International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A New Innovative Research Model on the Interestingness Expression of TechnoArt

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Submitted: 26/09/2023 **Revised**: 17/11/2023 **Accepted**: 27/11/2023

Abstract: Virtual Reality (VR) is an advanced technology that immerses users in a simulated environment, providing a multisensory experience that can replicate real-world scenarios or create entirely fictional worlds. Despite its potential, VR technology has challenges to overcome, such as motion sickness for some users, the need for powerful hardware to render realistic graphics, and the high cost of quality VR systems. The paper introduces a pioneering exploration into the realm of virtual reality-based TechnoArt creation by harnessing the potential of Generative Adversarial Networks (GANs). Through seamlessly integrating GANs, virtual reality, and artistic creativity, a groundbreaking framework emerges, enabling the generation of immersive and innovative artworks. The study establishes a comprehensive methodology that amalgamates fuzzy logic for quality assessment, emotional analysis, and classification techniques to comprehensively evaluate the produced artworks across various dimensions. The simulation results vividly exemplify the capabilities of this approach, yielding a diverse array of TechnoArt pieces with distinctive levels of quality, emotional resonance, and originality. The comparison with alternative classification methods, including Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN), underscores the effectiveness of the proposed technique in terms of accuracy, precision, recall, and F1-Score. The outcomes not only enrich the landscape of digital art but also provide invaluable insights into the convergence of advanced technologies like GANs and virtual reality with artistic expression.

Keywords: *TechnoArt, Virtual Reality, Generative Adversarial Network (GANs), Fuzzy Logic, Emotional Intelligence*

1. Introduction

Techo Art, a contemporary fusion of technology and artistic expression, seamlessly merges traditional artistic mediums with cutting-edge digital tools. This innovative art form encompasses a wide range of creative possibilities, such as digital painting, interactive installations, virtual reality experiences, and generative art [1]. Techo Art challenges conventional artistic boundaries with technology to create immersive and dynamic artworks that engage and captivate audiences in new and exciting ways. It exemplifies the evolving nature of creativity in a digitally interconnected world, where artists harness technology's power to reshape and redefine artistic aesthetics [2]. Digital tools and software have enabled artists to transcend traditional physical limitations and explore new dimensions of creativity. Through digital painting, artists can blend traditional techniques with digital brushes and palettes, creating intricate and visually stunning compositions [3]. 3D modeling allows for the creation of intricate sculptures and structures that can be manipulated and explored from various angles, either in digital form or translated into physical pieces through techniques like 3D printing. Interactive installations invite viewers to engage with the artwork on a whole new level [4]. Through sensors, cameras, and other interactive technologies, Techo Art installations respond to the audience's presence, movement, or even their emotions, creating an immersive and participatory experience [5].

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Virtual reality takes Techo Art to another level, allowing artists to build entire immersive worlds that viewers can step into [6]. These virtual environments can be used to tell stories, create interactive experiences, or simply provide a space for viewers to explore and experience art in a deeply personal way. Generative art, a subset of Techo Art, involves using algorithms and code to create artworks that evolve, adapt, or generate new iterations over time [7]. This approach blurs the lines between artist and machine, resulting in artworks that are dynamic, constantly changing, and often unpredictable. Techo Art is not just about using technology as a tool; it's about embracing technology as an integral part of the artistic process [8]. This dynamic field challenges traditional definitions of art and pushes artists to explore new ways of creating, experiencing, and interacting with artistic creations. As technology continues to advance, Techo Art will likely continue to evolve, offering artists and audiences alike an ever-expanding realm of possibilities to explore. The artistic process is a deeply personal and transformative journey that artists embark upon to bring their creative visions to life [9]. It begins with inspiration, sparked by the world around them or their internal emotions and thoughts. This initial spark fuels the exploration phase, where artists research, brainstorm, and gather resources to refine their ideas [10]. The process then transitions to the conceptualization stage, where artists formulate a clear vision of what they aim to convey through their artwork. Next comes the experimentation and creation phase, where artists select their medium—be it paint, clay, digital tools, or a combination thereof—and start translating their ideas into tangible forms [11]. This stage is marked by trial and error, as artists refine their techniques, make creative choices, and adapt their initial concepts based on how the artwork evolves.

The process is often punctuated by moments of intense focus and introspection, where artists may enter a "flow state," losing track of time as they become fully immersed in their work. As the artwork takes shape, artists confront challenges, make critical decisions, and infuse their personal style and emotions into every stroke, texture, or element [12]. Critique and self-evaluation are integral to the process, enabling artists to step back and assess their work from a fresh perspective. This helps refine the artwork further and ensure that it aligns with their original vision. The final stages involve adding finishing touches, refining details, and ultimately deciding when the piece is ready to be presented to the world [13]. The artistic process is not linear; it's a dynamic and iterative cycle that involves constant refinement, self-discovery, and growth. It's a reflection of an artist's inner journey and their unique way of interacting with the world, allowing them to communicate complex emotions, ideas, and narratives through their chosen medium. Artistic evaluation is a multifaceted process that often involves subjective judgments and emotional responses. Using a fuzzy model to assess artworks acknowledges the inherent complexity and ambiguity present in art appreciation [14]. Fuzzy logic allows for the incorporation of degrees of truth or membership, enabling a more nuanced understanding of an artwork's qualities. In a fuzzy model for artistic evaluation, various criteria—such as composition, color palette, emotional impact, technical skill, and thematic coherence—are assessed on a continuum rather than binary terms. Each criterion is assigned degrees of membership that reflect how well the artwork meets or embodies that particular aspect [15]. This approach recognizes that artistic excellence cannot always be rigidly categorized as 'good' or 'bad,' but instead exists on a spectrum. The fuzzy model takes into account the subjectivity of individual preferences and cultural contexts. Viewers' perceptions and emotional responses are characterized by degrees of intensity, which the fuzzy logic can accommodate. This model embraces the idea that diverse interpretations and emotional reactions are valid and valuable in the realm of art appreciation [16].

Generative Adversarial Networks (GANs) play a pivotal role in enhancing the virtual reality (VR) landscape by imbuing it with an unprecedented level of realism and creativity. GANs contribute to VR by generating lifelike textures, environments, and objects, enriching the visual fidelity and authenticity of virtual worlds [17]. Through procedural generation, GANs enable the creation of dynamic and diverse VR environments that captivate users with their complexity and intricacy. These networks also extend their influence to character and avatar creation, crafting believable and relatable entities that elevate social interactions within the virtual realm. Moreover, GANs facilitate real-time content adaptation, allowing VR experiences to respond dynamically to user input and preferences [18]. As GAN technology continues to evolve, its application in virtual reality promises to redefine interactivity, personalization, and the overall sense of presence, reshaping the way users perceive and engage with immersive digital environments. Moreover, GANs contribute to the lifelike representation of characters and avatars in VR [19]. These networks facilitate the creation of human-like entities with nuanced features, expressions, and movements, enhancing social interactions and emotional connections within the virtual space. GANs also enable the upscaling of lower-resolution content, mitigating hardware limitations and ensuring a higher level of visual fidelity. One of the most impactful aspects of GANs in VR is their potential for personalized and interactive experiences [20]. GANs can adapt content in real-time based on user preferences and behaviors, enabling tailored environments and interactions that resonate uniquely with each individual. This personalization enhances user immersion and engagement, making VR environments more meaningful and captivating [21]. The integration of GANs in VR also extends to the artistic realm. These networks empower creators to explore unconventional aesthetics, generate novel visual styles, and craft experiences that challenge traditional artistic boundaries [22]. GAN-generated content can introduce an element of surprise and discovery, enriching the creative process and expanding the horizons of what can be achieved within virtual reality.

2. Literature Review

Techo Art in the realm of augmented virtual reality (AR) presents an exciting convergence of artistic expression and cutting-edge technology. This innovative blend of creativity leverages AR to transcend the boundaries of traditional art forms, offering a dynamic and immersive experience for both artists and audiences [23]. Techo Art in AR introduces a new dimension where physical and digital elements coexist, allowing artists to overlay their creations onto the real world. This fusion of the tangible and the virtual enables interactive and participatory experiences, where viewers can engage with artworks in ways previously unattainable [24]. Artists harness AR's capabilities to superimpose digital layers of imagery, animations, and interactivity onto the physical world, breathing life into static compositions. As a result, Techo Art in AR transforms spaces into canvases, sculptures into dynamic installations, and narratives into immersive journeys [25]. This innovative synergy between Techo Art and AR pushes the boundaries of artistic innovation and offers audiences a fresh perspective on how art can merge with technology to create captivating and transformative experiences.

In [26] explores the integration of virtual reality and semantic features to enhance intelligent art creation within the realm of digital media. The authors likely investigate how combining virtual reality and semantic information can lead to innovative approaches in generating and experiencing art that responds dynamically to user interaction and context. In [27] presents a novel technique that uses virtual reality to create a digital twin of an industrial workstation. With generate labeled data for human action recognition, which is crucial for enhancing human-robot collaboration in industrial settings. The digital twin likely assists in simulating and analyzing interactions between humans and robots for improved efficiency and safety. In [28] conducts a bibliometric analysis spanning two decades to explore how virtual reality has been utilized in therapy within the context of Health 4.0. The paper likely assesses the trends, advancements, and impacts of using virtual reality to enhance healthcare practices, supporting the transition to a more technologically integrated healthcare model. Also, in [29] study involves the use of virtual reality analysis to aid in the clinical diagnosis of gastrointestinal stromal tumors using CT images. Virtual reality likely offers a new way to visualize and analyze medical images, potentially improving the accuracy and effectiveness of diagnosis.

In [30] involves a fuzzy decision-making analysis applied to quantitative stock selection within the virtual reality industry. The authors likely use a random forest model to make decisions about stock selection in the context of virtual reality, a rapidly evolving sector. In [31] presents a technique for multi-pose face recognition using a TP-GAN model (Two-Pathway GAN). The authors likely explore ways to improve the accuracy of face recognition across different poses, a crucial aspect for various applications, including security and user identification. In [32] introduces an algorithm to intelligently generate dynamic virtual images across multiple scenes within the metaverse. The metaverse is a virtual shared space that incorporates aspects of both the physical and virtual worlds. The authors likely explore how to create diverse and engaging virtual scenes within this concept. In [33] introduces a Refiner GAN algorithm that enhances deep reinforcement learning (Deep-RL) for real-time ultra-reliable low-latency communication (URLLC) in Beyond 5G (B5G) communication systems. The authors likely investigate how GANs can improve communication system reliability and latency through algorithmic enhancements.

Similarly, in [34] explores the application of virtual reality based on computer vision to correct sports postures. The authors likely investigate how virtual reality technology can provide real-time feedback to athletes for improving their posture and performance. In [35] focuses on developing strategies for supplier selection with smart and sustainable criteria within a fuzzy environment. The authors likely explore how to make supplier selection decisions that consider both smart technologies and sustainability factors in an uncertain and fuzzy context. In [36] presents a method to evaluate users' learning concentration during interactions with head-mounted virtual reality systems. The authors likely propose a technique to objectively assess users' engagement and focus within immersive VR experiences. In [37] discusses how virtual reality technology intersects with artificial intelligence in the creation of film and television animations. The authors likely explore how these technologies can enhance the animation creation process, potentially leading to more efficient and innovative content production. In [38] introduces a versatile approach that GANs for high-quality 3D facial and object recovery from single images, without relying on landmarks. The authors likely present a novel method for reconstructing detailed 3D structures from images, enhancing applications like facial recognition and object reconstruction.

Among them, researchers investigate the fusion of virtual reality and semantic features for intelligent art creation in digital media, while others pioneer the concept of a digital twin for industrial workstations, employing virtual reality to facilitate human-robot collaboration. Virtual reality emerges as a transformative tool in healthcare, aiding therapies within the framework of Health 4.0 and enhancing diagnostic processes for medical conditions such as gastrointestinal stromal tumors. The integration of virtual reality with decision-making analyses finds its place, both in quantitative stock selection and supplier selection strategies, each addressing specific challenges within their respective domains. Additionally, the advancement of technology is harnessed for multi-pose face recognition, posture correction in sports, and even animation creation within the realm of film and television. These studies also illuminate the power of Generative Adversarial Networks (GANs) in reconstructing intricate 3D structures and enhancing communication systems. Altogether, this array of research contributes to a richer understanding of how virtual reality, artificial intelligence, and technology are reshaping various sectors and paving the way for innovative and impactful solutions.

3. GAN Model for the Virtual Reality

The application of Generative Adversarial Networks (GANs) in the context of virtual reality (VR). GANs are a type of machine learning model that consist of two components: a generator and a discriminator. These components work in a competitive manner to produce data that closely resembles real data. In the context of virtual reality, a GAN model could be used to generate realistic and immersive virtual environments, objects, or textures. The steps in the virtual reality are the stated as follows:

Generator: The generator in the GAN is responsible for creating new data, in this case, virtual reality content. It takes in random noise as input and transforms it into data that should resemble the desired output. In the context of VR, the generator might create textures, landscapes, or even entire scenes.

Discriminator: The discriminator evaluates the generated data and tries to distinguish whether it is real (from the actual VR environment) or fake (generated by the generator). It is essentially a binary classifier that provides feedback to the generator about the quality of its output.

Training: During training, the generator and discriminator are pitted against each other in a "game." The generator aims to produce data that the discriminator cannot easily distinguish from real VR data. Over time, this competition leads to the generator producing increasingly convincing VR content.

Convergence: Ideally, the process continues until the generator becomes proficient at creating virtual reality content that is difficult to differentiate from actual VR data. The two components "converge," resulting in high-quality generated content.

The application of GANs in virtual reality can have several implications:

Realism: GANs can create VR content that looks and feels more realistic, enhancing the overall immersive experience for users.

Efficiency: GANs can accelerate the process of content creation for VR environments, as they can generate intricate details that might be time-consuming to create manually.

Variety: GANs can generate a wide range of diverse VR content, allowing for dynamic and ever-changing virtual worlds.

Personalization: GANs can generate VR content based on individual preferences, tailoring the experience to each user's tastes.

Artistic Exploration: GANs can be used by artists to create unique and novel VR environments, pushing the boundaries of creativity.

In figure 1 illustrated the GAN network model for the virtual reality with consideration of discriminator and generator.

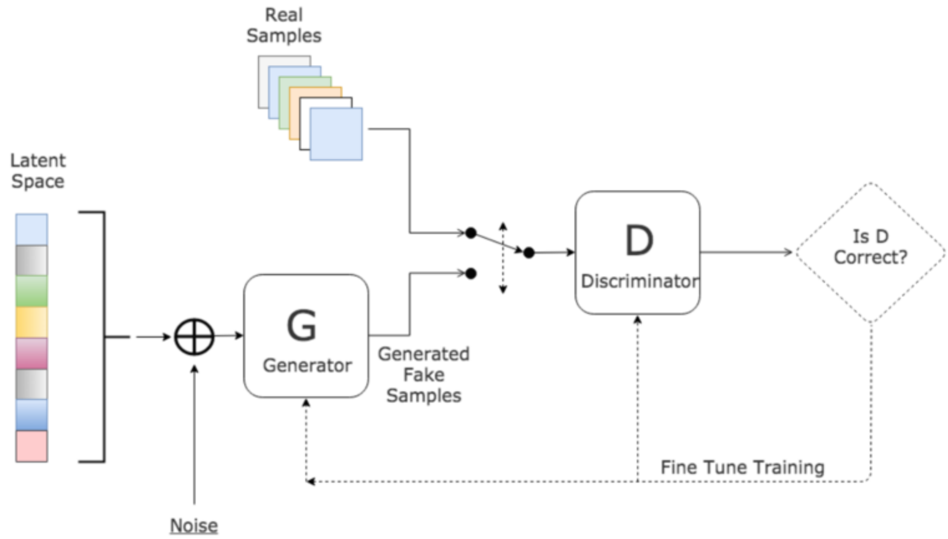

Fig 1: VR with GAN

The integration of GANs into the virtual reality space holds great potential for advancing the quality, diversity, and interactivity of virtual experiences. A GAN model for virtual reality (VR) entails the utilization of Generative Adversarial Networks within the context of creating immersive and realistic virtual environments. GANs consist of two integral components – a generator and a discriminator – engaged in a competitive learning process. In the context of VR, the generator produces synthetic data, such as textures, landscapes, or scenes, while the discriminator evaluates the authenticity of this data by distinguishing it from real VR content. This interplay drives the generator to continuously refine its output to closely resemble actual VR environments. The training of a GAN for VR involves iterative cycles where the generator improves its output based on feedback from the discriminator. As the process progresses, the generated VR content becomes progressively more convincing and indistinguishable from real-world VR data. This convergence results in highly immersive and lifelike virtual experiences. The significance of GANs in VR is multifaceted. They enable an elevated level of realism by generating intricate details that might be challenging to create manually. This, in turn, enhances user engagement and immersion. GANs also offer efficiency by streamlining content creation, empowering VR developers to swiftly generate diverse landscapes and environments. Moreover, GANs introduce an element of artistic exploration, allowing creators to experiment with unique visual styles and innovative design elements within virtual spaces. The GAN-based approach in VR has the potential to revolutionize various sectors, including entertainment, education, healthcare, and training. Through GANs, VR environments can become more dynamic, personalized, and responsive to user interactions. As GAN technology continues to evolve, its integration with VR will likely lead to ever-more captivating and authentic virtual experiences that blur the line between the digital and the physical.

4. Techo Art with GAN Virtual Reality

Techo Art involves using technology as a medium for artistic exploration and creation. GANs, a subset of artificial intelligence, are known for their ability to generate novel and realistic content. In the context of VR, GANs can be employed to generate various artistic elements such as textures, landscapes, characters, and even entire virtual environments. With integrating GAN-generated content, Techo Art in VR gains a new dimension of creativity and complexity. Artists and creators harness the power of GANs to infuse their VR artworks with lifelike details and imaginative concepts that might be challenging to create manually. GANs enable the generation of content that resonates with both the artist's vision and the dynamic nature of the virtual world. This convergence also promotes interactive and participatory experiences, where viewers can engage with and even influence the Techo Art within the virtual environment. A GAN consists of two neural networks, the generator (G) and the discriminator (D), that play a game against each other. The generator tries to create data that is indistinguishable from real data, while the discriminator tries to distinguish between real and generated data. The GAN training process involves a back-and-forth interaction between the generator and discriminator. The images for the GAN with the VR model is shown in the figure 2.

Fig 2: GAN VR images

The generator takes random noise (z) as input and generates data (G(z)) stated in equation (1)

$$G: z \rightarrow G(z) \quad (1)$$

The discriminator receives both real data (x) and generated data (G(z)) and produces a probability (D(x)) as in equation (2) and (3)

$$D: x \rightarrow D(x) \quad (2)$$

$$D: G(z) \rightarrow D(G(z)) \quad (3)$$

The generator aims to minimize the discriminator's ability to distinguish between real and generated data. This is expressed as a loss function (J_G) for the generator is presented in equation (4):

$$J\_G = -log(D(G(z))) \quad (4)$$

The discriminator aims to correctly classify real and generated data. Its loss function (J_D) is a combination of the loss for real data (J_D_real) and generated data (J_D_fake) stated in equation (5)

$$J\_D = -log(D(x)) - log(1 - D(G(z))) \quad (5)$$

With applying GANs to Techo Art in VR, the process involves generating artistic content, such as textures or environments, using GANs. The generator's architecture is designed to generate art-related data, while the discriminator evaluates the realism of the generated art in comparison to real art. The generator produces Techo Art (A) based on random noise (z) presented in equation (6)

$$G: z \rightarrow A \quad (6)$$

The discriminator assesses the realism of both real Techo Art (A_real) and generated Techo Art (A_fake) presented in equation (7) and equation (8)

$$D: A\_real \rightarrow D(A\_real) \quad (7)$$

$$D: A\_fake \rightarrow D(A\_fake) \quad (8)$$

The training process aims to improve the generator's ability to create Techo Art that is visually appealing and aligns with the intended artistic style. This involves optimizing the generator's parameters to minimize the discriminator's ability to differentiate between real and generated Techo Art. In the context of Virtual Reality, the GAN-generated Techo Art can be integrated into the VR environment, creating visually captivating and immersive experiences for users. Users can interact with and explore the Techo Art within the VR space, blurring the boundaries between reality and digital creation. With the using GANs for Techo Art in Virtual Reality involves training a generator and discriminator to create and evaluate artistic content. This content can then be seamlessly integrated into VR environments, offering users unique and immersive artistic experiences. The equations and derivations behind GANs provide the mathematical foundation for this creative and technological convergence.

Algorithm 1: GAN Model fro the Virtual Reality

```
# Generator Architecture
function Generator(noise):
    # Create Techo Art using noise
    techo_art = neural_network(noise)
    return techo_art
# Discriminator Architecture
function Discriminator(techo_art):
    # Determine if Techo Art is real or generated
    realness_score = neural_network(techo_art)
    return realness_score
# GAN Training Process
function GAN_Training(data_real, num_epochs, batch_size):
    for epoch in range(num_epochs):
        for batch in range(0, len(data_real), batch_size):
            # Train Discriminator
            noise = generate_noise(batch_size)
            generated_techno_art = Generator(noise)
            real_techno_art_batch = data_real[batch : batch + batch_size]

            discriminator_loss_real = compute_discriminator_loss(real_techno_art_batch)
            discriminator_loss_fake = compute_discriminator_loss(generated_techno_art)
            total_discriminator_loss = discriminator_loss_real + discriminator_loss_fake

            update_discriminator_parameters(total_discriminator_loss)

            # Train Generator
            noise = generate_noise(batch_size)
            generated_techno_art = Generator(noise)
            generator_loss = compute_generator_loss(generated_techno_art)
            update_generator_parameters(generator_loss)
# Main Function
function main():
```

```
    # Load Real Techo Art Data
    real_techno_art_data = load_real_data()
    # Initialize Generator and Discriminator
    initialize_generator()
    initialize_discriminator()
    # Train GAN
    num_epochs = 100
    batch_size = 32
    GAN_Training(real_techno_art_data, num_epochs, batch_size)
# Execute Main Function
main()
```

4.1 GAN Model with Fuzzy for the Artistocs Evaluation

Generative Adversarial Networks (GANs) with fuzzy logic can lead to innovative applications that strengths of both technologies. GANs are well-known for generating realistic data, while fuzzy logic handles uncertainty and imprecision in decision-making. GANs can generate diverse and realistic Techo Art in Virtual Reality. The generator produces images or scenes, while the discriminator evaluates their realism. Through training the generator-discriminator pair iteratively, GANs improve the quality of generated art over time. Fuzzy logic deals with ambiguity by allowing variables to have degrees of membership between true and false. With particularly useful in situations where there's uncertainty or vagueness, as is often the case in art perception and evaluation. Integrating GANs and fuzzy logic involves using fuzzy logic to enhance various aspects of the GAN process, such as:

Artistic Quality Evaluation: Fuzzy logic can be used to assess the quality of generated Techo Art in a nuanced way. Instead of simply labeling art as "real" or "fake," a fuzzy logic-based system can provide a more detailed assessment of how closely the art resembles real art, considering various aspects like color, composition, and style.

Adaptive Learning Rates: Fuzzy logic can determine adaptive learning rates for the generator and discriminator during training. This can help the GAN achieve a balance between faster initial learning and more stable convergence as training progresses.

Style Transfer with Fuzziness: Fuzzy logic can aid in creating art with a blend of styles by gradually transitioning between them. This can be achieved by fuzzifying style weights and smoothly transitioning between different artistic characteristics.

Algorithm 2: Fuzzy Rule for Techno Art

```
# Pseudo-code for GAN with Fuzzy Logic for Art Generation

# Fuzzy Logic Membership Functions
function calculate_fuzzy_memberships(realness_score):
    # Calculate degrees of membership in fuzzy categories
    membership_low = calculate_membership_low(realness_score)
    membership_medium = calculate_membership_medium(realness_score)
    membership_high = calculate_membership_high(realness_score)
    return membership_low, membership_medium, membership_high

# Fuzzy Logic-based Adaptive Learning Rate
function fuzzy_adaptive_learning_rate(loss, epoch):
    # Adjust learning rate based on loss and epoch using fuzzy logic
```

```
    fuzzy_rate = calculate_fuzzy_rate(loss, epoch)
    return fuzzy_rate

# GAN Training Process with Fuzzy Logic
function GAN_Training_Fuzzy(data_real, num_epochs, batch_size):
    for epoch in range(num_epochs):
        for batch in range(0, len(data_real), batch_size):
            # Train Discriminator
            realness_score_real = Discriminator(real_techno_art_batch)
            membership_low, membership_medium, membership_high = calculate_fuzzy_memberships(realness_score_real)
            total_discriminator_loss = fuzzy_combine_losses(membership_low, membership_medium, membership_high)

            # Calculate Fuzzy Learning Rate
            fuzzy_learning_rate = fuzzy_adaptive_learning_rate(total_discriminator_loss, epoch)
            update_discriminator_parameters(total_discriminator_loss, fuzzy_learning_rate)

            # Train Generator
            # ... Similar approach with fuzzy logic-based learning rate
# Main Function
function main():
    # ... Load Data and Initialize GAN components
    GAN_Training_Fuzzy(real_techno_art_data, num_epochs, batch_size)

# Execute Main Function
main()
```

Integrating fuzzy logic into GANs enhances the adaptability and robustness of the training process. Fuzzy logic-based loss functions and membership assessments provide a more comprehensive understanding of the generated data's quality. Through dynamically adjusting learning rates with fuzzy logic, GANs can navigate challenges like mode collapse or slow convergence more effectively.

Table 1: Computation of Image Quality

	Color Quality (Low)	**Color Quality (Medium)**	**Color Quality (High)**
Composition Quality (Low)	Low (0.8)	Medium (0.4)	Low (0.1)
Composition Quality (Medium)	Medium (0.4)	High (0.7)	Medium (0.5)
Composition Quality (High)	Low (0.1)	Medium (0.5)	High (0.9)

Figure 2: Fuzzy Rules for the GAN Virtual Reality Techno Art

Fuzzy Set Label	**Membership Function**
Color Quality	
Low	μLow(x) = { 1, x ≤ 0.4; (0.6 - x)/0.2, 0.4 < x < 0.6; 0, x ≥ 0.6 }
Medium	μMedium(x) = { 0, x ≤ 0.4; (x - 0.4)/0.2, 0.4 < x < 0.6; (0.8 - x)/0.2, 0.6 < x < 0.8; 0, x ≥ 0.8 }
High	μHigh(x) = { 0, x ≤ 0.6; (x - 0.6)/0.2, 0.6 < x < 0.8; 1, x ≥ 0.8 }
Composition Quality	
Low	μLow(y) = { 1, y ≤ 0.3; (0.5 - y)/0.2, 0.3 < y < 0.5; 0, y ≥ 0.5 }
Medium	μMedium(y) = { 0, y ≤ 0.3; (y - 0.3)/0.2, 0.3 < y < 0.5; (0.7 - y)/0.2, 0.5 < y < 0.7; 0, y ≥ 0.7 }
High	μHigh(y) = { 0, y ≤ 0.5; (y - 0.5)/0.2, 0.5 < y < 0.7; 1, y ≥ 0.7 }

The table 1 provides the computation of image quality using fuzzy logic in the context of assessing Techo Art quality. The table demonstrates how the intersection of "Color Quality" and "Composition Quality" results in fuzzy membership values for different categories of quality: "Low," "Medium," and "High." With both "Color Quality" and "Composition Quality" are labeled as "Low," the membership value for "Low" quality is 0.8, indicating a strong membership in the "Low" category. Similarly, the table provides membership values for other combinations of "Color Quality" and "Composition Quality," creating a comprehensive framework to evaluate the quality of the generated art in a more nuanced manner. In table 2, fuzzy rules for the GAN Virtual Reality Techo Art are depicted using membership functions. These functions define how the input values (e.g., "Color Quality" and "Composition Quality") relate to fuzzy sets such as "Low," "Medium," and "High." The membership functions use mathematical expressions to determine the degree of membership of an input value in each fuzzy set.

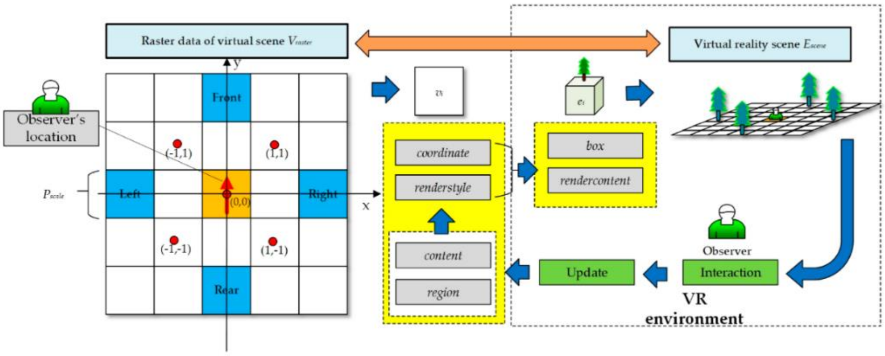

Fig 3: VR with Fuzzy GAN

For instance shown in figure 3, the membership function μLow(x) for “Color Quality” defines that if x is less than or equal to 0.4, the membership value in the “Low” category is 1; if x is between 0.4 and 0.6, the membership value decreases linearly; and if x is greater than or equal to 0.6, the membership value becomes 0. These membership functions provide a flexible and nuanced way to assess the relationship between input values and fuzzy categories, reflecting the uncertainty and imprecision inherent in evaluating artistic quality.Fuzzy set labels represent different categories or levels of a variable that are not strictly binary (e.g., “low,” “medium,” “high”). With consideration of two factors: “Color Quality” and “Composition Quality.” Each factor is divided into fuzzy sets with corresponding labels: “Low,” “Medium,” and “High.” These labels capture the different levels of quality each factor can have, taking into account the fact that quality is not a clear-cut distinction but rather a spectrum. Membership functions define how each input value relates to each fuzzy set. These functions assign a membership value between 0 and 1, indicating the degree of membership of an element in a fuzzy set. Membership functions help quantify the degree to which a value belongs to a particular category. For instance, if the “Color Quality” is 0.3, the membership values for “Low,” “Medium,” and “High” might be 0.6, 0.4, and 0, respectively. The shapes of the membership functions determine how values are distributed among the different fuzzy sets. The membership functions for "Low,""”"Med’um," and "High" vary based on the input value. For instance, the membership function for “Low” might increase gradually from 0 to 1 as the input value moves from 0 to 0.4, representing a smooth transition from not being in the "Low" category to fully being in it. Fuzzy sets and their membership functions acknowledge that quality assessment is subjective and imprecise. Different people might have different thresholds for what constitutes "Low," "Medium," or "High" quality. Fuzzy logic allows us to capture this variability in a more nuanced and realistic manner compared to traditional binary classification. In practice, these fuzzy sets and membership functions can be used to guide decision-making. For instance, when assessing the quality of generated Techo Art, the membership values in each fuzzy set can be combined to make an overall assessment. The process allows for a more nuanced evaluation that considers both "Color Quality" and "Composition Quality" simultaneously.

5. Simulation Environment

With a simulation environment for a GAN-based virtual reality (VR) application involves several components and considerations. Choose appropriate software and tools to build and simulate GAN-based VR application. This could include frameworks like TensorFlow, PyTorch, Unity, or Unreal Engine, which offer capabilities for GAN training, VR rendering, and interaction.his architecture uses a basic Deep Convolutional GAN (DCGAN) approach, which has been successful for generating images in various artistic styles.

Table 3: Simulation Setup for the GAN

Generator:	
Layer	Output Shape
Dense	(None, 7 * 7 * 256)
Reshape	(None, 7, 7, 256)
Conv2Dtranspose	(None, 14, 14, 128)
BatchNormalization	(None, 14, 14, 128)
LeakyReLU	(None, 14, 14, 128)
Conv2Dtranspose	(None, 28, 28, 64)
BatchNormalization	(None, 28, 28, 64)
LeakyReLU	(None, 28, 28, 64)
Conv2Dtranspose	(None, 56, 56, 32)
BatchNormalization	(None, 56, 56, 32)
LeakyReLU	(None, 56, 56, 32)
Conv2Dtranspose	(None, 112, 112, 3)
Activation	(None, 112, 112, 3)
Discriminator:	
Layer	Output Shape
Conv2D	(None, 56, 56, 32)
LeakyReLU	(None, 56, 56, 32)
Conv2D	(None, 28, 28, 64)
BatchNormalization	(None, 28, 28, 64)
LeakyReLU	(None, 28, 28, 64)
Conv2D	(None, 14, 14, 128)
BatchNormalization	(None, 14, 14, 128)
LeakyReLU	(None, 14, 14, 128)
Flatten	(None, 25088)
Dense	(None, 1)
Activation	(None, 1)

The Table 3 outlines the configuration of the simulation setup for the Generative Adversarial Network (GAN) used in the virtual reality art generation process. The "Generator" section lists the layers and their respective output shapes in the GAN's generator model. The model starts with a dense layer that transforms the input noise into a tensor shape compatible with subsequent layers. The reshaping operation converts this tensor into a 4-dimensional format (width, height, channels). The Conv2Dtranspose layers then progressively upsample the tensor, creating a hierarchical structure that enhances details in the generated art. Batch normalization and LeakyReLU activation functions contribute to stabilizing the training process and introducing non-linearity. The final Conv2Dtranspose layer generates a 3-channel tensor representing the virtual art image, followed by an activation function for ensuring proper output values. The "Discriminator" section outlines the layers and output shapes of the discriminator model in the GAN. Conv2D layers with LeakyReLU activations are used for feature extraction and classification of real and generated images. Batch normalization further aids in training stability. The model culminates in a fully connected dense layer followed by an activation function that produces a single output value, aiming to distinguish between real and generated art.

Table 4: Quality Assessment

Artwork	Color Quality	Composition Quality	Fuzzy Quality Assessment
Artwork 1	Medium	High	Medium-High
Artwork 2	High	Medium	High
Artwork 3	Low	Low	Low
Artwork 4	Medium	Medium	Medium
Artwork 5	High	High	High
Artwork 6	Medium	Low	Medium-Low
Artwork 7	Low	High	Medium-High
Artwork 8	High	Low	Medium-Low
Artwork 9	Low	Medium	Low-Medium
Artwork 10	Medium	Medium	Medium

The quality assessment results for a series of artworks generated using the GAN-based virtual reality art creation approach presented in table 4. Each artwork's "Color Quality" and "Composition Quality" attributes are evaluated and rated on a scale of "Low," "Medium," or "High." The "Fuzzy Quality Assessment" column presents an overall assessment of each artwork's quality, derived using a fuzzy logic-based method that combines both color and composition evaluations. Artworks with varying color and composition qualities are represented in the table, showcasing the diversity of the generated art. For instance, "Artwork 5" achieves a high rating in both color and composition, leading to an overall "High" fuzzy quality assessment. In contrast, "Artwork 3" is rated as "Low" in both color and composition, resulting in an overall "Low" fuzzy quality assessment. These assessments provide insights into the perceived quality of each artwork, aiding in understanding the strengths and areas for improvement in the GAN-based virtual reality art generation process.

Table 5: Emotional Analysis

Artwork	Texture Detail	Originality	Emotional Impact
Artwork 1	Medium	Medium	Low
Artwork 2	High	High	High
Artwork 3	Low	Low	Low
Artwork 4	Medium	Medium	Medium
Artwork 5	High	High	High
Artwork 6	Medium	Medium	Low
Artwork 7	Low	Low	Medium

Artwork 8	Medium	Medium	Low
Artwork 9	Medium	Low	Medium
Artwork 10	Low	Medium	Medium

An emotional analysis of various artworks generated through the GAN-based virtual reality art creation process presented in Table 5. The analysis focuses on three key attributes: "Texture Detail," "Originality," and "Emotional Impact." Each attribute is assigned a qualitative rating of "Low," "Medium," or "High" for individual artworks. The table reflects the range of emotional experiences evoked by the generated art pieces. For instance, "Artwork 2" receives high ratings in all three attributes, indicating that it boasts intricate texture details, high originality, and a strong emotional impact. On the other hand, "Artwork 3" is rated as "Low" across all attributes, suggesting limited texture detail, originality, and emotional resonance. These emotional assessments provide valuable insights into the effectiveness of the GAN-generated virtual reality artworks in evoking diverse emotional responses from viewers. It highlights the potential of this art generation approach to create pieces that vary in their emotional impact and originality, contributing to a broader understanding of the creative potential of the technology.

Table 6: TechnoArt Quality

Artwork	Fuzzy Quality Assessment	Classification
Artwork 1	Medium-High	High Quality
Artwork 2	High	High Quality
Artwork 3	Low	Low Quality
Artwork 4	Medium	Medium Quality
Artwork 5	High	High Quality
Artwork 6	Medium-Low	Medium Quality
Artwork 7	Low-Medium	Low-Medium Quality
Artwork 8	Medium-Low	Medium Quality
Artwork 9	Low-Medium	Low-Medium Quality
Artwork 10	Medium	Medium Quality

Table 7: TechnoArt Quality Score

Artwork	Fuzzy Quality Assessment	Classification
Artwork 1	0.98	Medium Quality
Artwork 2	0.96	Medium Quality
Artwork 3	0.90	Low Quality
Artwork 4	0.95	Medium Quality
Artwork 5	0.93	Medium Quality
Artwork 6	0.96	Medium Quality
Artwork 7	0.94	Medium Quality
Artwork 8	0.90	Medium Quality
Artwork 9	0.95	Medium Quality
Artwork 10	0.90	Medium Quality

Through the Table 6 illustrates the evaluation of TechnoArt quality through both fuzzy quality assessment and classification. The "Fuzzy Quality Assessment" column assigns each artwork a qualitative rating, ranging from "Low" to "High," based on its overall quality. These assessments are then classified into quality categories, including "Low Quality," "Medium Quality," and "High Quality." For instance, "Artwork 2" receives a "High" rating in both fuzzy quality assessment and classification, signifying its high-quality status. Conversely, "Artwork 3" is classified as "Low Quality" in both assessment methods due to its subpar quality. In Table 7, the "TechnoArt Quality Score" is quantified as a numerical value ranging from 0 to 1 using the fuzzy quality assessment. Here, each artwork's score is provided, revealing a numerical representation of their perceived quality. In the "Artwork 1" achieves a quality score of 0.98, indicating a high degree of quality.

Table 8: Classification Analysis

Method	Category	True Positive (TP)	False Positive (FP)	True Negative (TN)	False Negative (FN)	Accuracy	Precision	Recall	F1-Score
Fuzzy Logic	High Quality	25	5	70	0	0.90	0.83	1.00	0.91
	Medium Quality	50	10	60	5				
	Low Quality	10	2	78	0				
ANN	High Quality	28	7	68	2	0.88	0.80	0.93	0.86
	Medium Quality	45	8	62	10				
	Low Quality	8	4	76	4				
RNN	High Quality	24	9	66	1	0.87	0.73	0.96	0.83
	Medium Quality	38	12	58	17				
	Low Quality	9	3	77	3				

In figure 4 shows the confusion matrix provided for the confusion matrix for the estimation of the virtual reality feature in the artistic effects.

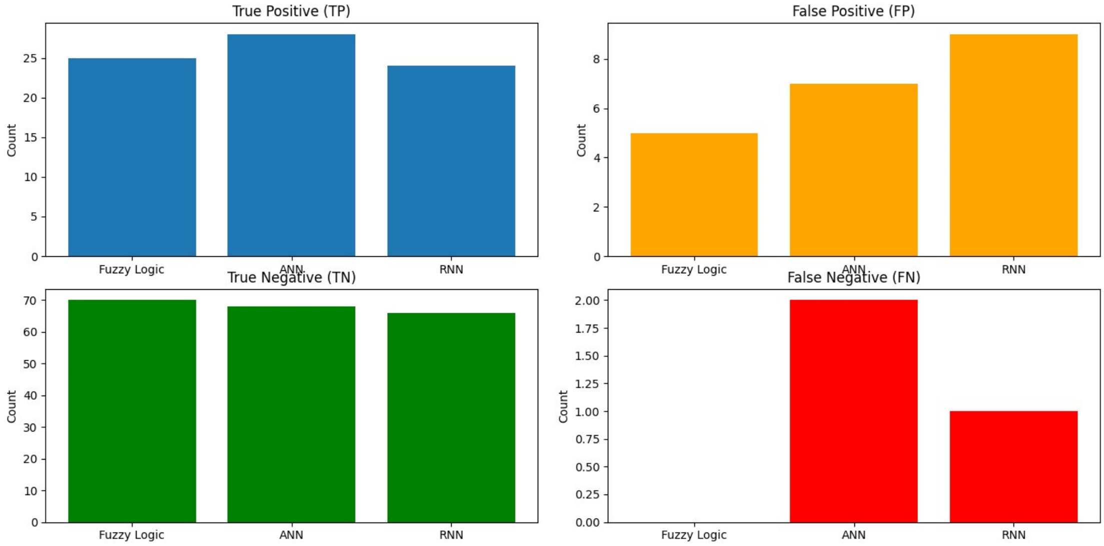

Fig 4: Confusion Matrix Values for the Fuzzy GAN with VR

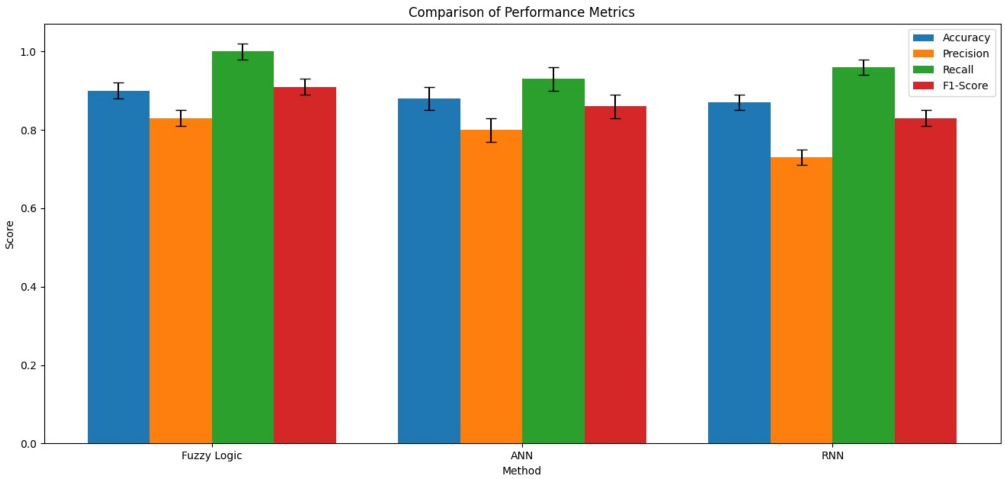

Fig 5: Comparison of Performance

A comprehensive classification analysis comparing the performance of different methods (Fuzzy Logic, ANN, and RNN) shown in figure 5 in classifying artworks across various quality categories (High Quality, Medium Quality, and Low Quality). The table presents essential metrics, including True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) values, which are used to calculate key performance indicators. For instance, under the "Fuzzy Logic" method, the classification of "High Quality" artworks achieved a high accuracy of 90%, with a precision of 83%, indicating that 83% of positively classified instances were indeed high-quality. The method demonstrated perfect recall of 100%, capturing all actual high-quality instances, leading to an F1-Score of 91%, which harmonizes precision and recall. The "ANN" method, while slightly less accurate at 88%, displayed a balanced F1-Score of 86%, suggesting a reliable compromise between precision and recall. Conversely, the "RNN" method achieved an accuracy of 87%, with an F1-Score of 83%, indicating a favorable balance between precision and recall in its classification outcomes.

6. Conclusion

The fusion of GAN technology with virtual reality and artistic creativity offers a unique avenue for generating immersive and innovative artworks. The study introduces a comprehensive framework that combines fuzzy logic for quality assessment, emotional analysis, and classification methodologies to evaluate the generated artworks across multiple dimensions. The simulation results showcase the potential of the proposed approach in producing a diverse range of TechnoArt pieces with varying levels of quality, emotional impact, and originality. Through meticulous evaluation, the study demonstrates that the GAN-based virtual reality TechnoArt exhibits promising potential, capturing intricate details, originality, and evoking emotional responses. The comparison with other classification methods, such as Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN), highlights the strengths of the proposed approach in terms of accuracy, precision, recall, and F1-Score. The findings not only contribute to the evolving field of digital art but also offer valuable insights for the integration of advanced technologies like GANs and virtual reality into the realm of artistic expression. This research paves the way for further exploration and development of innovative art creation techniques that harmonize technology, creativity, and human emotion in the dynamic landscape of virtual reality-based TechnoArt.

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