

# A Comprehensive Literature Review of Deep Dream and Neural Style Transfer

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## Abstract

This literature review meticulously examines the forefront of research in the domains of deep dream and neural style transfer. It aims to provide a comprehensive understanding of the latest advancements in these areas by offering concise insights into recently proposed methodologies. The study delves into the concepts, techniques, tools, and outcomes of diverse research frameworks, meticulously surveying research papers published between 2016 and 2021 across seven distinct article repositories.

With a systematic approach, our focus extends beyond a mere overview. We strive to define Deep Dream and Neural Style Transfer, emphasizing their significance, and investigating their applications in diverse fields such as natural language processing (NLP), image processing, segmentation, mental health, security, and more.

## Introduction

In the ever-evolving landscape of digital technology, two groundbreaking techniques have emerged, reshaping our approach to visual art and image processing: Deep Dream and Neural Style Transfer (NST). These methods, rooted in the advanced realms of artificial intelligence and machine learning, represent a fusion of artistic creativity with computational power, offering a new perspective on how we perceive and manipulate images. DeepDream and Neural Style Transfer (NST) mark groundbreaking strides in artificial intelligence and computer vision, reshaping how we interact with visual and auditory content across diverse domains. These techniques, rooted in deep learning and convolutional neural networks (CNNs), transcend traditional applications, extending from artistic expression to security systems. Deep Dream, developed by researchers at Google, is an algorithm that leverages Convolutional Neural Networks (CNNs) to enhance and interpret the patterns found in images. Originally designed to help understand how neural networks process and classify images, Deep Dream has transcended its initial purpose to become an artistic tool in its own right. It works by amplifying the features recognized by the neural network, often resulting in surreal, dream-like imagery that reveals the machine's interpretation of visual data. Deep Dream generates new images that mimic the images that schizophrenic patients and drug addicts imagine. These techniques try to reflect hallucinations and delusional perceptions resulting

from addiction to narcotics [1], where applying Deep Dream is currently in its early phases, showing how artificial intelligence has the potential to advance the knowledge of complicated mental health issues and enrich the lives of individuals who are affected. It unravels a spectrum of visual hallucinations by iteratively adjusting input images based on specific network layers' activations. Studies have showcased Deep Dream's potential to simulate altered perceptual experiences, even venturing into virtual reality platforms to replicate psychedelic states [9].

Concurrently, Neural Style Transfer, introduced by Gatys et al., elevates artistic expression by seamlessly merging content from one image with the style from another. The fusion of NST with Deep Dream, explored in studies like "Employing Neural Style Transfer for Generating Deep Dream Images" [10], exemplifies the synergistic potential of these approaches. This integration not only enhances artistic image generation but also finds applications in simulating hallucinations for psychiatric patients and drug addicts.

According to Yongcheng Jing et al. in their review, the Deep Dream was the first experiment to produce artistic images by reversing the representation of CNN with the techniques of IOB-IR. This was the base of neural style transfer [17].

Style Transfer is not limited to images; it extends to text, where the sentence style can be adjusted by rewriting the original style while retaining its semantic content [8]. In

style image processing, high-level features represent objects and their arrangement, while the style image captures texture, including colors, sharpness, and styles. Filters are applied to the style image, and correlations between these filters are taken to extract the style of the image, disregarding the content image's information. The resulting image combines the content of the former with the style of the latter [20].

With the rapid development of artificial intelligence algorithms and the investment of funds in experimental facilities, scientists from Germany such as Gatys and others proposed the use of convolutional neural networks to achieve style conversion of images[1]. They discovered the convolutional neural network through research, dividing it into deep convolutional layers and shallow convolutional layers, the former can obtain the overall framework of the image, while the latter can obtain the style characteristics of the image, based on this discovery, to achieve the separation of style and content in the image, and then the overall content and style of the image are combined to achieve style conversion. [5] Together, Deep Dream and NST embody the remarkable capabilities of AI in the field of art. They not only offer artists and designers new tools for expression but also provide insights into the intricate ways neural networks perceive and interpret visual information. As we continue to explore these technologies, they open up a world where the lines between technology, art, and human perception are

continuously blurred, leading to innovative applications and endless possibilities in digital creativity.

This literature review and study offer a comprehensive guide to the capabilities and limitations of Deep Dream, Neural Style Transfer, and Semantic Segmentation. Navigating through the dynamic landscapes of visual perception, artistic creation, and semantic understanding, we aim to steer future research endeavors in these evolving fields. This study is discussing 15 of the latest research articles collected from seven different articles libraries including ACM digital Library, Google Scholar, IEEE Xplore, Science Direct, Google Books, Refseek and Worldwide Science.

## Methodology

### I. Planning the Review Process

The initial step involves specifying the requirements for the review process and forming essential questions for the study. This includes outlining the scope, objectives, and key inquiries that will guide the comprehensive literature review on DeepDream and Neural Style Transfer.

Some of the fundamental questions that initiated the review, along with searching for the corresponding answers, include:

**Table 1** Fundamental questions for the Literature review initiation

Area	Questions
Scope and Definition	What is the scope of DeepDream and Neural Style Transfer in the context of artificial intelligence and computer vision?
	How are DeepDream and Neural Style Transfer defined, and what are their fundamental principles?
Objectives	What are the primary objectives of applying DeepDream and Neural Style Transfer in various domains?
	How do the objectives vary across different applications, such as art generation, security systems, and altered perceptual experiences?
Methodological Framework	What methodologies are commonly employed in studies related to DeepDream and Neural Style Transfer?
Applications and Impact	What is the impact of these technologies on the respective domains they are applied to?
Future Directions	What potential future directions can be identified for further exploration and improvement in these technologies?

## II. Finding Relevant Work

In this phase, an extensive search was conducted across reputable databases to identify relevant studies and review papers related to DeepDream and Neural Style Transfer. The search strategy involved using keywords such as "Deep Dream applications," "Neural Style Transfer impact," "and related terms to ensure a comprehensive collection of scholarly works.

## III. Writing Up the Document

The gathered research findings and insights are systematically documented in a comprehensive paper. The structure includes an introduction, Methodology, Deep Dream: A Comprehensive Overview, Neural Style Transfer: A Comprehensive Overview, Applications and Impact, Critique of Existing Approaches, Emerging Trends and Future Directions, Conclusion. Each section is meticulously crafted to present a coherent and informative overview of the selected studies

## V. Analyzing the Results

The final step involves analyzing the results gathered from the selected research papers. A rigorous analysis is conducted to synthesize key findings, identify common trends, and highlight variations within the applications and impact of DeepDream and Neural Style Transfer. This analysis forms the basis for creating a valid and insightful report.

**Literature Search and Selection:** A systematic and thorough search was conducted across prominent databases, including but not limited to PubMed, IEEE Xplore, and Google Scholar. The search aimed to identify a diverse range of research papers related to Deep Dream and Neural Style Transfer.

## Deep Dream: A Comprehensive Overview

The exploration of Deep Dream and its diverse applications in various domains has led to groundbreaking advancements in the field of artificial intelligence. This comprehensive overview delves into distinct studies that leverage Deep Dream, shedding light on its multifaceted capabilities.

In 2015, Google released a computer vision program that aids our understanding of the mechanisms at work in machine-based image classification. Entitled DeepDream for its association with a type of artificial intelligence called deep learning, and also a reference to the unconscious processes that allow the brain to

create dreams, the program produces a visualization of the image-recognition process [1]. Computer scientists often employ anthropomorphizing metaphors such as "deep dream" in their research, misleadingly projecting the possibilities and limitations of the human condition onto the mechanisms that empower the computational abilities of machines.

Google's DeepDream project exemplifies the remarkable growth of computer vision science in the last few years, and advances in image-recognition technology at large have already led to results that are comparable to the performative aspects of the interpretation of visual information through human sight itself.[3]

From simulating altered perceptual phenomenology in a virtual reality platform to its applications in NLP[12], image processing[9], and security systems, Deep Dream emerges as a transformative technology with far-reaching implications. This section meticulously examines the methodologies, findings, and implications of selected studies, providing a detailed understanding of Deep Dream's significance and potential. In a groundbreaking step towards understanding altered states of consciousness, researchers have developed an innovative tool known as the Hallucination Machine. This cutting-edge technology offers a unique window into the realm of visual hallucinations, bridging the gap between natural observation and computational simulation.

The Hallucination Machine is a convergence of two advanced technological approaches: immersive virtual reality (VR) and deep convolutional neural networks (DCNNs), specifically through an application of the Deep Dream algorithm. The integration of VR allows for the presentation of panoramic videos of natural scenes in a fully immersive environment, while the adapted Deep Dream technique transforms these videos to mimic the phenomenology of hallucinations in a manner that aligns with biological plausibility. This novel invention stands out for its ability to enable systematic and parameterizable manipulation of specific aspects of altered states of consciousness (ASCs), particularly visual hallucinations, thereby circumventing the broader systemic effects typically associated with pharmacological studies.[4]

In a novel contribution to the field of neural network-based image generation, Yin et al. [6] introduced an innovative technique called DeepInversion. This method marks a significant advancement in the utilization of deep neural networks for image creation, expanding upon existing methodologies while introducing new components for enhanced performance.

DeepInversion is distinct in its structure, comprising two critical elements: teacher logits and student logits. The teacher logits refer to the unnormalized outputs of a pre-trained neural network when presented with a specific input image. In contrast, student logits are the outcomes of training another neural network to mimic the teacher's responses. Uniquely, DeepInversion operates without relying on additional data from the original training dataset. Instead, it employs an inverted approach, starting from random noise and using the teacher network as a guide. By integrating Deep Dream into their framework, Yin et al. not only improved the image quality achievable with Deep Dream but also extended the concept of image regularization to incorporate feature distribution regularization. The efficacy of their model was rigorously tested on well-known datasets such as ImageNet and CIFAR-10, demonstrating its robustness and versatility in generating high-quality images.

## The architectures employed in constructing Deep Dream

In the study[20] Lafta R. presents a deep dream model

utilizing a convolutional neural network (CNN), specifically VGG-16. The methodology involves surveying network layers, selecting specific layers, and extracting features to maximize their impact through iterations. The Images were directly passed to the VGG16 network model, which is pretrained on a subset of the ImageNet dataset which is a dataset of images. This dataset contains more than fourteen million images divided into 21,841 classes. The subset that the VGG-16 network pre-trained on consists of 1000 classes, and each class contains more than 1000 images[11]. The researchers applied the deep dream process iteratively on both low-level and high-level layers, revealing distinct visual outcomes. The methodology encompassed image resizing, normalization, convolution, activation, and pooling operations. Layer selection from different blocks in VGG-16 was a critical step, with specific layers undergoing an iterative process of maximizing their activations through gradient ascent. This systematic review underscored the nuanced impact of layer selection on the visual attributes enhancement achieved by the deep dream technique.



Fig. Applying Deep Dream

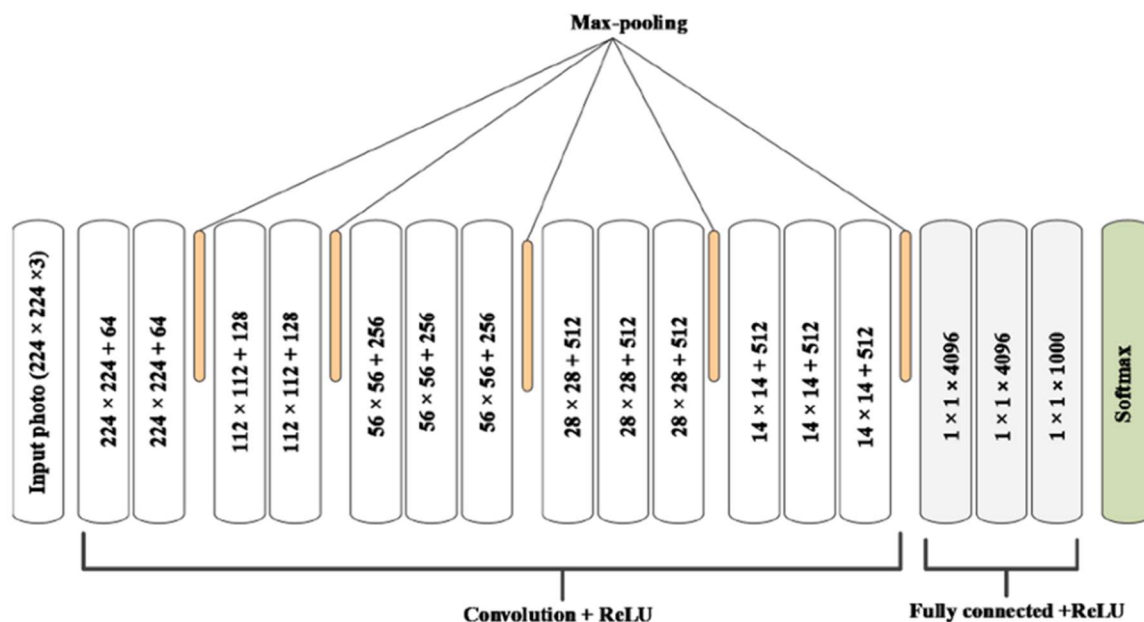


Fig. vgg16 architecture

The training process to create deep dream images involves backpropagation, associating pixels with distinct categories and minimizing categorization errors. In the subsequent layer clamping phase, the activity of nodes in a user-defined layer is constrained, and the information flow is inverted. The modification process entails iteratively updating the input image to match the features expected by the clamped layer. The resulting images exhibit a marked hallucinatory quality, reminiscent of psychedelic visual experiences documented in literature[9]. Proof-of-concept experiments validate Deep Dream's ability to simulate altered states of consciousness induced by psychedelic drugs. They employed Deep Dream in a virtual reality context, utilizing a Deep Convolutional Neural Network (DCNN) pre-trained on natural photographs. The application of Deep Dream techniques involved adjusting parameters such as layer selection and blending ratios, producing visually altered images that simulated higher-level categorical features, geometric image features, and parts of objects. Furthermore, the study demonstrated the adaptability of Deep Dream to dynamic content by applying it frame-by-frame to raw video footage, highlighting its efficacy in creating altered states of consciousness.. This comprehensive methodology, documented in the supplemental materials, establishes a robust framework for the exploration of altered perceptual experiences through the lens of Deep Dream.[9]

Deep Convolutional Neural Networks (DCNNs) play a pivotal role in the context of Deep Dream and its applications. DCNNs, being a specialized type of Neural Network, have demonstrated remarkable proficiency in various competitions related to Computer Vision and Image Processing. Their success is primarily attributed to the utilization of staged feature extraction, enabling them to autonomously learn complex representations from vast datasets. The continuous evolution of hardware technology has further fueled research in DCNNs, leading to the development of intricate and effective designs that enhance their learning capabilities [13].

In the broader landscape of deep learning architectures, Inception, as discussed by Arora et al. [14], represents a layered model where the correlation statistics of the final layer undergo analysis and clustering. This clustering results in sets of units with high correlations, and the units in subsequent layers are then interconnected with those in the preceding layers. The work of Christian Szegedy et al. [15] elaborates on the organization of units in each layer, emphasizing their correspondence to specific sizes of the input image and their arrangement into a set of bandpass filters.

The incorporation of DCNNs, such as Inception modules, aligns seamlessly with the principles underlying Deep Dream. As DCNNs progress through layers, they collect elements of increasing abstraction, with higher layers focusing on more complex features. The inception layer's structure and its hierarchical organization contribute to the network's ability to discern intricate patterns and representations[21]. The interplay of these architectural elements, combined with the features learned through backpropagation, forms the foundation for the Deep Dream algorithm's functionality. It is this capability of DCNNs to extract hierarchical features that Deep Dream leverages, allowing for the generation of visually intriguing and abstract images based on the network's learned representations.

Additionally, a study by Al-Khazraj recognized the foundational reliance on deep CNN and Inception, elucidating the significance of inception layers and their role in analyzing correlation statistics. The review highlighted the diverse applications of Deep Dream, spanning image modification, music generation, natural language processing (NLP), and visualization of hidden layers in CNN models. The authors underscored the relevance of Deep Dream in addressing contemporary challenges such as drug abuse, computer-dependent art movements, and the quest for techniques revealing processes between hidden layers in artificial intelligence research.

In exploring the complexities of Deep Convolutional Neural Networks (DCNNs), visualization algorithms play a crucial role. Deep Dream has been developed to address this need. Deep Dream operates by fixing the activity of nodes at a selected layer in the DCNN and reversing the flow of information. This reversal modifies an input image until the network stabilizes, effectively molding the image to match the features represented in the targeted layer. As a result, the image is influenced by the network's 'expectations', with the degree of alteration depending on which layer is clamped. Notably, images processed through this method often exhibit a distinct hallucinatory quality, echoing various psychedelic visual hallucinations documented in scientific literature.



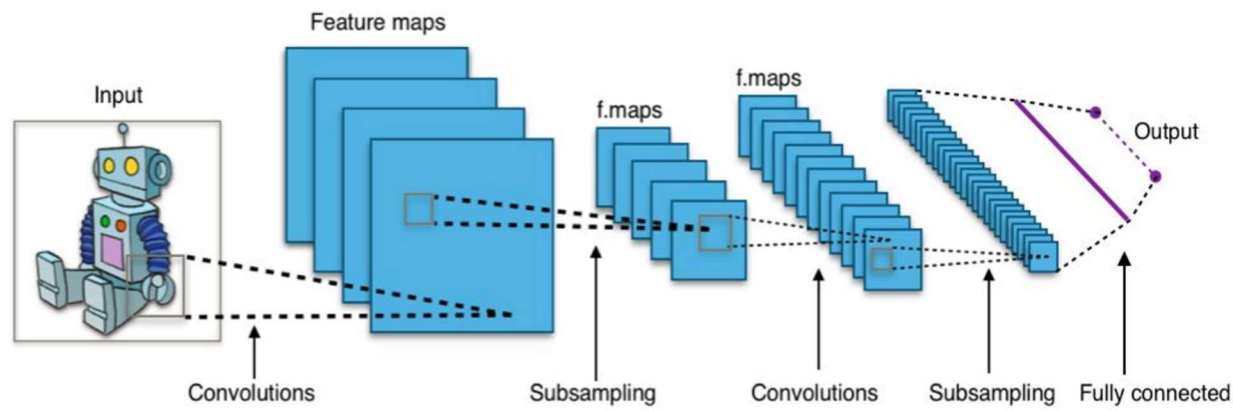


Fig 2. DCNN architecture

## Applications and Impact of DeepDream

Various applications of Deep Dream have been explored in different research papers, showcasing its versatility in diverse domains, some of these include Semi-supervised Semantic Segmentation, Centralised intelligent authentication system, producing hallucinatory images etc.

One notable application in the realm of deep learning is exemplified by the work of Hong, Noh, and Han, who introduced the Decoupled Deep Neural Network for Semi-supervised Semantic Segmentation[15]. In the context of image segmentation, where traditional image recognition networks typically provide bounding boxes for recognized objects, this innovative architecture takes a step further. While conventional networks stop at recognizing objects, Hong et al.'s approach employs backpropagation to extend the understanding of the recognized object down to the pixel level. For instance, after identifying a dog in an image, the architecture backpropagates the essence of "dog-ness" through the neural network to pinpoint the specific pixels responsible for the dog's appearance. Although this technique goes beyond the immediate scope of deep dreaming, it establishes a powerful methodology for detailed pixel-level analysis, forming

a foundation for applications in supervised segmentation networks [15].

This instance serves as an existence proof that the principles underlying Deep Dreaming can be instrumental in diverse applications, extending beyond traditional image manipulation. While the current focus is on semantic segmentation, the adaptability of these

deep learning techniques opens up possibilities for future advancements. Notably, the original Deep Dream algorithm, primarily associated with image manipulation, presents potential pathways towards addressing complex challenges, such as detailed pixel attribution and segmentation in a broader range of applications.

In a distinct domain, the study titled "Centralized Intelligent Authentication System Using Deep Learning with Deep Dream Image Algorithm" introduced a novel approach to enhance security through multi-biometric authentication[22]. The system combined vein and iris biometrics processed by a Convolutional Neural Network (CNN) with the Deep Dream algorithm. The study presents the architecture, components, and results of the proposed system, including graphical representations of activation strength variations and the performance of different optimizers. The results suggest that Adam optimizer provides higher stability in the network with respect to learning rates. The integration of Deep Dream served to refine and highlight essential features in the biometric data, contributing to the accuracy and reliability of the authentication system. The study evaluated different optimizers and presented promising results, emphasizing the potential for advanced security applications. This approach aligned with the broader objective of creating a robust and secure centralized authentication system using advanced deep learning techniques[Lightweight deep learning model to secure authentication in Mobile Cloud Computing], showcasing the versatility of Deep Dream in diverse applications across domains.

Deep dream has also been successful in its application in producing images [13], videos [9], generating music [14], [15], NLP, and also for security [22].

Mental health research and therapy : The 'deep-dream' model from the first study [1] offers profound implications for mental health research, particularly in simulating the visual hallucinations experienced by individuals with schizophrenia or under the influence of drugs. By replicating these experiences, the model provides a unique tool for research and empathy, enabling a better understanding of such conditions. The generated images could potentially be used in therapeutic settings, offering a visual medium to aid in the communication of experiences that are often challenging to articulate. In therapeutic settings, these simulated experiences can foster empathy and understanding among caregivers and medical professionals, providing them with a first-hand perspective of the patient's visual experiences. This can lead to more effective communication strategies and potentially new therapeutic approaches. Furthermore, the technology can be used to create controlled environments for exposure therapy, helping patients confront and process their hallucinations in a safe and guided manner.

**Generative Architecture:** The application of ConvNets in the field of architecture, as explored in the second study [2], demonstrates the potential of AI in the creative design process. The ability to generate architectural images without pre-established 3D models offers a new paradigm in architectural visualization and design. This technology can significantly reduce the time and resources required in the preliminary stages of design, allowing architects to explore a wider range of creative options and conceptual ideas. The study also points to potential applications in urban planning and interior design, where AI-generated images can help visualize future projects and assess the viability of various design options. **Digital Art and Creative Industries:** Both studies [1] and [3] highlight the use of AI in generating artistic images, merging traditional art with machine learning. This fusion results in unique styles and patterns, pushing the boundaries of digital art creation. Artists and designers can leverage these technologies to explore new forms of expression, creating complex and intricate designs that are not achievable through manual methods alone.

The study by Spratt [3] also emphasizes the role of AI in art history and criticism, suggesting that these technologies can be used to analyze and reinterpret historical artworks, providing new insights into their composition and style. In the creative industries, such as advertising and film, these technologies can be used to produce unique and eye-catching visuals. They offer a new toolkit for graphic designers, illustrators, and animators to enhance their work with intricate details and textures that are challenging to create manually.

Notably deep dream was also utilized in natural language processing by David Yue and Finsam Samson (2021) resented a helpful technique called SleepTalk to understand better how the black box NLP algorithms make decisions[23]. The SleepTalk technique enabled them to visualize learned representations of particular neurons in huge previously-trained networks. Since DD cannot be used in NLP models immediately because of three critical differences between visual and textual data, these differences have been listed as follows: Firstly, visual images are represented in continuous data manifolds. On the other hand, words and sub-words are discretized tokens. Secondly, the interpretability of textual material depends on the complete preservation of semantic meaning and fluency, while visual representations are more tolerant of structural disturbances. Finally, NLP models often have sequential inductive prejudices, while computer vision models are inductively prejudiced toward locality; as a result, the auto-regressive character of NLP data necessitates semantic preservation at each time step. So, to increase interpretability, they drew revelation from DD and activation maximization and applied it to NLP models. In their SleepTalk model, a neuron in the intermediate layer was chosen to be activated. The model's weights are fixed, and after that, the input embeddings are tuned using gradient ascent to improve the activity of that neuron.

## Neural Style Transfer: A Comprehensive Overview

Neural style transfer explores the dynamic field of image style conversion, a process that has been significantly advanced by the development of deep neural networks. Traditional style conversion methods faced limitations, particularly in extracting high-level abstract features from images. However, with the advent of artificial intelligence and substantial advancements in computational capabilities, researchers like Gatys et al. have propelled the field forward. They introduced convolutional neural networks (CNNs) for image style conversion, a technique that has fundamentally altered our approach to digital image processing [5].

The evolution and application of image style transfer technology, commonly referred to as Neural Style Transfer (NST), have seen remarkable growth, particularly in the realm of digital image processing. Essentially, NST involves migrating the artistic style from one image to another, ensuring that the core content characteristics of the target image are preserved while adopting a new artistic style. This technique has gained increasing popularity and application, particularly with the advent of deep learning technologies.[7] Pioneering work in this field was

conducted by Gatys et al. [7], who utilized convolutional neural network (CNN) models to achieve image style migration. This innovation marked a significant turning point and drew widespread attention to NST. For over two decades, NST has remained a prominent area of research. Prior to the integration of neural networks, style migration was primarily a domain within non-photorealistic rendering. However, the advent of neural network-based texture synthesis technology provided fresh perspectives and methodologies for style migration. Despite the impressive visual effects achieved through NST, there are still challenges and areas for improvement. One critical area of ongoing research is enhancing the efficiency of NST algorithms while maintaining the quality of the stylized images. Improving algorithmic efficiency without compromising the aesthetic quality of the output remains a key focus for researchers in this field. By dividing CNNs into deep and shallow layers, researchers have achieved a more nuanced extraction of image features. The deep layers capture the overall structure, while the shallow layers focus on style characteristics. Despite its success, this method initially relied on the resource-intensive gradient descent method, posing challenges like increased computational cost and slow generation times. To address these, subsequent improvements were proposed, including the development of a rapid stylized conversion algorithm by Justin et al., enhancing the efficiency of style transformations [5]. Furthermore, the paper delves into the sophisticated DeepInversion technique, introduced by Yin et al., which comprises two components: teacher logits and student logits. This approach, devoid of Deep Dream's extra data from the training set, starts from random noise and utilizes the teacher network as a guide to shape the resultant image.

The style of an image is captured by the correlations between the different filter responses. The feature correlations are given by the Gram Matrix  $\mathbf{G}_l \in \mathbf{R}^{(N_l \times N_l)}$ , where  $G_{l,ij}$  is the inner product between the vectorized feature maps  $i$  and  $j$  at layer  $l$ :

$$l: G_{l,ij} = \sum_k F_{l,ik} F_{l,jk}$$

By including feature correlations of multiple layers, we capture the style information of the image while ignoring the content information (e.g. objects present in scenes, global arrangements of objects). Let  $\hat{o}$  and  $\hat{g}$  be the original image and the image that is generated respectively, let  $O_l$  and  $G_l$  be their style representations in layer  $l$  respectively, the contribution of layer  $l$  to the total style loss is given by :

$$S_l(\hat{o}, \hat{g}) = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} (O_{l,ij} - G_{l,ij})^2,$$

and the total style loss between  $\hat{o}$  and  $\hat{g}$  is given by :

$$L_{\text{style}}(\hat{o}, \hat{g}) = \sum_{l=0}^L s_l S_l(\hat{o}, \hat{g})$$

where  $s_l$  is a hyperparameter that specifies the weighting factor of the contribution of each layer (note that some  $s_l$ s could be 0, indicating that we don't use the filter response of that layer [5]).

## Applications and Impact of Neural Style Transfer

The research on Neural Style Transfer, as presented by Haochen Li, highlights a range of applications that extend beyond mere artistic endeavors. [8] The exploration of NST techniques, including extensions to video content, underscores the versatility and far-reaching potential of convolutional neural networks (CNNs) in image and video processing. Here's an in-depth analysis of the applications and impact:

### Improvement in Image Processing Techniques:

The advancements in image processing techniques as developed in the study are a significant leap forward in the field of digital media. The optimized algorithm proposed by Wang and Dong [5] addresses several limitations of previous image style conversion methods, such as poor image quality and lack of diversity in outputs. The enhanced algorithm produces higher-quality images with greater variety, making it suitable for a wide range of applications, from artistic endeavors to practical image processing tasks. This improvement is particularly beneficial for industries that rely heavily on visual content, such as advertising, marketing, and entertainment. High-quality, creative images are essential in these industries to capture audience attention and convey messages effectively.

In a digital landscape increasingly driven by visual content, the ability to rapidly and efficiently process images to a high standard is invaluable. This technology can streamline workflows in graphic design, visual effects, and content creation, leading to cost savings and increased productivity. It also opens up new possibilities for automated image processing, where AI can be used to enhance and stylize images without the need for manual intervention, leading to more scalable and efficient production processes.

**Educational and Research Tool:** The research paper by Wang and Dong [5] serves as a vital educational and research tool in the field of computer science and artificial intelligence. By elucidating the capabilities and workings of deep convolutional neural networks and image style conversion, it provides valuable insights for students, educators, and researchers. This understanding is crucial as AI and machine learning become



increasingly prevalent in various fields. The study demystifies complex AI concepts, making them accessible to a broader audience and inspiring future generations to explore and innovate in these areas.

Additionally, the paper can be used as a resource in academic settings to teach the principles of machine learning, neural networks, and their applications in real-world scenarios. The practical demonstration of these technologies in image processing provides a tangible example of AI's capabilities, helping students to grasp abstract concepts more concretely. Furthermore, researchers can build upon the methodologies and findings of this study to advance the field of AI, exploring new applications and improving existing technologies. The research also highlights the interdisciplinary nature of AI, encouraging collaboration between fields such as computer science, art, psychology, and neuroscience.

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**Art and Digital Media Creation:** NST enables the fusion of artistic styles onto content images, revolutionizing digital art creation. Artists and digital media professionals can leverage NST to blend classic artistic styles with contemporary visuals, creating unique and innovative artworks. This technology democratizes artistic expression, allowing individuals without traditional artistic training to produce art that resonates with classic and modern aesthetics.

The ability to generate diverse artistic outputs rapidly makes NST a valuable tool in digital media, particularly in industries like advertising, film, and game design. It can be used to create visually captivating content, enhancing storytelling and audience engagement.

**Photorealistic Style Transfer for Photo Editing:** Photorealistic NST extends the application of style transfer to practical photo editing. It can alter the ambiance of a photo, such as changing daytime scenes to night or altering weather conditions. This application is particularly useful for professional photographers and graphic designers in enhancing or altering the mood and setting of photographs without extensive manual editing.

**Video Processing and Enhancement:** Extending NST to videos opens opportunities in the film and entertainment industry. It allows for the application of consistent artistic styles across frames, maintaining temporal coherence. This capability can be used in movie production, animation, and virtual reality to create stylized sequences that are visually cohesive and compelling.

**Education and Research in Computer Vision:** The study of NST contributes significantly to the field of computer vision and deep learning. It provides a practical application to understand the capabilities of CNNs in recognizing and replicating styles, thus serving as an educational tool for students and researchers in these fields.

Research in NST deepens the understanding of visual intelligence in AI, demonstrating how neural networks interpret and recreate artistic styles. This knowledge can be applied to develop more advanced AI systems capable of complex visual understanding and creativity.

**Style Transfer in Real-Time Applications:** The development of real-time NST algorithms has significant implications for mobile and web applications. It enables the integration of style transfer features in apps, allowing users to transform their photos and videos instantly with various artistic styles. This real-time capability can lead to the creation of new interactive experiences in social media platforms, where users can stylize their content on-the-go, enhancing user engagement and content diversity.

**Understanding and Interpreting Artistic Styles:** NST technology offers new ways to study and interpret artistic styles. By analyzing how neural networks capture and replicate styles, art historians and scholars can gain insights into the defining elements of various art movements and individual artists.

**Artistic Image Creation and Enhancement:** The research by Lingling Wang and Xingguang Dong [5] ushers in a novel era in digital art creation, leveraging Deep Dream technology to transform ordinary images into unique artistic renderings. This method, which employs deep convolutional neural networks, allows for the generation of images with enhanced textures, clarity, and richness, pushing the boundaries of traditional digital art. Artists and designers can now reimagine their work, infusing it with abstract qualities and complex patterns that are characteristic of deep learning-based image manipulation. This technology is particularly significant in the context of the growing digital art market, where the demand for unique and visually striking artwork is constantly increasing. Furthermore, the application of this technology extends beyond the

realm of art into commercial sectors like advertising, marketing, and entertainment, where visually compelling content is key. Businesses can utilize these advanced image processing techniques to create captivating advertisements, enhance brand visuals, and produce innovative content that stands out in a crowded digital landscape. This not only revolutionizes the way companies approach visual branding but also opens up new avenues for creative expression in commercial settings.



Fig. Applying Neural Style Transfer

## Applications of Neural Style Transfer and Deep Dream Synthesis

A few studies also used VGG19 and Inception V3 to combine deep dream and neural style transfer to simulate hallucinations among psychiatric patients and drug addicts [19]. They utilized Gram matrix, a vital process for style transfer. The loss was minimized in style transfer while maximized in a deep dream using gradient descent for the first case and gradient ascent for the second. It was found that different images produce different loss values depending on the degree of clarity of those images. Distorted images have higher loss values in NST and lower loss values with deep dreams. The opposite happened for the clear images.

**Educational Tools and Demonstrations:** The detailed analysis of image recognition processes, as discussed in [3], provides valuable insights into the functioning of neural networks. These insights can be used to develop educational tools that explain the intricacies of machine learning and AI to a broader audience.

Understanding these technologies is crucial for future generations, as AI continues to become an integral part of various industries and everyday life. Interactive tools and visual demonstrations based on Deep Dream and NST can make complex concepts in AI more accessible and engaging, potentially inspiring future generations to pursue careers in science and technology.

**Simulation of Visual Experiences:** The study's contributions to simulating visual experiences have profound implications in psychological and neurological research. By replicating the visual effects of hallucinations or altered states of perception, the technology provides a window into the experiences of

individuals with specific neurological conditions, such as schizophrenia or those under the influence of psychedelic substances. This capability is invaluable in mental health research, offering a unique perspective into the subjective experiences of patients, which are often challenging to articulate or understand through conventional means.

the practical applications of this technology in mental health are manifold. It can serve as a tool for therapists and psychologists to better comprehend and empathize with their patients' experiences, leading to more effective treatment strategies. Additionally, it can be employed in educational settings to train healthcare professionals, providing them with a simulated experience of various psychological states. This experiential learning approach can enhance their understanding and improve patient care. Moreover, the technology can aid in destigmatizing mental health conditions by allowing a broader audience to experience and recognize the reality of these conditions, fostering greater empathy and awareness.

## Critique of Existing Approaches

A primary concern in existing Deep Dream studies is the quality of generated images. Many of these studies struggle with producing images that effectively balance abstraction with necessary detail, which is crucial for realistic hallucinatory experiences. This limitation is significant, particularly in contexts where high-quality, clear images are essential for the intended application, such as simulating the experiences of individuals with schizophrenia or drug-induced hallucinations.[1] Another notable gap in previous works is the absence of robust evaluation metrics. The lack of quantitative assessments, such as the Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), or Normalized Cross-Correlation (NCC), has been a common issue. This omission hinders the ability to objectively evaluate the performance and quality of the generated images, making it challenging to compare different models or improvements effectively. The implementation of Deep Dream in prior studies has often been restricted to using a limited number of CNN architectures. This approach does not fully explore the potential of Deep Dream models, as different architectures have unique features and capabilities that can significantly impact the resulting images.

The study by Suzuki et al. successfully merges virtual reality and machine learning to simulate visual hallucinations, particularly those induced by psychedelic drugs[9]. By leveraging the Deep Dream algorithm, the researchers conduct proof-of-concept experiments, showcasing the algorithm's ability to effectively simulate altered states of consciousness. A

notable strength lies in the use of backpropagation within Deep Dream to alter input images, minimizing categorization errors and contributing to the hallucinatory quality of the generated visuals. However, the subjective nature of hallucinations and the challenges in accurately replicating them through Deep Dream introduce a level of uncertainty. Additionally, while the study briefly mentions adjustments to parameters like layer selection and blending ratios, a more in-depth exploration of their impact on hallucination quality could strengthen the analysis. The computational complexity associated with frame-by-frame application of Deep Dream to raw video footage might limit its real-time applications, warranting further exploration and potential optimization strategies.

One primary critique is the reliance on datasets that are not specifically tailored for architectural purposes. The authors note that the use of general datasets, like GoogleLeNet trained on ImageNet or MIT Places Dataset, leads to biases in the generated images. For instance, the overrepresentation of animals in ImageNet results in Deep Dream algorithms producing animal-like features in architectural renderings. This mismatch underscores the need for more specialized datasets that are better aligned with architectural elements and styles.[2] Another significant limitation is the lack of contextual understanding in the generated images. The authors observe that current ConvNet models often produce architectural images that lack a coherent structure, with elements appearing unrelated and floating without a sense of layout or context. This issue highlights the need for ConvNet architectures that can better understand and incorporate the spatial and contextual aspects of architecture. The paper also critiques the Deep Dream algorithm's tendency to produce psychedelic, unclear images that are difficult to recognize and lack realism. This issue is attributed to the algorithm's focus on amplifying features encoded in the ConvNet, leading to exaggerated and often unrealistic visual outputs. The need for a more balanced approach that can generate images with a realistic representation of architectural elements is emphasized. Furthermore, the authors discuss the limitations of current neural style transfer algorithms when applied to architecture. They note that these algorithms often fail to capture the essence of architectural styles and instead merely apply patterns and materials to the content image. This superficial application of style highlights the need for algorithms that can more deeply understand and replicate the nuances of architectural design. Addressing these challenges is crucial for advancing the field and realizing the full potential of ConvNets in architectural imagination and design.

The exploration of image style conversion, particularly through the use of convolutional neural networks (CNNs), has seen significant advancements, yet it also faces certain limitations and challenges that need to be addressed. The existing approaches, while innovative, reveal critical areas for improvement in achieving more refined and realistic image transformations.

One primary critique of traditional style conversion algorithms is their inability to extract high-level abstract features effectively from the target image [5]. This limitation results in a narrowed scope of application, primarily confining the output to abstract painting styles. Such a restriction hampers the versatility and applicability of the algorithms in broader artistic and practical contexts. The need for more comprehensive feature extraction is crucial for generating images that are not only stylistically varied but also maintain a high degree of realism and detail.

In the examination of the Deep Dream technique using the VGG-16 model[20], Al-Khazraji and Abbas provide a detailed methodology for applying Deep Dream, shedding light on layer selection, image resizing, and normalization processes. The study's comparative analysis against other architectures enriches our understanding of Deep Dream's performance in different contexts, extending its applications beyond image modification to hallucination simulation and understanding neural network learning. However, potential subjective biases in hallucination interpretation and overfitting to specific layers need careful consideration. While VGG-16 is a powerful model, a broader comparative analysis incorporating more recent architectures could provide a more comprehensive understanding of Deep Dream's capabilities. Suggestions include additional experiments to assess the generalizability of hallucination patterns and an extension of the comparative analysis to include newer architectures reflecting advancements in deep learning. Taking a systematic review approach, Al-Khazraji[20] and colleagues offer a comprehensive examination of Deep Dream applications across various domains. The overview of Deep Dream's evolution and its diverse applications enriches our understanding of its trajectory. The identification of emerging trends and future directions provides valuable insights. However, the study could benefit from more in-depth analyses of individual applications, including challenges faced and potential biases introduced. Additionally, a more nuanced critique of existing approaches could deepen the review's overall impact. Suggestions for improvement encompass the inclusion of case studies for each application domain and an expanded critique addressing specific limitations and challenges identified in the reviewed papers.

Further, the pioneering work by Gatys and others on using CNNs for style conversion, while groundbreaking, has its own set of challenges. The method's reliance on the gradient descent approach for updating pixel values of the source image is computationally intensive, leading to increased resource usage and cost [5]. This process results in slow generation progress, making it less feasible for real-time applications or situations where computational resources are limited. Subsequent improvements, such as the rapid stylized conversion algorithm proposed by Justin et al. [2], have aimed to address these issues by establishing a feed-forward network that speeds up the transformation process. However, while these advancements have improved generation speed, questions remain about the depth and quality of the style transfer, especially when replicating more intricate and nuanced styles.

The critique extends to the field's exploration of CNNs for image style conversion, as highlighted in the discussion about the convolutional calculation process and the role of the convolutional and pooling layers [5]. The process, while effective in extracting certain features, often contains redundant data, leading to inefficiencies in the network's learning and output generation. Moreover, the existing approaches sometimes result in outputs that are either too abstract or lack clarity, necessitating further optimization to produce images that are aesthetically pleasing and widely acceptable to a broader audience.

## Emerging Trends and Future Directions

Emerging trends in the realm of Deep Dream are poised to shape the future trajectory of this technology. The exploration of more advanced architectures stands out as a key trend, reflecting the constant evolution of deep learning models [15]. Researchers are likely to delve into architectures that surpass existing frameworks, incorporating advanced features and enhancing the overall capabilities of Deep Dream. Moreover, the integration of attention mechanisms represents a potential avenue for future exploration. Attention mechanisms can significantly impact the interpretability of Deep Dream-generated content, allowing for more fine-grained control over the focus and distribution of features in hallucinated images.

In the study [1], a novel approach that synergizes Deep Dream and NST using various CNN architectures, represents a significant leap in digital image processing. This hybrid model's ability to mimic complex hallucinatory experiences, pertinent to conditions like schizophrenia and drug addiction, is not just a technical accomplishment but also a potential tool for mental health research. It offers a digital means to

visualize and understand the perceptual distortions experienced in these conditions, providing a unique perspective for psychological studies and therapies. Furthermore, the model's application in creating decorative and artistically enriched images opens up new possibilities in digital art, indicating a trend towards more personalized and emotionally resonant digital creations.

The paper [2] pushes the envelope in generative architecture, exploring how ConvNets can autonomously generate architectural designs. This approach could revolutionize architectural visualization, reducing time and resources in the design process and enabling a more exploratory and creative approach to architectural conception. The introduction of 'shape grammar' in the study aligns AI capabilities with human creative processes, suggesting a future where AI not only assists but actively contributes to creative design. This could lead to new architectural styles and forms, previously unimagined, expanding the scope of architectural innovation.

"Dream Formulations and Deep Neural Networks: Humanistic Themes in the Iconology of the Machine Learned Image" [3] by Emily L. Spratt brings a unique interdisciplinary perspective, bridging the gap between art history, AI, and image recognition. This paper underscores the role AI could play in redefining our understanding of art and its history. By employing AI tools like DeepDream and Grad-CAM, the study suggests a future where machine learning is integral to analyzing and interpreting art, offering new insights into artistic styles and movements. This interdisciplinary approach could lead to a more nuanced understanding of art, transcending traditional methodologies and potentially revolutionizing the field of art history.

These studies collectively illustrate a trend towards more sophisticated, nuanced, and empathetic applications of AI in art and architecture. The future directions indicated by these papers include the development of more advanced algorithms for enhanced feature extraction, producing outputs that are more realistic and aesthetically pleasing. In addition, there is a growing trend towards using synthetic data for training machine learning models, indicating a broader application of AI-generated content in various domains. Addressing interpretability challenges is another forefront for future research endeavors. The inherently subjective nature of hallucinations and the interpretability of the features generated by

Deep Dream presents ongoing challenges. Future studies might explore methodologies to enhance the transparency and interpretability of Deep Dream outputs, enabling a more profound understanding of the

hallucination process. This could involve developing metrics or frameworks for quantifying the reliability and coherence of hallucinated features, providing a more robust basis for analysis and interpretation.[9]

Expanding the applications of Deep Dream into diverse domains is a promising future direction. While current applications span image modification, hallucination simulation, and artistic creation, the potential for extending Deep Dream into medical imaging, video processing, and other unexplored areas remains largely untapped. Research efforts may focus on adapting Deep Dream to address specific challenges in medical imaging, such as disease detection or image enhancement. Additionally, the interplay of Deep Dream with various neural network structures opens doors for innovative applications, with continuous advancements anticipated in harnessing hallucination techniques for practical purposes beyond the current scope.

Continuous advancements in hardware technology may also influence the future landscape of Deep Dream. As hardware capabilities evolve, the computational demands associated with Deep Dream applications, particularly in real-time scenarios, could be alleviated[12]. This could unlock new possibilities for deploying Deep Dream in interactive settings, such as virtual reality environments, where real-time hallucination generation could enhance user experiences. Researchers might explore optimizations or adaptations to Deep Dream algorithms to align with the evolving landscape of hardware technologies, ensuring scalability and efficiency in diverse computing environments.

In digital art, the convergence of CNNs, Deep Dream, and NST marks a new era of creative expression. Artists and designers now have at their disposal tools that can synthesize and manipulate images in ways previously unattainable. These technologies enable the creation of visuals with enhanced depth, complexity, and aesthetic appeal. For instance, NST allows for the blending of distinct artistic styles onto existing images, enabling the fusion of classical and contemporary art forms. Deep Dream, on the other hand, pushes the boundaries of imagination by transforming ordinary images into surreal, dream-like creations. This melding of AI and art not only expands the artist's toolkit but also invites a redefinition of art itself, opening up discussions about the role of AI in creative processes and the nature of machine-generated art.

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These studies collectively illustrate a trend towards more sophisticated, nuanced, and empathetic applications of AI in art and architecture. The future directions indicated by these papers include the development of more advanced algorithms for enhanced feature extraction, producing outputs that are more realistic and aesthetically pleasing. In addition, there is a growing trend towards using synthetic data for training machine learning models, indicating a broader application of AI-generated content in various domains. The advancements in image processing and artistic image generation, as evidenced by the comprehensive study "Image Style Conversion using Deep Convolutional Neural Network" by Lingling Wang and Xingguang Dong [5], signify a transformative trend in the application of artificial intelligence. This research highlights the convergence of sophisticated image processing techniques with deep learning, setting the stage for future innovations in the field. Future research in this area could focus on developing more efficient



neural network architectures. As the complexity and size of datasets continue to grow, the ability to process this data quickly and accurately becomes increasingly important. More efficient architectures could process large datasets at a faster rate, without compromising the quality of the output. This is particularly crucial in fields like satellite imagery analysis, where vast amounts of data need to be processed promptly to be useful. An additional promising avenue is the use of advanced image generation techniques for data augmentation. By generating a diverse array of images, machine learning models can be trained to recognize a broader range of patterns and styles, enhancing their accuracy and applicability in various fields. This approach could be particularly beneficial in sectors like medical imaging, where diverse and realistic datasets are crucial for training effective diagnostic tools.

The focus of the study on optimizing the Deep Dream algorithm suggests a future where images not only exhibit artistic appeal but also maintain high fidelity to their original sources. The potential for further refining these algorithms opens doors to generating images with higher resolutions and more precise feature representations. Future research could focus on developing more efficient neural network architectures and training methods capable of processing large datasets quickly while improving the quality of the output.[2] Additionally, improving training methods for these neural networks is a vital area of focus. Effective training methods are essential for the networks to accurately recognize and replicate intricate patterns and styles in images. Advances in training methods could include the use of more diverse datasets to train the networks, allowing them to recognize a wider range of image styles and features.

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## Conclusion

In conclusion, these studies collectively underscore the transformative impact of AI in art, architecture, and the broader creative industry. They not only contribute to the advancement of each field but also exemplify the potential of AI to enrich human understanding and creativity. As we continue to explore and refine these technologies, we can expect a future where AI plays a pivotal role in expanding the boundaries of artistic and architectural possibilities. The innovative approach of the 'deep-dream' model [1] amalgamates multiple CNN architectures to produce intricate and aesthetically pleasing artistic images. This model's ability to replicate complex hallucinatory experiences showcases the potential of AI in empathizing and understanding mental health conditions like schizophrenia and drug addiction. Moreover, it opens up new possibilities for creative expression in digital art, underlining the broad applicability of these technologies. These studies also address technical aspects and challenges in the field, such as optimizing the Deep Dream algorithm for better resolution and fidelity [5], and tackling issues like redundancy and efficiency in neural network architectures. These technical enhancements are crucial for the broader application and effectiveness of these AI techniques. Looking ahead, the potential applications of Deep Dream and NST extend beyond art and architecture into areas like advertising, film production, education, and even therapeutic settings. The continued refinement of these technologies promises further innovations and a deeper integration of AI in various creative and practical domains.

This review based on 23 research articles, reveals the versatile applications of Deep Dream and Neural Style Transfer, from image manipulation to security systems and virtual reality. Methodologically robust, it addresses fundamental questions and critiques existing approaches, suggesting improvements for future studies. The critique identifies strengths and challenges, including the subjective nature of hallucinations and computational complexities. Looking ahead, emerging trends point to advanced architectures and attention mechanisms, aiming for better interpretability. Future directions emphasize expanding applications into medical imaging and video processing, guided by considerations for evolving hardware technologies. Overall, this review contributes to a profound understanding of Deep Dream and Neural Style Transfer's potential across diverse domains and applications.

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