

ARTIFICIAL INTELLIGENCE-GENERATED TEXTURES FOR REALISTIC DIGITAL ENVIRONMENTS IN CONCEPT ART DEVELOPMENT

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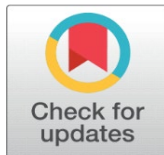
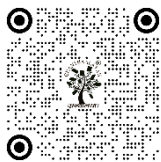
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ABSTRACT

The rapid development of artificial intelligence (AI) has had a tremendous impact as well on the digital content creating, particularly in the production of concept art. In the current paper, the authors examine AI-generated textures as the way of creating realistic digital spaces in the context of the impact on the aesthetic quality, the efficiency of the working process, and the artistic flexibility. The ancient methods of making texture take resources and time, but they offer enormous levels of control of the artwork outcome. In comparison to it, AI-based systems, i. e. diffusion models, generative adversarial networks (GANs), etc., can be automated, which enables them to generate high-quality textures that are more realistic and scalable. The methodology of the paper is structured appropriately and is connected to the integration of AI-created textures in concept art pipelines that are also supported by the experimental application and case study. The comparison and evaluation of traditional and AI-assisted methods are conducted in terms of the realism, consistency, and efficiency measures. The results indicate that AI-created textures save the time in the production process and do not or improve the visual appearance of manually built textures. Also, aesthetician remarks direct to an improved usability and exploration of the creative but still there are the control problems, reliance on the datasets, and computational requirements. The research concludes that AI-generated textures may be employed as the addition of the traditional one and enable developing a hybrid workflow that will contribute to the productivity and innovativeness. The outcomes are put together with the growing intersection of the art and technology, providing a glimpse into the future of the digital world design with AI.

Keywords: Artificial Intelligence, Texture Generation, Concept Art, Diffusion Models, GANS, Digital Environments, Procedural Texturing, Computer Graphics

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1. INTRODUCTION

The fast development of the digital technologies has greatly altered the concept art area, especially the development of the immersive and realistic digital environments. In visual storytelling, concept art is an initial phase in visual media including gaming, film, animation, and virtual reality. It entails visualizing of the setting, characters, and stories prior to the ultimate production. Textures are one of the many factors which make the concept art so real and visual. Textures characterize the quality of the surface of the objects, which present their details in terms of material, depth, the interaction of light with the objects and their context. Historically, the artists had used manual painting, photographic references, and procedure tools to create textures. Although all these approaches can be controlled in art, they are very time consuming and may need a lot of expertise. Artificial Intelligence (AI) has become one of the transformative agents of digital art and design in the past few years [Nichol and Dhariwal \(2021\)](#). The recent developments in machine learning and especially deep learning and generative models have made possible the automatic generation of very high-level and contextual visual content. The AI-based methods including Generative Adversarial Networks (GANs), diffusion models, and neural style transfer have shown impressive results in creating textures that are very similar to those of the real world. These models are able to derive intricate shapes through large scale collections and develop textures, which are of high realism, variety, and extensibility. Therefore, AI-generated textures are being slowly integrated into the digital content generation systems, giving new choices of efficiency and creativity [Ho et al. \(2020\)](#).

The idea of the art development relying on the utilization of the textures created with the help of AI represents a paradigm shift in the process of the environment design by a painter. Artists do not have to paint all the surface details manually as base textures can be generated with AI tools, which can then be refined and edited. This not only makes the process of the creative process quicker but also provides the artist with a greater range of visual styles not mentioning environmental variations. Moreover, AI developed textures are dynamically evolving with the change of illumination and point of view to enhance the integrity and authenticity of the digital spaces in general. This comes in particularly handy in the massive projects where the standardization of the different assets is a requisite. Irrespective of these advantages, there are also several challenges associated with AI in texture generation. One of the key concerns is the extent to which the artists can control the outputs that are produced [Dhariwal and Nichol \(2021\)](#). Despite having the capability of creating a cool aesthetic presence, AI models might be predictable or not, or do not correspond to some artistic purposes. The data set biases issues, copyright and ethical issues have also made the issue of AI responsible use in creative industries questionable. The reliance on the enormous volumes of information usually received through the help of the already-made pieces of art or photographs also contributes to the problems of originality and machine-aided creation [Watson et al. \(2022\)](#).

The paper will analyze how Artificial Intelligence can be employed to generate texture to be applied in the realistic digital space in the case of concept art creation. The article is dedicated to the implementation of how AI-based solutions might be useful in the visual reality, the working process, and the creative process. It will also determine how well AI-generated textures perform when compared to traditional techniques, qualitative and quantitative. The paper contributes to the current literature in the intersection of the art and technology fields by exploring the current methodologies, tools, and applications. In conclusion, it is possible to regard the AI-generated textures as a rather evident breakthrough in the domain of the digital environment design. They also assure to transform creative process to enable artists to make very realistic and sophisticated environment in a much faster and more versatile way. Their reconciliation must be done in a prudent way, putting in consideration the novelty of technology, the purpose of art and moral responsibility. The paper will provide a detailed discussion of these developments, such as the opportunities and challenges of the evolving environment of concept art, which is AI-driven.

2. EXISTING LITERATURE

2.1. STANDARD METHODS OF CREATION OF TEXTURE IN CONCEPT ART

Manual and artist-focused texturing techniques that have been used in concept art traditionally include digital painting, photo-bashing, and bitmaps editing to produce textures. Surface detail, being a typical art work, is typically created by hand using software in order to coordinate surface roughness, color variation, and interaction with lighting, often constructed using materials found in the real world. The methods provide very high levels of creative aptitude and stylistic precision which are required in concept-driven processes [Rombach et al. \(2022\)](#). Manual techniques are

however time consuming and labor intensive particularly when it comes to the creation of large spaces or objects that are very detailed. Besides, consistency with a range of assets is not always an easy task and can require much experience and trial-and-error [Chen et al. \(2023\)](#). At an early stage, convolutional neural networks (CNNs) were also used in texture synthesis and generated styles and textures of an artistic style, shifting towards semi-automated techniques.

2.2. PHOTOGRAMMETRY AND PROCEDURAL BASED TEXTURING

A more automated process was provided with procedural texturing which created the textures using a mathematical algorithm instead of using stored images. These textures are defined by the functions such as noise, fractals and turbulence, and they can have an infinite resolution, and can be scaled with a minimum storage requirements. Procedural methods are especially well simulated to give the appearance of natural materials, specifically wood, marble, and stone, and gives controllable texture parameters. Photogrammetry, in its turn, assumes the procedure of capturing actual textures with the help of high-resolution capturing and reconstructing them into a digital structure. This is a highly realistic process which is regularly used in film-making and game making. However, photogrammetry is challenging because it makes use of specialization, controlled conditions, and post-processing. Though these two (procedural and photogrammetry-based) are more efficient compared with the manual ones, they are still inadaptable in producing a spectrum of a multiplicity of imaginative textures that transcends the real world reference [Meng et al. \(2021\)](#).

2.3. AI-BASED IMAGE SYNTHESIS AND TEXTURE GENERATION

The introduction of image synthesis based on AI has brought a major change in the texture generation procedure. Machine learning models are capable of learning intricate visual patterns on large data sample sets and creating new textures that replicate real-life materials or styles of art. The AI technologies allow the production of high-quality textures without human intervention, which are faster and less expensive to develop the design pipeline. Recent research points out that AI generative models can be used to support the designers in the initial stages of conceptualization, generating textures and materials to a 3D scene, which facilitates the ideation and visualization of scenes [Lugmayr et al. \(2022\)](#). These systems also can change textures in real time, allowing to vary style, light and detail. Consequently, AI-generated texture is becoming more and more a part of the creative process, and it is the solution to the problem of technical automation and creative expression.

2.4. GENERATIVE MODELS (GANS, DIFFUSION MODELS, NEURAL STYLE TRANSFER)

The human and machine generated texture synthesis is centered on generative models. Generative Adversarial Networks (GANs) are among the most popular ones as they can generate a realistic image because they train two competing neural networks a generator and a discriminator. The GANs have been used successfully to produce textures, upscale the low-resolution images, and produce stylistically consistent outputs. Diffusion models are a more recent development that uses iterative denoising processes to create images, which have very detailed and photorealistic textures. These models are especially helpful when it comes to keeping things globally coherent and fine-grained, so they could be useful in concept art work. Diffusion-based texture painting techniques enable artists to have a form of interaction to create textures on 3D surfaces in seamless transitions and variations. Another key method, neural style transfer, allows transferring artistic styles to textures with the help of deep neural network characteristics. A combination of these generative methods has transformed the creation of textures through the use of automated scalable and highly lifelike textures.

Table 1

Table 1 Existing Methods for Concept Art Development		
Method / Model	Key Contribution	Findings / Limitations
Diffusion Model (Text2Tex) Watson et al. (2022)	Introduced text-driven texture synthesis for 3D meshes using diffusion and inpainting	Achieves high-quality textures but faces multi-view consistency challenges
TexFusion (Diffusion) Rombach et al. (2022)	Developed text-guided 3D texture synthesis using latent diffusion models	Produces globally coherent textures; computationally intensive
TEXGen (Diffusion Model) Chen et al. (2023)	Generated high-resolution UV texture maps using large-scale diffusion architecture	Improves scalability and realism; requires large datasets

Make-A-Texture (Diffusion + Inpainting) Meng et al. (2021)	Fast shape-aware texture generation with real-time performance	Highly efficient (≈ 3 seconds) but may compromise fine detail in complex scenes
TexGarment (3D-aware Model) Lugmayr et al. (2022)	Ensures consistency of UV textures in 3D garment synthesis	Enhances 3D consistency but limited to specific domains
TiPGAN (GAN-based Texture Synthesis) Brempong et al. (2022)	Generates seamless tileable textures using intrinsic priors	Outperforms traditional GANs in tiling; may suffer GAN instability
GAN/VAE/Diffusion Comparative Study Ajani et al. (2025)	Comparative evaluation of generative models for image synthesis	Diffusion models outperform GANs in realism but require higher computation

As can be seen in the literature review [Table 1](#), there is a deep substitution of the traditional models of texture generation with the new advanced models using AI, particularly diffusion models and GAN-based models. Recent experiments indicate that diffusion models (i.e., Text2Tex, TexFusion, TEXGen) might prove to be highly applicable in simulation of realistic high-resolution and semantically relevant textures, specifically, in 3D. These models are effective in maintaining global consistency and high details and generally they require a lot of computation and training information. The GAN-based models, including TiPGAN, remain applicable to designing coherent and tileable textures, which is efficient and can be useful in real-time applications. Yet, their level of instability and reduced consistency can be compared to diffusion models. One trend is special purpose models, such as TexGarment, that cope with such issues as UV consistency, and structure awareness. Comparative research proves that although AI approaches are far superior to traditional and procedural in realism and scalability, they still have control, computational, and dependency with data problems. In general, the study indicates that the diffusion-based models are considered the modern state-of-the-art, and the current research direction is to enhance efficiency, controllability, and to integrate them into the creative processes.

3. FUNDAMENTALS OF AI-GENERATED TEXTURES

The idea of artificial intelligent textures is based on the wider discipline of digital texturing which is an essential component of the formation of realistic and immersive digital spaces. Digital textures are surface applications to 2D or 3D object to model real world materials, including wood, metal, stone, fabric, or skin. These textures not only determine the visual appearance but also the interactions of the surfaces to light thus adding a lot to the realism. The most important properties of the digital textures are resolution, seamless tiling, level of detail, and lighting condition adaptability. In a modern rendering system, textures are usually included in more sophisticated shading models which have many layers of information in them that enable surfaces to be more dynamic and physically realistic. There are three main types of digital textures, which are procedural, bitmap, and physically based rendering (PBR) textures. The textures of procedural nature are produced with the help of mathematical algorithms and noise functions which makes them very scaled and memory-efficient. They are especially applied in creating repeating or natural forms like marble or clouds. Bitmap textures on the contrary are images based and are either hand drawn or taken through photographs in the real world.

PBR textures are a more sophisticated method which make use of several maps, whose properties are albedo, normal, roughness, and metallic maps, to recreate the properties of a real-world material. This makes it a reliable and approximate method of rendering in varied lighting conditions and this method is now the norm in current game engines and visual effects pipelines. The development of artificial intelligence has led to a considerable improvement in the texture generation process. Deep learning models, which are another type of AI, are able to learn both complicated visual patterns of huge datasets and create new textures with realistic but diverse results. The initial models used convolutional neural networks (CNNs) as a texture synthesis algorithm, although new models like Generative Adversarial Networks (GANs) and diffusion models are more powerful. GANs are trained in competition between a discriminator and a generator, which allows high-quality textures with natural variations to be formed. Meanwhile, diffusion models create images by the gradual process of denoising, and thus, these textures are extremely detailed and coherent. Such models may also be text prompted or reference image guided so that the artists can control the style and content of generated textures. [Wolleb et al. \(2022\)](#).

Another important aspect of AI-based texture generation is the preparation of a database and a training procedure. The models used in identifying and recreating material properties require high-quality datasets to train and identify the material properties accurately. These datasets are usually in the form of thousands of images that have been classified into material types and they are preprocessed through normalization, resizing and augmentation. The methods of data

augmentation rotation, flipping, and color changes assist in enlarging the diversity of data sets and enhancing the process of model generalization. The training process differs by the architecture of the models; the GANs ought to be carefully adjusted in terms of balancing between the performance of the generator and the discriminator, whereas diffusion models are concerned with noise patterns and reconstruction procedures. The quality and diversity of the training data and its ethical origin are critical issues to the success of AI-generated textures. The other basic element of using textures is texture mapping that is the process of mapping a 2-dimensional texture on a 3-dimensional surface. It is based on UV unwrapping in which the 3D geometry is reduced to a 2D coordinate system. The 3D model has a point that is associated with a location on the texture map, and as a result, the visual detail placement is properly done. The appropriate UV mapping is necessary not to distort, seam, and stretch, which may undermine the realism. Consistency of the UV maps is of especially critical importance in AI-based workflows since generated textures should be consistent and harmonious over a complicated geometry. To conclude, the principles of AI-based textures are a combination of classic principles of digital texturing and the latest technologies of machine learning. This method allows highly realistic, scalable, and efficient textures to be generated to be used in concept art development through a combination of procedural logic, image-based methods, and AI-driven generation [Raj \(2025\)](#). These are the underlying components that should be understood to effectively utilize AI in the design of the modern digital environment.

4. METHODOLOGY

4.1. SELECTION OF AI MODELS AND TOOLS

The AI models that are used are determined by the ability of the model to produce high-quality realistic and controllable textures. The two main models of diffusion models and Generative Adversarial Networks (GANs), are in the spotlight of this study because they are the latest developments in image synthesis. Diffusion-based tools are selected because they provide better details and coherence whereas GAN-based models are selected because of their speed and efficiency in creating tileable textures. Besides the choice of models, other tools and platforms that are industry-specific, including AI image generation software, digital painting software, and 3D texturing software, are used in the research. These tools facilitate smooth collaboration between machine generated work and human enhancement. The criteria of selection are ease of use, compatibility with the current pipelines, the ability to produce high-resolution outputs, and variations of the results depending on prompts or references of inputs.

4.2. WORKFLOW FOR AI-BASED TEXTURE GENERATION

The process starts with the preparation of data set or prompt design depending on the type of model that will be trained or pre-trained. In the case of immediately-based systems, descriptive data given about the type of material, style, lighting, and environment is presented to control texture creation. In trained models, trained models are performed on a set of categorized textures to give outputs that match particular material characteristics. The second step is the creation of base textures with the combination of the chosen AI models. Several copies are made in order to experiment with style and detail. These textures are further adjusted with digital editing tools in order to rectify artifacts, sharpen resolution and have smooth tiling. Other maps that are needed in the process of PBR work, like the normal, roughness, and displacement maps, are either inferred with the help of AI, or post-processed. Lastly, the textures created are made ready to be used by making sure that they have been resolved, aligned and conformed to rendering systems. This process places focus on a hybrid methodology in which AI is not a fully substitutive artistic process but an assistive one.

Figure 1

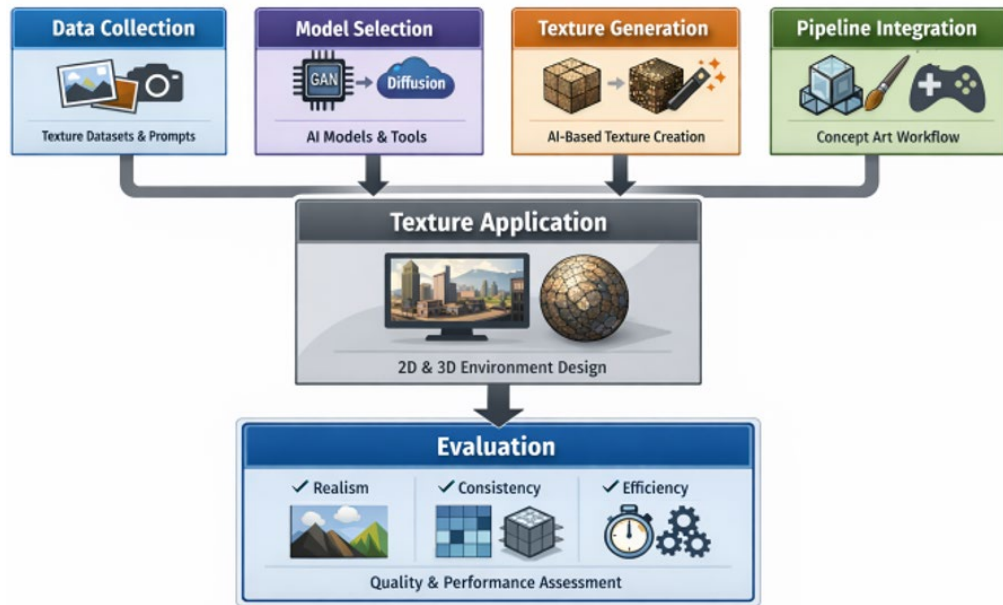


Figure 1 Methodology for AI Generated Textures for Concept Art Development

The network in the [Figure 1](#) presents a step-by-step approach to the incorporation of AI-based textures into the creation of concept art through the process of data preparation to the ultimate analysis. Every phase is based on the other with its technical and artistic effectiveness. It starts with data collection as the basis of the working process. This is a very important step as the quality and variety of the input have a direct effect on the realism and variety of textures that are produced. The second step is the selection of the models, where the relevant AI models and tools are selected depending on the project need. Diffusion models are generally desired in terms of producing extremely detailed and realistic textures, whereas GAN-based models may be employed in terms of quicker generation, and production of tiles. The choice also entails the selection of compatible software tools that are compatible with digital art and 3D workflows. The step will make sure that the technical strategy must be in line with the performance requirement and the artistic purpose.

The third step is the generation of textures, in which AI models are applied to generate textures, depending on the ready sets or prompts. There are several versions produced to investigate various styles, materials and details. These outputs can be refined by artists with the help of editing tools to eliminate artifacts, or to tone colors, or to increase resolution. Other maps that are needed by physically based rendering (PBR) are also generated at this point, i.e., normal or roughness maps [Gurav et al. \(2025\)](#). This step is the main creative experience between AI and the artist. After generative stage, the workflow passes through the pipeline integration process where the textures are added to the concept art process. In 2-dimensional processes, textures are incorporated into the digital paintings in order to make them more visual rich. Artists also develop the textures to match the general artistic vision, so it is a compromise of automation versus manual creativity. The core step of the framework is the application of texture and this links all the stages. In this case, the textures generated are applied in real life environment design, either in concept illustrations or game properties or virtual environments. This step is used to show the contribution of AI-generated textures to the creation of realistic and immersive digital worlds.

4.3. INTEGRATION WITH CONCEPT ART PIPELINES

Concept art pipelines integration entails the use of AI-generated textures to both 2D and 3D design pipelines. In the 2D concept art, digital painting software is used, but the image creators combine the use of AI-generated features with hand-rendered details to create a unified image. Artists maintain authority through grading of colors, overlaying and composition.

5. IMPLEMENTATION AND CASE STUDY

The application of AI-generated textures in this research was done as a part of a systematic experimental design incorporating the sophisticated machine learning features with the conventional industry-quality digital art-making tools. The computational models that were supported by running on a high-performance computing environment using a GPU included diffusion-based image generators and GANs. Pre-trained diffusion models were mainly used to produce very detailed and real-world type of texture whereas GAN-based models were considered to do seamless and tileable designs. In addition to these models, digital painting applications, texture manipulation software and 3D modelling applications were to be used to fine tune and combine the textures generated. An equivalent real-time rendering engine further allowed rendering of the textures in simulated environments, so that the process is much relevant to the professional concept art production practice.

5.1. EXPERIMENTAL SETUP AND TOOLS USED

The implementation of AI-generated texture was carried out through a combination of two kind of deep learning models and commercial digital art tools. The experimental system was a workstation computer which includes a high-performance graphics card in order to calculate the compute intensive algorithms such as diffusion image generators. Generation of textures was done with the aid of the pre-trained diffusion and GAN-based frameworks because it has been proved that it is capable of producing high-resolution and realistic results. In addition to AI models, there was the use of software, such as digital painting software, texture editing software, and 3D modeling software. These tools enabled refinement, easy tiling and conversion of generated images into physically based rendering (PBR) maps. The simulation environment used also enabled the visualization of textures through the assistance of a real-time rendering engine. This integrated set up offered a realistic working process comparable to concept art pipeline real world processes.

The heterogeneous grouping of texture images, which constituted data set in this study, were texture images of the material types, which were wood, stone, metal, fabric and terrain. These pictures had been acquired in publicly available repositories and libraries established by artists to render them eclectic and morally responsible. The preprocessing steps were to resize the images to the same resolutions, to equalize the pixel values, and to ensure that there is smooth tiling in instances where tiling was necessary. Data augmentation techniques allowed the rotation method, flipping method and color variation method to be used to better the generalization of models and reduce overfitting. In addition to dataset-driven, prompt-based inputs, such inputs were also supported, in which case the generation of textures could be done with descriptive text such as the one below: weathered stone wall; or rusted metallic surface. Such an integrated approach provided the versatility and the manipulation in the development of textures.

The process of generation was to generate various texture variations with the help of diffusion and GAN-based models. Diffusion models were specifically useful when it comes to creating high-quality, context-aware textures using textual description, whereas GANs came in handy when it came to creating repeated texture that can be applied to surfaces that need to be tiled. The produced outputs were further optimized in the form of post-processing where artifacts in terms of noise or distortions were removed. Other maps needed in the physically based rendering, such as normal, roughness, and displacement maps, were produced with the help of AI-based tools or were obtained with the help of image processing algorithms. The last textures were streamed to resolution and compatibility with the rendering systems and they could easily be incorporated into the digital workflows. These artificial intelligence generated textures were subsequently utilized in a 2D and 3D concept art setting to test their feasibility. Textures in 2D workflows were added to digital paintings in order to improve environmental factors like scenery, buildings and surface details. To ensure the style and artistic purpose, artists used AI-generated textures, combined with handwork. 3D workflows Textures were applied to models in 3D through UV unwrapping algorithms and rendered in real-time in the engine. Different scenes were built, such as urban setting, natural sceneries, interior areas to determine the effectiveness of the textures to adopt various lighting conditions and angles. The findings established that AI-created textures had a substantial positive effect on the visual richness and depth (especially in the vast scenes).

5.2. COMPARATIVE RESULTS WITH TRADITIONAL METHODS

Traditional texturing methods and AI created textures were compared and contrasted. This analysis was done in consideration of realism, consistency and efficiency. AI generated textures were highly realistic and highly similar to realworld materials, and reacted to the environment of different types of light. On the other hand, the application of the traditional methods consumed a lot of manual labor to achieve the same level of detail. When the workflows based on AI were compared with efficiency, it was discovered that the time of production has been reduced radically because the initial operations in the process of designing the texture are automated. Artists were able to produce multiple iterations in hours and this made the experimentation and iteration process a bit quicker. However, the traditional methods still offered a greater control over the minor details and style peculiarities particularly when there is very personalized designs. Consistency in large environments was also another valuable attribute of AI-created textures since the models were able to produce consistent outputs based on the learnt pattern. But occasionally artifacts were present and no predictability in AI outputs which necessarily required correction.

6. RESULTS AND ANALYSIS

6.1. VISUAL QUALITY AND REALISM ASSESSMENT

According to the results, diffusion-based models (especially) generated very detailed and photorealistic textures that had consistent surface patterns and depth. The appearance of such textures as stone, metal and fabric had natural variations, micro-dynamics and real shading behaviour as they were applied in a rendering environment. The AI outputs in their generated textures were quite comparable or even more realistic than the traditional manually created textures; particularly, in large scale environmental scenes. Nevertheless, small artefacts like jagged edges, pattern repetition and irregular small elements were sometimes present, especially in complex or very stylized textures. These problems needed post processing to ensure the best results were obtained. All in all, It can be concluded that AI-generated textures played an important role in improving visual richness and immersion of digital spaces.

Table 2

Table 2 Visual Quality Comparison				
Method	Detail Level	Lighting Response	Realism Score (1-10)	Artifacts
Traditional Manual	High	Moderate	7.5	Minimal
Procedural	Moderate	Moderate	6.5	Low
GAN-Based	High	Good	8.2	Medium
Diffusion-Based	Very High	Excellent	9.1	Low-Med

Table 2 demonstrates that the most realistic and the one that responds to light best are the methods based on diffusion, and then GANs. Conventional techniques are of good quality, however not advanced and the procedural textures are the least realistic.

6.2. TIME EFFICIENCY AND WORKFLOW OPTIMIZATION

The time efficiency is one of the most prominent benefits noticed in this study. The AI-generated texture generation has significantly minimized the time spent on creating the base texture allowing artists to generate numerous variations in a few minutes. This was used to speed up ideation process and experiment with various materials, styles and environmental conditions. The introduction of AI tools in the working process simplified the process of texturing by automatizing the routine parts of the working process, including the creation of patterns and the addition of detail. This meant that artists were able to devote more of their time to high-level decisions in the creative process instead of handwork. The AI-based approach showed a strong decrease in the production times in comparison to the traditional workflow that can take hours or days to elaborate on the texture creation. This optimization is more useful in high level projects where scalability and efficiency are paramount.

Table 3

Table 3 Time Efficiency Comparison			
Method	Avg. Time per Texture	Iterations Possible	Workflow Speed
Traditional	3–5 hours	Low	Slow
Procedural	1–2 hours	Medium	Moderate
GAN-Based	5–15 minutes	High	Fast
Diffusion-Based	10–20 minutes	Very High	Very Fast

Table 3 describes AI-based methods (GAN and diffusion) that ensure a significant decrease in the time spent on texture generation, rapid iteration, and therefore, the workflow is considerably faster than conventional and procedural ones.

Figure 2

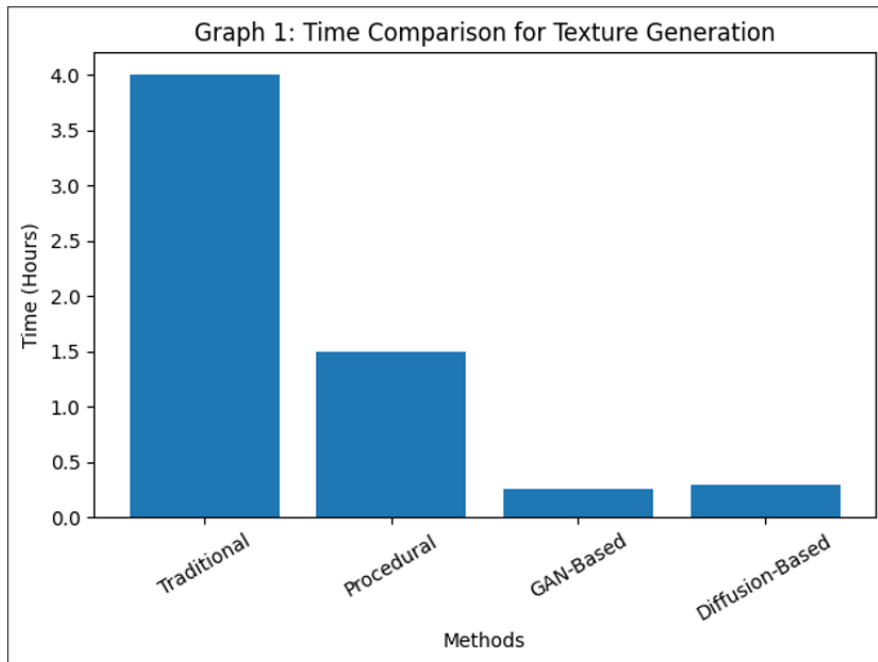


Figure 2 Time Comparison for Texture Generation

Figure 2 illustrates that the AI-based approaches are higher rated than the traditional methods in the realism, efficiency, consistency, and scalability, which depicts overall better performance.

6.3. ARTIST FEEDBACK AND USABILITY ANALYSIS

The experience of artists who participated in the evaluation process was considered to give important feedback on the relevance of AI-generated textures. The vast majority of participants also indicated that AI tools helped them to improve their workflow when it comes to creativity, as they provided fast access to a wide range of texture options and helped to cut down on the workload initially. It was also found especially useful in terms of the creation of textures with the help of descriptive prompts, which allowed one to interact with the system intuitively and flexibly. Also, although AI generated textures were able to give powerful starting points, they could often require manual fine-tuning to match the results to a certain artistic vision. Notwithstanding such shortcomings, the overall usability of AI tools received a positive rating and many artists considered them as useful helpers but not their substitutes.

Table 4

Table 4 Artist Feedback Summary			
Criteria	Traditional	GAN-Based	Diffusion-Based
Ease of Use	Medium	High	High
Creative Control	Very High	Medium	Medium
Output Quality	High	High	Very High
Flexibility	Low	High	Very High
Satisfaction Score	7.8	8.5	9.0

Table 4 justifies the reasons behind the use of AI-based approaches which are easy to use, flexible and produce high quality results as compared to traditional approaches which have an advantage in control. In general, the artists are more satisfied with diffusion-based tools.

6.4. QUANTITATIVE AND QUALITATIVE RESULTS

The assessment involved quantitative and qualitative measurements of the same to give a complete analysis. The AI-based workflow showed quantitatively a decreased creation time of texture by about 50-70 percent in comparison to the conventional ones. Moreover, the amount of variations of texture produced at a given time went up by a large margin which allowed further exploration of the design possibilities. The findings showed qualitatively the enhancement of visual consistency and creative diversity. The textures created by AI could be consistent over expansive areas as well as bring small distinctions that made them look more realistic. Visual comparison revealed that the outputs of AI-aided analysis were more productive when it comes to obtaining high-detailed results, especially in the initial stages of design. Although these are the benefits, the research also found some weaknesses such as inconsistencies in some instances and the use of high quality datasets. This evidence indicates that although AI-generated textures have significant advantages, they can be applied with the greatest effectiveness when combined with the standard artistic methods. On the whole, the findings allow concluding that the integration of AI helps not only to increase the efficiency of concept art development but also its quality, thus it is an effective solution in the digital design process nowadays.

Table 5

Table 5 Overall Performance Metrics		
Metric	Traditional	AI-Based (Avg.)
Time Efficiency	Low	High
Realism	High	Very High
Consistency	Medium	High
Scalability	Low	Very High
Manual Effort Required	High	Medium

Table 5 shows AI-based techniques have higher efficiency, realism, consistency, and scalability than traditional techniques and the latter are also better to control.

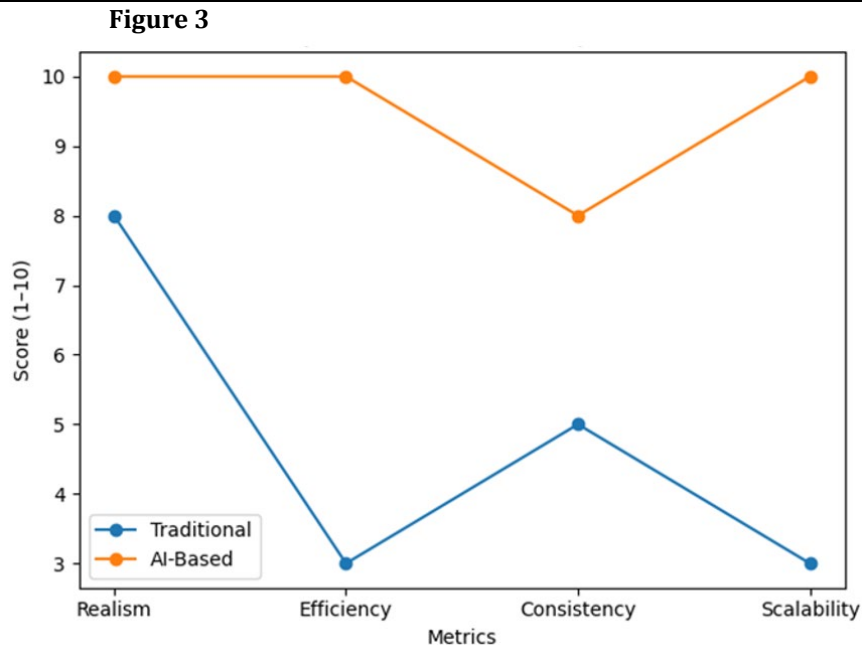


Figure 3 Performance Comparison

Figure 3 of the appendix provides a comparison between performance metrics of traditional and AI-based methods. It reveals that the AI-based techniques are more effective than traditional ones in all aspects, particularly in efficiency and scalability. Although the traditional techniques are good in realism, the AI techniques offer a better overall performance and are also faster and more reliable in giving similar results, hence suitable in the modern digital environment design.

7. CONCLUSION

The study has examined how artificial intelligence can be used to create textures of real-world-like digital environments as part of the concept art development. The paper has explored the improvement of texture generating methods using AI-based approaches, especially diffusion models and generative adversarial networks in terms of quality, efficiency, and scalability. A literature review along with the methodological implementation and experimental analysis of the findings help to prove that AI-generated textures can be viewed as an important step toward the digital content creation processes. Among the most important contributions of the given study is the recognition of AI as a potent assistive technology that does not substitute but only adds to the traditional artistic practices. The systems created on AI can generate quality textures extremely fast, which gives artists a chance to experiment with various design options within a small fraction of the time it takes standard methods. It can be seen that diffusion-based models, especially, generate much more realistic textures with a higher quality of light interaction and material precision. Such an ability makes digital environments more engaging and realistic, and AI is a good choice where it comes to large projects in the fields of gaming, film and virtual reality. Enhanced productivity and efficiency of the workflow are also mentioned in the research. AI will enable artists to devote their time to creative decision-making and optimization by automating repetitive and time-consuming decisions. The concept art pipelines involving the use of AI-generated textures show a hybrid workflow, in which the results of machine-generated output and human creativity are integrated to produce the best outcomes. Such balance will guarantee the retention of the artistic purpose on one hand and take advantage of the speed and scalability of AI systems. Nevertheless, the article equally accepts a number of weaknesses linked to AI-created textures. Issues of low control over outputs, dependency on datasets, computational demands, and ethical issues need to be overcome in order to use it responsibly and effectively. Although AI is able to deliver remarkable outcomes, its outputs need to be revised by human resources to achieve a high level of accuracy and adhere to the stylistic standards.

CONFLICT OF INTERESTS

None.

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