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Modern Heritage Restoration Using GANs: Insights into Polymer–Composite Aging

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Abstract

In the Era of modernization, accomplish a Net Zero goes beyond installing more solar panels and wind turbines but we also need to make sure their lifespan possibility. With the help of Polymer compound for protective coatings to find the applications in solar cells, turbine blades, batteries that degrade over the course of time causes by sun exposure, moisture, and pollution. However, due to these same types of degradation have seen in the protective varnishes and materials used in paintings and sculptures. In the context there is technology plays a main role with the machine learning plays a main role for transitioning the approach in restoration work both for artwork as well as energy infrastructure which has traditionally depended on skilled manual inspection. The modern artwork restoration methods that use the algorithms of machine learning with a specific emphasis on CNNs, GANs, and reinforcement learning techniques. But there is challenges also arise which include the problem in fetching quality training data, computation method for a power needed substantial and we have to be careful about ethical issues especially when it comes to maintaining genuineness. The scientific tools of this study examine how varnishes and coatings on artworks break down over time and how polymer composites in renewable energy devices age and wear out. The true value of this study lies in assessing ML approaches on diverse datasets ranging from centuries old painting to modern solar panels in order for us to construct more robust algorithms to minimize waste and extend equipment life, directly advancing the net-zero clean energy transition.

Keywords: Machine learning, deep learning, artificial intelligence, cultural heritage, restoration, CNN

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INTRODUCTION

Similar battles are being fought by solar panels aging in the desert sun and renaissance paintings fading in museum galleries. The prolonged exposure to UV radiation, humidity swings, and environmental pollutants gradually breaks down polymer-based materials namely protective coatings, binders, composite structures on which both of these rely upon. Over the past decade, materials scientists working on renewable energy have developed sophisticated polymer composites and UV-resistant coatings to help solar panels and wind turbines survive harsh conditions. When dealing with polymer-based composites in cultural heritage objects, the primary goal of restoration is to stabilize the artifact's structural and aesthetic integrity while prolonging its lifespan against environmental stress. This requires a delicate balance of preventing further material breakdown while strictly preserving the historical essence and authenticity of the artwork. The primary mechanisms of aging and degradation in these materials are largely driven by environmental exposure. Specifically, prolonged exposure to UV radiation induces photo-oxidation, while severe humidity swings and environmental pollutants lead to hydrolytic and chemical breakdown. In polymer-based protective coatings, varnishes, binders, and composite structures, these continuous stressors gradually break down the polymer chains, resulting in micro-cracking, loss of structural cohesion, and visible fading. Furthermore, as highlighted by recent material science literature, the specific structural makeup of a composite—such as the natural or synthetic reinforcing fibers, hybridization techniques, and chemical pre-treatments—significantly dictates its degradation profile. When the outer polymer matrix begins to wear due to sun exposure or moisture, the underlying fiber structure can become vulnerable, accelerating mechanical failure. Understanding how these materials deteriorate under environmental stress at the microstructural level is essential for developing advanced algorithms that can accurately predict decay and guide precise restoration interventions. In additional, these similar things in innovations are finding their relevance and significance in the art conservation, where conservators need similar protective solutions. The connection of renewable energy engineering and cultural preservation now offers tangible, real-world solutions rather than just theoretical insights. Additionally, we drive towards net zero targets, we must ensure that solar and wind installations run as long as possible. Simultaneously, we need to preserve the historical treasures for the future and the machine learning is becoming a vital tool to address both critical challenges. Traditional approaches have always been labor-intensive. Just like you need qualified conservators to look for signs of deterioration in paintings, you need experienced specialists to check solar arrays for hotspots and micro cracks. These inspections are capital intensive, take time, and suffer from the constraint of subjectivity because of human judgment which can vary from one expert to another. Machine learning provides a robust codified system having the ability to scan multitudes of solar and wind installations [2] and point out those needing immediate attention or an algorithm that can analyze high-resolution images of a deteriorating fresco and maps exactly where intervention is needed. Machine learning approaches particularly Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and reinforcement learning models have demonstrated great outcomes to solve these problems. The main advantage lies in their capacity to process humongous datasets and learning to distinguish between normal wear and serious damage. To enabling data-driven, sequential decision-making, reinforcement learning optimizes the operational lifecycle of solar assets. The actual benefit here isn't just automation it's scalability and consistency. A solar farm might have fifty thousand panels. In addition to automation, ML also provides us with the scalability and consistency. For example, when dealing with thousands of solar panels or museum artifacts, human labor cannot consistently provide the same level of detailed, efficient, and objective inspection training. If you train a crack-detection system only on images from one type of solar panel in one climate, it might be failed spectacularly when deployed in different conditions. The same applies for artwork restoration: an algorithm trained on European oil paintings might not work well on Asian ink scrolls. When the goal is sustainability, we should have striven towards efficient use of computation, as training these models need serious computation cost which translates to energy consumption and cost. And then there are the ethical questions, which we'll come back to later.

LITERATURE REVIEW

Jaya Vineela P., Sravani M., and Anuradha G. execute a study about the deployment of deep learning algorithms along with explainable AI frameworks for detection of monuments. This would help to support tourism and preserve cultural heritage. The research study brings to light the difficult recognition of monuments, caused by complex architectural patterns through the application of VGGNET along with ResNet and Inception. The study demonstrates how satellite images can detect distant monuments and through XAI tools LIME and SHAP the system provides explanation to stakeholders including tourists and local officials during AI-assisted decisions. Jaya Vineela P. et al. analyze monument identification techniques [1] in their study titled "A Comprehensive Study on Monument Recognition Techniques and its Integration with Explainable AI." The research implements the CNN network type through ResNet and VGGNET structures to identify and categorize distinctive monument elements. A core aspect of this research involves the adoption of XAI methods LIME and SHAP that make the AI system explain its decision logic and create outputs that remain transparent and easy to interpret. The technique supports heritage conservation through better monument detection along with educational and touristic data that must be accessible and understandable [3].

Artificial Intelligence image generators find application in architectural education while locating their use in the teaching of architectural history according to the study "Exploring the Potentials of Artificial Intelligence Image Generators for Educating the History of Architecture." The research project combines Leonardo AI software with student workshops for educational experiments about technology effects on educational performance. Artificial intelligence carries the enormous potential to boost the learning and promote students; comprehension and visualization of architectural topics through various angles. These findings indicate that academic tool policies should establish guidelines for the effective use of these tools in educational settings [4]. The study encompasses the "Heritage Identification of Monuments using Deep Learning Techniques" by Jindam et al. examines CNN applications for historical site identification, they use satellite data to do so. A variety of preprocessing and feature extraction techniques, such as Mean Standard Deviation (MSD) and Local Binary Patterns (LBP) are used to create the image data for CNN models. The identification of the cultural sites becomes very easy for visual features create accurate classification results. It also addresses the merits and demerits of using CNN applications for cultural heritage preservation. The method shows encouraging outcomes although researchers need to work on additional development to boost accuracy and resolve educational and preservation application difficulties [5] This study examines how deep learning and machine learning (ML) techniques perform virtual restoration of deteriorated artworks like sculptures and paintings alongside drawings. Research proves that CNNs and GANs successfully analyze and reconstruct patterns and textures along with colors [7]. The implementation of AI technologies in restoration enables improved efficiency as well as economical savings and fewer mistakes made by human workers. The research identifies two major ethical obstacles involving training data prejudice and legal resistance to maintain honest artistic origin. The research supports controlled AI application to protect restored artifacts from manipulation while exploring possible uses of technology for making important cultural collections accessible digitally.

The paper promotes using AI correctly to verify historical accuracy of restoration projects yet studies ways AI might advance public access through digital archives and virtual gallery displays [8] Varun Gupta et al introduce in "Restoration of Artwork Using Deep Neural Networks" two simultaneous approaches for executing virtual artwork restoration through extensive learning methods. The method uses U-Net architecture and partial convolutions for image inpainting with Mask R-CNN automatic mask synthesis to deal with various artwork damage patterns while preventing restoration from affecting clean zones. The model demonstrates strong performance in tackling extensive damaged regions but its computations require significant resources and trained datasets need to have optimal quality. The analysis demonstrates that this method offers digital restoration potential for artwork maintenance as supported by numerical measurements and expert judgment [9]. "Using Machine Learning to Classify Art Style in Naturalism and Realism" examines ML techniques for differentiating these closely related art forms. Meticulousness precision is attained by models like LeNet, ResNet-50, and MobileNetV3 with MobileNetV3 outperforming the other models with 95% accuracy. The study points out the practicality in refining and improving the curatorial and art categorization procedures while indicating dataset limitation. So as to get better results research should work on comparatively larger datasets and try to implement more advanced ML models. The study "Image Inpainting and Classification Agent Training Based on Reinforcement Learning and Generative Models with Attention Mechanism" is one such advanced method that takes into account the previous presumptions for better results. It merges both Reinforcement Learning and Generative Adversarial Networks to achieve high-quality and detailed image restoration [10]. Advanced prompting-based restoration frameworks further improve degradation perception and reconstruction quality [6]. By incorporating models designed for diverse damage levels and leveraging attention mechanisms for detail retention, this framework enhances restoration precision. Nevertheless, the integration of Reinforcement Learning agents with GANs presents difficulties in maintaining stable training. Overall, the study highlights the pivotal role of advanced machine learning techniques in advancing image restoration "Digital Restoration of Cultural Heritage With Data-Driven Computing: A Survey" paper provides us with a comprehensive analysis of advanced, data based techniques which used to restore cultural artifacts.[11]. The authors explain how GANs is helpful to use to restore the absent parts of artifacts while maintaining its authenticity. The work strains the importance of stabilizing technological advancements with the goal to preserve the historical essence of cultural artifacts [12]. The ultimate goal of this is technological integration to guarantee that the authenticity of ancient structures is maintained and their lifespan is extended [13]. Bishwa Ranjan Das and his team investigated the application of artificial intelligence in safeguarding cultural and historical artifacts, particularly for managing linguistic archives. Their contributions highlights how AI enhances the accessibility and preservation of these valuable resources. Preferable on digital restoration, Shutian Zhou and Yanhong Xie apply machine learning and filtering techniques to fix damaged murals [14], ensuring the artwork's original style is maintained. The technique helps to attain impressive repair accuracy (over 95.7%), but it demands notable resources and premium training data [15] Kholoud Ghaith point outs the significance of preserving the authenticity of the culture while using artificial intelligence, reporting biases in training dataset, and maintaining balance of the technical modernization with ethical liabilities. The work brainstorms over AI methodologies for cultural historic preservation, restoration and prediction of artwork deterioration. A. Kumar concluded in depth review and analysis of advanced AI based artwork preservation [16].

Li and the team investigated the twin technology usage to monitor and manage the location [17]. By replicating the heritage site, digitally enabling twin technique for real-time tracking of potential hazards and ecological factors. The research practically studies the case the blends the digital twin technology into art conservation projects [18] Brown, M., and Lee, A. investigate the use of deep learning to improve conservation methods, such as reconstructing damaged portions of historical objects and predicting the original colors and details of faded artifacts [19] Garcia, S., & Kumar, R. focused on using CNNs for analyzing imagery of cultural heritage sites, this paper presents a framework for monitoring deterioration and suggesting preventive measures for long-term preservation. [20] Nguyen, H., & Torres, C. present a methodology combining machine learning with 3D scanning technology for the digital restoration and recreation of damaged archaeological artifacts. Deep learning models have proved to work efficiently for deep fake datasets [21], anomaly detection [24] and sentiment analysis [22]. YOLO models are used for vehicle detection [26]. Advanced machine learning models are used for crowdfunding success evaluation and security enforcement [23] and for digitalization of objects using augmented reality [25]. CNN based models are used for generating handwritten notes from voice [27]

Recent studies have investigated the chemical, thermal, and environmental aging mechanisms in polymer-based composites relevant to conservation science and material durability. These include investigations into polymer oxidation pathways, UV-induced degradation, mechanical fatigue, and structural transformation under environmental stress conditions [28–33]. These studies provide the material-science foundation necessary for developing GAN-based predictive aging frameworks.

METHODOLOGY

This study aims to leverage machine learning techniques to improve the conservation and restoration of cultural heritage artifacts. The primary objectives include automating the restoration of damaged artwork, forecasting deterioration trends, and reconstructing lost or faded details of artifacts. High-resolution image collection of artifacts and heritage sites included environmental data about temperature, humidity and air quality because these factors affect heritage material conditions. The images needed normalization modifications together with augmentation methods before starting the analysis process. Technical adjustments of scaling together with rotation after flipping need to be implemented for images before they become suitable inputs to machine learning models. The system operated through supervised and unsupervised learning methods along with using 3D artifact scans in restoration procedures and historical records from past conservation for model training. The application of Convolutional Neural Networks (CNNs) worked on image restoration duties including segmentation and reconstruction of damaged painting and sculpture areas. To effectively simulate the long-term degradation of polymer composites, Generative Adversarial Networks (GANs) require training on comprehensive, high-resolution datasets that showcase materials across multiple stages of decay. The training relies on a continuous adversarial loop between two neural networks: a generator and a discriminator. The generator network attempts to synthesize highly realistic images of material wear—such as progressive micro-cracking, structural breakdown, and color fading—by applying real-world degradation variables. Meanwhile, the discriminator network critically evaluates these synthetic outputs by comparing them against actual, physically degraded material samples. Through this iterative process, the GAN learns the exact trajectory of polymer deterioration. Ultimately, this allows the algorithm to accurately forecast future aging patterns and generate photorealistic reconstructions of damaged artifacts, effectively restoring missing or degraded sections while preserving the object's authentic appearance. GANs produced photorealistic reconstruction results for lost artwork outlines by matching the original appearance of the artwork. The detection of unrecognizable artifact deterioration patterns and suspicious anomalies during unsupervised tasks was performed through the use of autoencoders. Tests in simulated environments used reinforcement learning to create better preservation strategies for artifacts over long-term periods. Additionally, the evaluation processes utilized different performance measurements. Image restoration quality assessment relied on Peak Signal-to-Noise Ratio (PSNR) in conjunction with Structural Similarity Index (SSIM) because these metrics evaluate how well the restored images compare to originals. The evaluation of model effectiveness in detecting conservation needs and deteriorating signs utilized accuracy and F1-score metrics in addition to PSNR and SSIM metrics for image restoration quality assessment.

RESULT

Experimental Setup

The training of restoration models took place by using high-resolution historical artwork datasets. Damaged regions were manually annotated or algorithmically generated to simulate real-world degradation**.**

- *Dataset:* Historical Places dataset and IHIRD dataset: Framework: TensorFlow with GPU acceleration.
- *Models:* U-Net with GANs (Baseline), MFR-GAN: Multi- Stage Feature Reasoning GAN,
- *PromptRestorer:* Dual- branch restoration framework.

The following metrics were used:

- *Peak Signal-to-Noise Ratio (PSNR):* Measures image restoration quality.
- *Structural Similarity Index (SSIM):* Evaluates structural similarity between original and restored images.,
- *Inference Time:* Time taken for restoration per image.
- *U-Net with GANs:* Restored textures lacked finer details, but structural integrity was good.
- *MFR-GAN:* Excellent in large damaged areas, the most realistic restoration was achieved with precise color and texture recovery.
- *Prompt Restorer:* Focused on handling localized degradation; it achieves high precision but needs more processing power.

Prior to undergoing further post-processing and augmentation techniques, the images required normalization processing. PromptRestorer's practical application through the use of pre-trained models is limited when it is operated using dual networks, which results in significant training processing requirements. The Prompt Restorer still has a number of limitations, but it currently shows significant progress.

Table 1. Model- Performance comparison of restoration models using PSNR, SSIM, and inference time.

Model	PSNR	SSIM	Interference time	Remarks
U-Net+GAN	28.7	0.89	2.1	Baseline performance
MFR-GAN	33.1	0.94	3.5	Best balance
PromptResto rer	31.6	0.93	4.0	Focused on sevre damages

Table 2. Model Comparison- Comparative analysis of machine learning techniques for cultural heritage restoration.

Model	Primary use case	Pros	Cons	Best suited for
CNN	Artifact restoration, segmentation	High accuracy for image-based tasks, automated feature extraction	Requires large annotated datasets	Restoring or predicting degradation in artwork
GAN	Artifact image generation, missing data restoration	High-quality results for complex image generation, natural- looking outputs	Can be hard to train, sensitive to hyperparameters	Generating missing parts of historical art
Reinforcement learning	Restoration simulation, optimization of conservation strategies	Can simulate real-world processes and optimize long-term strategies	Requires complex environment setups and computational resources	Optimizing conservation strategies over time
Autoencoder	Artifact image generation, missing data restoration	Efficient for unsupervised learning, anomaly detection	May lack the detail required for restoration tasks	Detecting anomalies in artifact degradation

In this paper Table 1 presents a comparative evaluation of different restoration models, namely U-Net with GAN, MFR-GAN, and PromptRestorer, using key performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and inference time.

Table 2 provides a comparative analysis of various machine learning techniques—CNN, GAN, Reinforcement Learning, and Autoencoders—used in cultural heritage restoration. Each model is evaluated based on its primary use case, advantages, limitations, and suitability for specific restoration tasks. CNNs are highly effective for image-based restoration and segmentation tasks due to their strong feature extraction capabilities but require large annotated datasets.

DISCUSSION

Artificial Intelligence and Machine Learning has reconstructed the restoration of cultural heritage and artworks by furnishing precise and scalable results. MFR-GAN safeguards texture and structure in the cultural and heritage artworks, concluding to improved image quality, as depicted by enhancements in PSNR and SSIM scores. Moreover, working with such technologies is burdensome due to their requirement of high computational resources and dependence upon the complex unpredictable dataset. Ethical concern is vital to preserve the authenticity of the artworks and artifacts. XAI makes the restoration procedure more transparent, helping the professional to evaluate, analyze and approve AI-generated restoration.

CONCLUSION AND FUTURE WORK

The timing for the renewable energy sector is at a critical point in modern human history in terms of environmental protection. However, in countries commit to aggressive Net Zero targets, The International Energy Agency estimates that we need to triple renewable energy capacity by 2030 just to stay on track. A crucial conundrum is essential to pay the attention in the degradation of those installations with the course of time, the solar panels and wind turbines installed in 2020s which come with approximately 20-25 years of warranty will start showing their age in the 2040s. We also need to focus on efficient ways of utilizing the condition, prioritize maintenance, and extend their operational lives. Also, in addition of this premature replacement would be economically and environmentally painful, given the embodied carbon in manufacturing new equipment. However, where ML-based monitoring and predictive maintenance becomes not just helpful but essential ML has unlatched numerous eventualities for the preservation and restoration of artifacts and locations with historical significance. These methods assist in easy identification of the area or portion that needs to be restored. However, several objections remain, including the insufficiency of extensive labelled datasets, the requirement for advanced computational resources, and probability of skewness in training dataset. In conclusion, due to their mutual reliance on polymers, composites, and material science, renewable energy materials and modern artwork restoration are closely related. Innovations created for renewable energy, like UV-resistant coatings and sophisticated nanocomposites, are helping art conservation more and more. Both fields strive to understand how these materials deteriorate under environmental stress. Analytical methods for studying these renewable energy materials also improve our capacity to evaluate the deterioration of pigments, binders, and protective layers in artwork. In conclusion section, we would like the the longevity, effectiveness, and long-term sustainability of modern restoration techniques are being strengthened by this interdisciplinary exchange.

The use of AI has now become the ton of promise in the field of art restoration utilizing a hybrid system with combing various mavhine learning techniques. Therefore, crafting of these systems will provide innovative and novel solutions leading to experts being able to comprehend and trsut machine decisions. Hence we will pave the path for enhanced collaboration between technology and human experts. The scope of these machine learning tools would thus expand to various settings because of improved datasets and easily accessible computational techniques. To effectively manage the exciting opportunities, ethical considerations are necessary througout the work . Through direct collaboration between AI researchers, art conservators, and historians, the field will advance responsibly through artifact preservation by managing technology to preserve cultural artifacts while maintaining their historical significance

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