testing, accuracy***

I. INTRODUCTION

It is always a time consuming and reiterated task when it comes to designing living spaces for a selected floor plan. The different processes an interior designer carries out is to start with sketching a design, evaluating and fine tuning and then repeating this cycle until satisfactory design results within a given time, budget and safety regulations are met. Also, the means of designing it effectively lies entirely only on a profession designer.

A GAN (Generative Adversarial Network), depicted in Figure 1, is a widely used model for unsupervised machine learning. It comprises two neural networks: a generator and a discriminator, which interact with each other. The generator produces images from random noise inputs, while the discriminator determines whether these generated images are fake or real by comparing them to images in a dataset. This iterative process continues across multiple epochs until the discriminator loss between fake and real images reaches a minimum. As the loss converges to its minimum, the generator becomes adept at generating images resembling those in the original dataset.

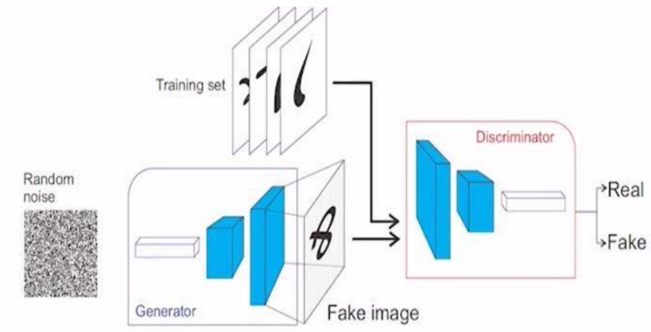

Fig 1: A General GAN Architecture [Courtesy *http://www.michaelhasey.com/publication_ganitecture*]

Various possible applications of GAN based interior design models are-

- GANs can be used to generate realistic 3D interior designs for virtual walkthroughs and presentations.
- GANs can be integrated into interior design software to generate real-time design options as the user makes changes to the design.
- GANs can be used to automate the entire interior design process, from generating initial designs to selecting colours and materials.
- Web/app-based designing tool for designers and real estate market - similar to Heavenly and Planner 5D.

- AI-powered interior design assistance for architects, interior designers, and homeowners.
- Interactive product visualization for e-commerce platforms such as IKEA.

Few different GAN models available are Vanilla GAN, DC GAN, Cycle GAN, Stable Diffusion GAN, Style GAN which are as depicted in figure 2:

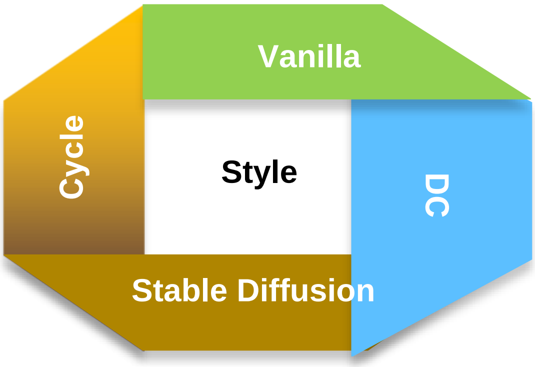

Fig 2: Different types of GAN

The Vanilla GAN comprises a single generator and discriminator network, utilizing multi-layer perceptrons for image classification and generation internally. Conversely, the Cycle GAN is tailored for image-to-image translations, facilitating mapping between different image domains such as summer and winter scenes. The Stable Diffusion GAN addresses high dimensionality by employing an autoencoder to compress images into low-dimensional representations, processing noise, timesteps, and prompts within a compressed latent space before decoding them back into images.

DCGAN, the first to utilize deep convolutional networks for generating high-resolution images, employs ReLU activation in the generator and Leaky ReLU activation in the discriminator, with the last layers using Tanh and sigmoid activation functions, respectively, and Adam optimizer with a learning rate of 0.0002. On the other hand, Style GAN focuses on enhancing the generator's capability, generating images based on a reference picture. The paper [1] evaluates the performance of DCGAN and Style GAN on the IKEA dataset, assessing issues such as mode collapse, vanishing gradient, number of epochs, and Fréchet Inception Distance.

II. LITERATURE SURVEY

The article [1] discusses how AI has been utilized in various industries to address complex problems and increase efficiency. However, the integration of AI in the architecture field is still in its early stages. The article focuses on the first step of the architectural design process, the Conceptual Design Stage, which is currently a manual process that limits the number of design iterations due to cost, time constraints, and human limitations. This leads to potentially subpar final building designs that may have negative economic, functional, performance, or psychological effects.

In [2], the Generative adversarial networks (GANs) represent a type of artificial intelligence algorithm devised to tackle the generative modeling problem. The primary objective of a generative model is to analyze a set of training instances and comprehend the probability distribution underlying their generation process. Subsequently, GANs leverage this knowledge to produce additional examples from the inferred probability distribution. While generative models rooted in deep learning are prevalent, GANs stand out as one of the most successful approaches, particularly notable for their capacity to generate realistic, high-resolution images. Although GANs have found successful applications across a wide array of tasks, predominantly within research settings, they continue to pose distinct challenges and offer significant avenues for further exploration. This is due to their foundation in game theory, setting them apart from the optimization-based approaches prevalent in other generative modeling methods.

The paper [3], reviews the state-of-the-art video Generative Adversarial Networks (GANs) models, which are increasingly used in various fields for content creation. It categorizes GANs review papers into general, image, Dept. of Electronics and Communication Engineering, Nitte Meenakshi Institute of Technology, Bengaluru 3 and special field GANs review papers. GANs consist of a generator and a discriminator network that are trained in an adversarial manner to generate new data points that conform to the distribution of the training dataset. The goal is to reach the Nash equilibrium where the discriminator is unable to differentiate between real and fake samples. The paper demonstrates an upward trend in publications on GANs since the mid-2010s.

From the reference [4], we got to know the basic principles of GANs, including the adversarial process and the roles of the generator and discriminator networks. The discriminator network's objective is to determine whether a sample belongs to a real or fake distribution, while the generator network's objective is to deceive the discriminator by generating a fake sample distribution. The GAN architecture consists of the generator and discriminator networks, which are updated iteratively during the training process. The generator network uses random noise to generate images, while the discriminator network determines whether an image is real or fake.

The paper [5], offers an overview of fundamental concepts related to GANs and explores various applications within the domain of image synthesis utilizing GANs. It delves into the advantages and disadvantages associated with these applications. Furthermore, it consolidates methodologies employed in GANs applications aimed at enhancing the quality of generated images. Despite the growing maturity of GANs research, challenges persist, including issues with unstable training dynamics and the difficulty of devising robust evaluation metrics.

The article [6], discusses the emergence of Deepfakes, a manipulation technique that allows swapping identities in videos. To address this threat, the authors have created the largest publicly available face swap video dataset, called the Deepfake Detection Challenge (DFDC) dataset, with over 100,000 clips sourced from 3,426 actors. The article describes the methods used to construct the dataset and provides an analysis of the top submissions from the accompanying Kaggle competition. The authors demonstrate that a Deepfake detection model trained on the DFDC dataset can generalize to real-world Deepfake videos and can be a useful tool in analyzing potentially manipulated videos.

The article [7], discusses how AAL (Ambient Assisted Living) in Smart Homes is not limited to tracking indoor location but also includes analyzing user behavior and activity patterns to improve their quality of life. It goes on to review recent AAL technologies that focus on activity recognition and analysis in Smart Homes.

In [8], the dataset was collected from IKEA.com website for the purpose of building Style Search Engine (note: only for non-commercial use). It consists of 2193 object (product) photos, 298 context (room scene) photos in which those objects appear, text descriptions for products, ground truth information on which items appear in which rooms.

In the research [9], the authors propose an innovative method named GlyphGAN for generating fonts with style consistency using Generative Adversarial Networks (GANs). GANs operate through a dual-network system where one network generates synthetic images from random input vectors, while the other network distinguishes between these synthetic images and real ones. The primary goal is to leverage the capabilities of GANs to create diverse fonts while ensuring a consistent style across all characters. GlyphGAN introduces a distinctive input vector for the generator network, composed of two components: a character class vector and a style vector. The character class vector is created through one-hot encoding, associating it with the character class of each sample image during the training process. On the other hand, the style vector is a randomly generated vector without any supervised information. This design choice empowers GlyphGAN to produce an extensive variety of fonts, offering independent control over both the character and style aspects of the generated fonts. In the experiments, they have observed that fonts generated by GlyphGAN exhibit a unique combination of style consistency and diversity. Importantly, this diversity is distinct from the fonts present in the training dataset, showcasing GlyphGAN's ability to create novel and diverse fonts without sacrificing legibility. The significance of GlyphGAN lies in its potential to revolutionize font design by providing a tool for designers to effortlessly generate fonts with desired styles while maintaining consistency across different characters. The results of the experiments demonstrate the effectiveness of GlyphGAN in achieving this delicate balance between style diversity and consistency, highlighting the promising applications of GANs in the creative domain of font generation.

The article [10], introduces a pioneering framework called the 3D Generative Adversarial Network (3D-GAN), designed to produce 3D objects from a probabilistic space by integrating recent advancements in volumetric convolutional networks and generative adversarial networks. The model offers several advantages: firstly, by employing an adversarial criterion instead of traditional heuristic criteria, the generator can implicitly capture object structure and generate high-quality 3D objects. Secondly, the generator establishes a mapping from a low-dimensional probabilistic space to the 3D object space, enabling object sampling without a reference image or CAD models and facilitating exploration of the 3D object manifold. Thirdly, the adversarial discriminator serves as a robust 3D shape descriptor, learned without supervision, with broad applications in 3D object recognition. Experimental results demonstrate that this approach yields high-quality 3D objects, while the unsupervised learned features exhibit impressive performance in 3D object recognition, comparable to supervised learning methods.

The article [11], introduces the TL-embedding network, a novel architecture for an object's vector representation. This representation is both generative in 3D, allowing the creation of new objects, and predictable from 2D images for interpretation. The network integrates an autoencoder for generativity, ensuring the representation's ability to generate diverse 3D objects. Additionally, a convolutional network guarantees predictability from 2D images. The TL-embedding network excels in tasks like voxel prediction from 2D images and 3D model retrieval, showcasing its versatility. Extensive experiments validate its effectiveness, marking a significant advancement in achieving a comprehensive vector representation for objects in 3D generative modeling and 2D-to-3D interpretation.

In this study [12], the extensive ONSF database, containing diverse variations in pose, expressions, and focus, was utilized. Additionally, an INF database was generated in a controlled laboratory environment to evaluate near infrared facial recognition performance. The authors introduce a novel approach for near infrared facial recognition within an end-to-end deep architecture. This methodology encompasses face detection and alignment, NIR-VIS image translation, and a face embedding module. Notably, it marks the first instance of employing image-image translation techniques to enhance near-infrared facial image recognition. By synthesizing virtual samples from input near infrared face images, they mitigate intra-personal differences stemming from disparate illumination conditions. Consequently, leveraging the existing pre-trained VLD deep neural network face recognition model yields notably improved recognition outcomes. Experimental validation conducted on the INF database and the CSIST dataset demonstrates promising results for the proposed method.

The paper [13], focuses on facial diagnosis and how using deep transfer learning can be helpful. It starts by explaining why facial diagnosis is important and introduces the idea of using deep transfer learning in this area. The beginning of the paper outlines what problem the research is trying to solve and what goals it has. The paper then reviews existing information on deep learning, face recognition, and facial diagnosis, finding places where transfer learning could be useful. In the methodology section, it explains in detail how deep transfer learning was used, including information about the datasets and steps taken to prepare the facial data. The paper also talks about the design of the model and how transfer learning was applied from face recognition to facial diagnosis. The experiments section gives details about how the tests were set up, what metrics were used to measure success, and the results, including comparisons with other methods. In the discussion part, the paper talks about what these results mean, the impact of using transfer learning in facial diagnosis, and what could be improved. The conclusion summarizes the main discoveries, emphasizes the contribution of the research, and suggests areas for future exploration. The paper ends with a carefully crafted list of references, citing studies that influenced the research.

In face recognition (FR) applications [14], especially in open or adapted domains, downtime arises due to the need for retraining or fine-tuning FR models, which is undesirable. Utilizing low-cost methods such as setting fixed thresholds like σ values may not deliver optimal performance and can compromise application security. To address this issue, this paper proposes an adaptive thresholding approach employing a dynamic ROI-based threshold adapter algorithm. This method significantly reduces the search space for optimal thresholds, making it 12 times faster compared to conventional techniques, thus enabling real-time threshold setting. Experimental results on two evaluation datasets demonstrate that the proposed algorithm notably enhances the performance of five state-of-the-art deep FR models, achieving the best results. Furthermore, in open-world FR applications, where positive pairs are minimal, considering the F1-score is crucial. The proposed method suggests that evaluating accuracy at the highest reported F1-scores serves as a superior metric for performance benchmarking in such applications.

The paper [15], introduces a novel face alignment technique termed APA, designed to enhance performance in face recognition and analysis tasks through refined data processing. APA not only minimizes intra-class variability, thereby augmenting intra-class similarity, but also rectifies noise introduced during the alignment process. Additionally, a straightforward yet impactful feature normalization method is proposed, resulting in consistent enhancements and attaining state-of-the-art outcomes. In summary, APA emerges as an efficacious data processing approach for achieving pose-invariant face recognition.

III. DESIGN METHODOLOGY

A. *The proposed approach for generating new interior designs using GANs involve the following stages:*

- Data preprocessing and cleaning
  - Data cleaning report
  - Preprocessed dataset
- Building the GAN architecture
  - GAN architecture design document
  - GAN code implementation
- Training the GAN model
  - Trained GAN model weights
  - Training loss plot
- Evaluating the GAN model
  - Evaluation metrics report
  - Sample generated images.
- Generating new interior designs
  - Final generated interior designs

B. The proposed project requirements were:

- Predefined StyleGAN3 Model by NVIDIA (https://github.com/NVlabs/stylegan3.git). Setting up and training with styleGAN3 is very challenging. It requires a very high system and GPU processor. High training epochs/ticks are required to achieve better results for both DCGAN and Style GAN.
- The system used in this proposed work were Google Colab, GPU - Tesla V100-SXM2-16GB (1 GPU) / Tesla T4, RAM - 25 GB, CUDA 11.3.

IV. DATASET DESCRIPTION

The Ikea dataset consisted of 2193 object(product)photos and 298 room scene photos which consists of objects, text description for the objects and ground truth information of items that appear in the room scenes. The images were RGB with various sizes and aspect ratios and were also uncategorized.

Variance of Laplacian shows some images are out of expected focus and can be treated as outliers as shown in figure 3.

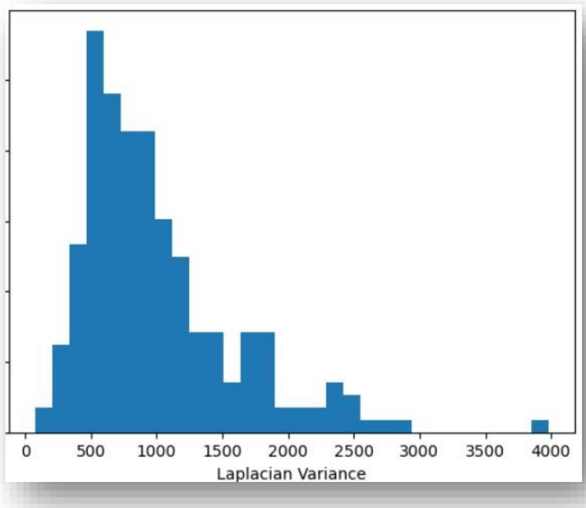

Fig 3: Laplacian Variance to detect the outliers

The individual sample of a room scene is as shown in figure 4. and stacked room scenes of all 298 room scenes are as shown in figure 5.

Fig 4: Individual Room Scene

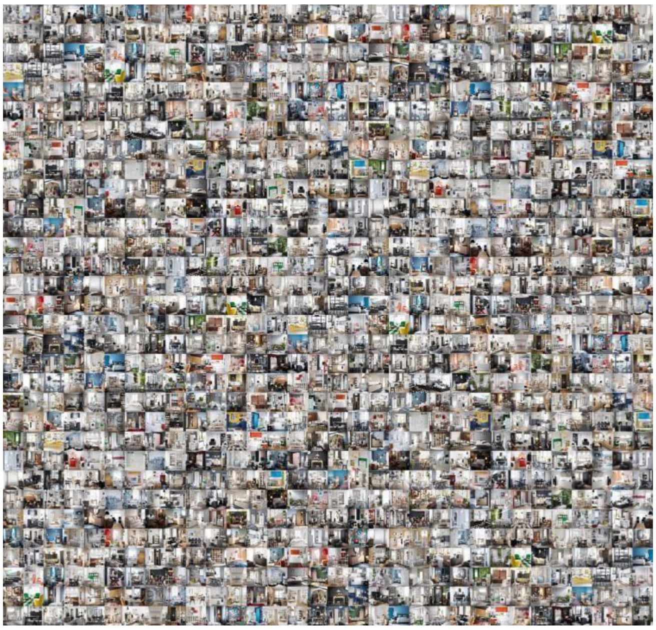

Fig 5 : Stacked Images of Room Scenes

V. IMPLEMENTATION OF THE MODEL

The implementation of interior design in our work is carried out using DCGAN and StyleGAN 3 and their performances are evaluated in this work.

A. *The DCGAN-based interior design model*

The DCGAN adheres to specific architectural guidelines to ensure network stability as tabulated in table 1. These guidelines include replacing pooling layers with strided convolutions in the discriminator and fractional-strided convolutions in the generator. Batch normalization is implemented in both the discriminator and generator. Fully connected hidden layers are eliminated in deeper architectures. The generator employs RELU activation function in all layers except the output, which uses tanh activation. Meanwhile, Leaky RELU activation function is applied in all discriminator layers, except for the output layer, which utilizes a Sigmoid activation function. The generator network comprises a total of 12,178,307 trainable parameters, while the discriminator network consists of 1,645,185 trainable parameters.

Table 1: Components

Component	Type
Batch Normalization	Normalization
Convolution	Convolutions
Leaky ReLU	Activation functions
ReLU	Activation Functions

The proposed DCGAN architecture for this work used the Discriminator and Generator Network as shown in figure 6 and 7 respectively.

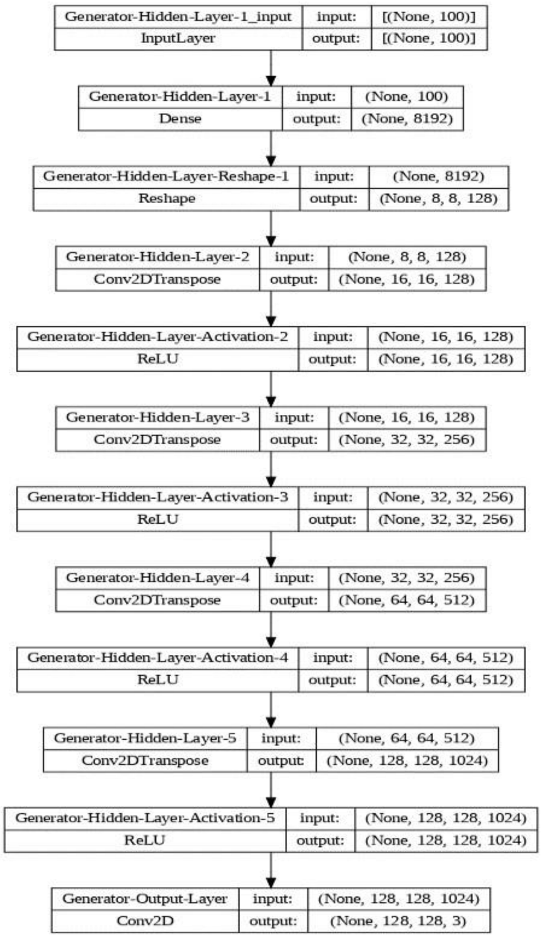

Fig 6: The DCGAN Generator Network

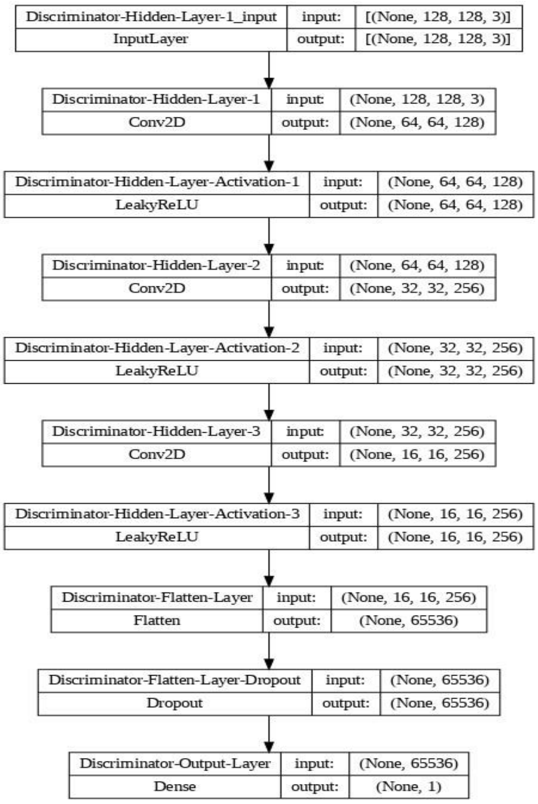

Fig 7: The DCGAN Discriminator Network

B. *StyleGAN3 Based Interior Design Model*

The implementation of StyleGAN3 follows the following steps.

- Mapping and Styles
  Instead of feeding the latent code z directly into the input layer, Z is fed into a mapping network f to obtain a latent code w.
  Replace the PixelNorm with AdaIN (responsible for styling).
- Constant Input
  In traditional GAN, we input the latent code to the first layer of the synthesis network. In StyleGAN, we replace it with a constant vector.
- Noise Inputs
  Introduce explicit noise inputs for generating stochastic details (e.g. hairs, facial details). Here, B stands for a learned scaling factor.
  The noise is broadcasted to all feature maps using learned per-feature scaling factors B and then added to the output of the corresponding convolution.
- Style Mixing
  By employing mixing regularization, mix the styles of different latent codes.
  Two latent codes z_1, z_2 through the mapping network, and have the corresponding w_1, w_2 control the styles so the progressive growth mechanism integration is the key architectural difference between StyleGAN and GAN. StyleGAN's progressive growth mechanism integration helps to fix some of the limitations of GAN. The training model of StyleGAN is different from regular GANs. StyleGAN's training model involves mixing two latent variable styles during training. Regular GANs use only one latent variable style during training which is as shown in figure 8.

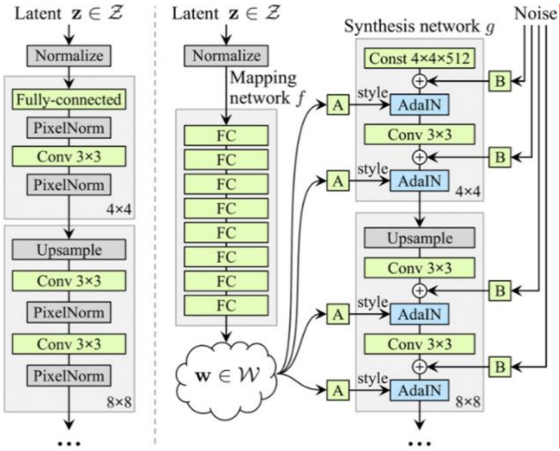

Fig 8: Tradition GAN vs StyleGAN based Generator

VI. RESULTS

The Fréchet Inception Distance (FID) serves as a crucial performance metric by quantifying the difference between the feature vectors of genuine images and those generated artificially by the generator. A reduced FID score indicates higher quality in the generated images, closely resembling real ones, as it relies on comparing the feature vectors of images. The Inception score, while useful, has limitations in evaluating the similarity between synthetic and real images. Thus, the introduction of the FID score aims to assess the fidelity of synthetic images by comparing their statistical properties with those of real images in the desired domain. Lower FID scores correspond to better-generated images, as depicted in the FID Graph, which illustrates the proximity of images concerning their distribution, as shown in figure 9.

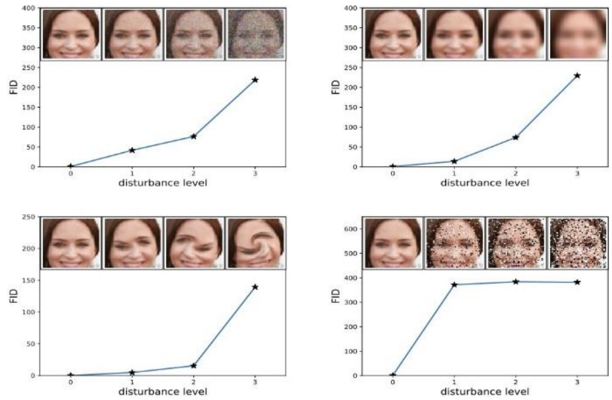

Fig 9: FID score plot

The generator of the DCGAN network needed around 21000 epochs to generate good quality images as in figure 10. The major issues with DCGAN network were its mode collapse as in figure 11 and Vanishing Gradient as in figure 12. The performance metric of DCGAN is tabulated in table 2

Table 2: DCGAN Network Performance Metrics

Epoch#	stats	FID Score
21000	Discriminator Loss: 0.0006483550532720983 Generator Loss: 13.37311553955078	237
19000	Discriminator Loss: 0.009213417768478394 Generator Loss: 18.83767318725586	355
16000	Discriminator Loss: 8.113920126062713e-12 Generator Loss: 26.006271362304688	382
13000	Discriminator Loss: 8.237818411352566e-12 Generator Loss: 25.84298324584961	419
10000	Discriminator Loss: 6.662484366287691e-12 Generator Loss: 25.632919311523438	439

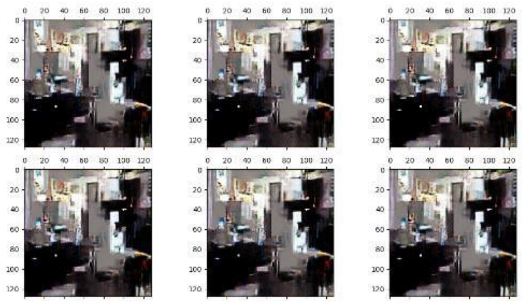

Fig 10: Generator Images [Blurry image]

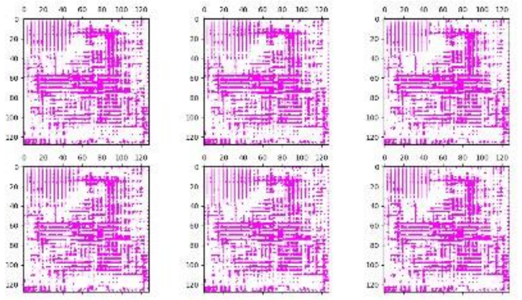

Fig 11: DCGAN Network with mode collapse issue [Blurry image]

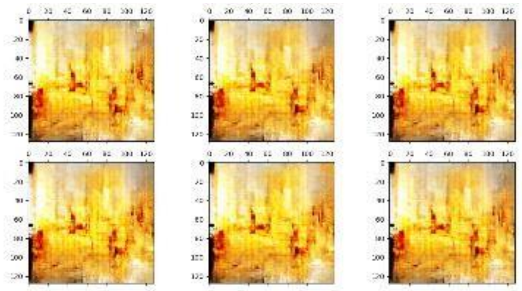

Fig 12: DCGAN Network with Vanishing Gradient issue [Blurry image]

The generator of StyleGAN3 needed around 2500 epoch to generate high quality images. Its performance metrics are tabulated in table 3 and figure 13.

Table 3: Epoch vs FID score of StyleGAN3

Ticks	FID SCORE	Ticks	FID SCORE
100	483.9971	1000	144.2901
200	366.1188	1100	122.8043
400	296.1188	1300	111.9371
500	202.7571	1600	111.361
600	202.2473	2000	107.368
700	185.1233	2200	106.9345
800	152.2309	2500	105.6143

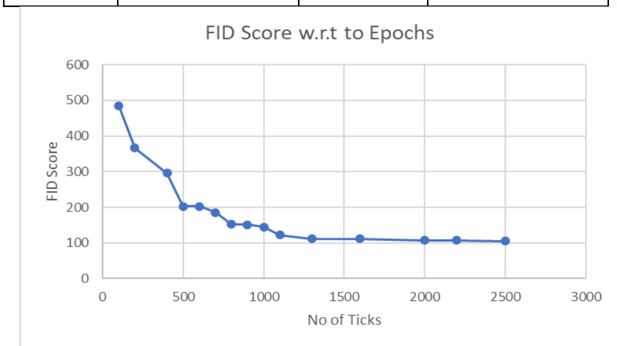

Fig 13: Epochs vs FID score of StyleGAN3 Network

Some good quality images can be seen after training for 2500 ticks as in figure 14. Images are still blurry and needs more training to get expected good outcome.

Fig 14: Good Quality Images Generated by StyleGAN

Table 4:Comparative analysis of DCGAN vs STYLE3GAN

	Epochs(Final value)	FID SCORE (performance Metrics)
DCGAN	21000	237
Style3GAN	2500	105

From Table 4 we can conclude that the DCGAN offers higher loss values alongside FID scores across epochs, indicating a focus on training progress and finding the optimal balance between the generator and discriminator. The StyleGAN captures FID scores more frequently (possibly) and lacks loss details, suggesting a focus on monitoring overall image quality over time. This aligns with StyleGAN's reputation for superior image generation, while DCGAN might provide more insights into the training process itself.

Table 5 compares the different state-of-the-art GAN architecture that are well suited for image classification, object detection, high resolution image generation, image analysis and natural language processing.

Table 5: State of the art comparison

GAN Architecture	Loss function	Training Performance	Suitable for tasks
Cycle GAN	GAN	Can be computationally sensitive, hyperparameter sensitive	Unpaired image-image translation, style transfer, domain adaptation
DCGAN	GAN	Simple to implement, Good quality, robust to overfitting	Image classification, object detection, image segmentation
Style GAN	GAN	Can be computationally sensitive, hyperparameter sensitive	High resolution image generation, photo editing image inpainting

VII. CONCLUSION

The challenges faced in our proposed work are System limitations, vanishing gradient issue, mode collapse, Unavailability of pre-trained models, Uncategorized dataset, small amount of data to train. If these challenges are overcome, then this model can be extended to be used for generating new interior designs. With more data, this model can be fine-tuned further to generate the expected high-quality images. Tuning the hyperparameters such as Latent Space and seed can give improved results. More training is required to get more diverse designs. Also, other GAN models can be tried with add on features such as generate designs from sketch, text to design, transform uploaded room image to a new design, addressing issues like mode collapse. In developing an interior design assistant, DCGANs enable the generation of realistic room scenes with detailed features, facilitating informed decision-making and creative exploration in interior design through their stability and capacity for diverse outputs.

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