Exploring Experimental Machine Learning in Film Restoration

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Abstract

The challenges of film restoration demand versatile tools, making machine learning (ML)—through training custom models—an ideal solution. This research demonstrates that custom models effectively restore color in deteriorated films, even without direct references, and recover spatial features using techniques like gauge and analog video reference recovery. A key advantage of this approach is its ability to address restoration tasks that are difficult or impossible with traditional methods, which rely on spatial and temporal filters. While general-purpose video generation models like Runway, Sora, and Pika Labs have advanced significantly, they often fall short in film restoration due to limitations in temporal consistency, artifact generation, and lack of precise control. Custom ML models offer a solution by providing targeted restoration and overcoming the inherent limitations of conventional filtering techniques. Results from employing these local models are promising; however, developing highly specific models tailored to individual restoration scenarios is crucial for greater efficiency.

Keywords: Machine learning, film restoration, artificial intelligence, color recovery, spatial recovery

Introduction

Artificial intelligence (AI), particularly its subset, machine learning (ML), has become a powerful tool in film restoration. ML enables the creation of specialized models better suited for restoration than general-purpose programs like Runway, Sora, and Pika Labs, which are designed for content creation and ill-suited to the unique challenges of cinematic preservation. A significant advantage of ML-based restoration is its capacity to address tasks that traditional methods struggle with, due to the limitations of spatial and temporal filters. This paper demonstrates the efficacy of custom ML models in recovering film color characteristics from references or by inferring them and in restoring spatial features using three techniques. To provide context, this paper first presents a concise conceptual framework, then addresses the rationale for creating custom models, details the methodology employed, explains the color and spatial recovery techniques, and concludes with a summary of the work.

Conceptual Framework

Artificial Intelligence (AI) has been defined in numerous ways. Russell and Norvig (1995) observe that definitions vary, with some emphasizing thought and reasoning, others focusing on behavior, some measuring success against human performance, and others against an ideal of intelligence. While John McCarthy coined the term in 1955, this paper adopts Bellman’s (1978) definition: AI is the automation of "activities we associate with human thinking, such as decision-making, problem-solving, and learning".

Machine Learning (ML), a subset of AI, programs computers to improve performance using data or past experiences. ML algorithms and models learn patterns from data, identify relationships, and make predictions based on that learning. ML models can be predictive or descriptive, relying on statistics for inferences and computation for efficient processing of large datasets [1].

In the context of film preservation, it is crucial to understand the types of damage that ML aims to correct. As Jack James (2006) explains, film damage originates from the physical nature of film stock and manifests in two forms: intra-frame (affecting single frames) and inter-frame (affecting sequences of frames).

Conceptual Framework Focused on Film Restoration

To provide a more relevant framework for film restoration, let's refine the definitions of AI and ML and elaborate on the specific types of film damage addressed in this context.

Artificial Intelligence (AI) in Media Restoration

In media restoration, AI, specifically narrow AI, facilitates the automation of tasks that traditionally require significant human intervention. Instead of aiming for general intelligence, the focus is on developing AI tools tailored for specific restoration challenges. For instance, in film restoration, AI is employed to:

- Automate repetitive tasks: AI algorithms can automate the removal of dust, scratches, and other artifacts, freeing up human restorers to focus on more complex creative decisions.
- Enhance image quality: ML models can be trained to increase resolution, reduce noise, and correct color fading, often surpassing the capabilities of traditional restoration techniques.
- Reconstruct missing information: AI can infer and reconstruct missing parts of an image or sequence, such as filling in scratches or stabilizing shaky footage.

Machine Learning (ML) for Film and Video Restoration

Machine learning, the driving force behind many AI applications in film restoration, involves training algorithms on data to improve their performance on specific tasks. Supervised learning is particularly relevant, where models learn from labeled datasets. In film restoration, this often entails:

- Training on paired examples: For color restoration, a model might be trained on pairs of degraded frames and reference frames to learn how to correct color fading.
- Feature extraction and pattern recognition: ML algorithms can identify patterns of damage and learn to distinguish between artifacts and genuine image information.
- Iterative refinement: ML models can iteratively refine their restoration results, gradually improving the quality of the output.

Convolutional neural networks (CNNs), a type of neural network, are frequently used in film restoration due to their effectiveness in image processing.

Detailed Breakdown of Film Damage

Understanding the nuances of film damage is essential for developing effective ML-based restoration techniques.

Intra-Frame Damage: Damage within individual frames includes:

- Scratches: Linear abrasions that disrupt the image.
- Dust and Dirt: Obscuring fine details.
- Stains: Discoloration caused by chemical reactions.
- Flicker: Brightness variations between frames.
- Grain: The film's inherent texture, which can be exaggerated by degradation.

Inter-Frame Damage: Damage across frame sequences involves:

- Instability: Warping or shrinkage causing image movement.
- Color Fading: Loss of color information over time.

ML can address these issues by learning to recognize and correct damage patterns.

Why Create Our Own Models?

ML's ability to learn patterns from datasets and apply that knowledge to new data makes it invaluable for film restoration. For example, a small set of frames could train a model to restore a larger set.

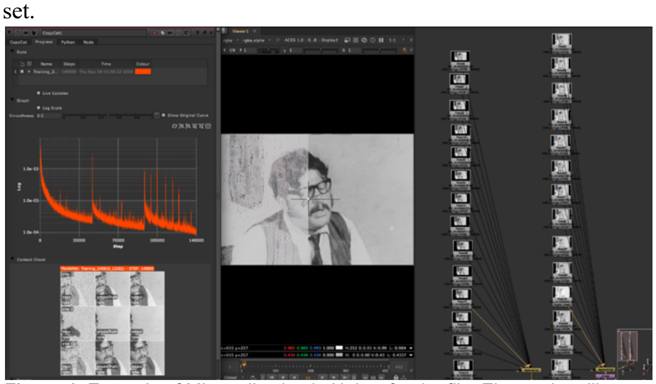

Figure 1. *Example of ML application in Nukex for the film El gran tinterillo (1975)*

Commercial programs like Runway, Sora, and Pika Labs are not designed for film restoration. While trained on massive datasets, they target modern content, risking homogenization and "plastic" restorations. Copyright is another concern, as many models use data without authorization. Therefore, creating small, locally executed models trained on ethically sourced data is crucial for addressing specific restoration challenges.

Rationale for Custom ML Models in Film Restoration

Creating custom ML models for film restoration is driven by the limitations of general-purpose AI tools and critical ethical considerations specific to preserving cinematic heritage.

Limitations of General-Purpose AI

General AI tools like Runway, Sora, and Pika Labs often fall short in film restoration due to:

- Aesthetic Mismatch: Programs trained on contemporary images tend to impose modern aesthetics, smoothing out film grain and erasing unique visual characteristics crucial to a film's historical context.
- Overfitting and Homogenization: Models trained on broad datasets may overfit to modern visual styles, leading to homogenized restorations that lack the texture and nuances of the original film.
- Lack of Granular Control: Film archivists require precise control over the restoration process (color grading, detail enhancement, etc.), which general AI tools often lack.
- Temporal Inconsistency, Artifacts, and Hallucinations: Video generation models often struggle with maintaining consistent details and motion across frames, introduce unwanted artifacts, and "hallucinate" or inaccurately reconstruct content, which is problematic for accurate restoration.

Ethical Imperatives in Film Restoration AI

Ethical considerations are paramount in film restoration:

- Data Provenance and Copyright: Using ethically sourced data, obtained with proper authorization, is essential to respect copyright and ensure legal compliance.
- Bias Mitigation: Training data must be carefully curated to minimize biases that could distort the restoration, such as misrepresenting skin tones or cultural artifacts.
- Authenticity and Transparency: Restoration should prioritize authenticity, preserving the film's original aesthetic and maintaining transparency about the alterations made.

Custom models offer the control, precision, and ethical grounding necessary for responsible and effective film restoration.

Methodology

Traditional film restoration often relies on spatial and temporal filters, which operate within individual frames or across neighboring frames. These filters have inherent limitations: they cannot "learn" from external references or apply knowledge across distant parts of a film. In contrast, the methodology for film restoration using custom ML models involves several key steps:

- Data Preparation: The film is digitized, and the damaged areas are identified. Reference materials (if available) are also prepared.
- Model Training: A small ML model is trained on a subset of frames, with the number of frames adjusted based on the complexity of the footage. More complex footage requires more training frames.
- Inference: The trained model is applied to the entire film, producing the restored output.
- Evaluation and Refinement: The restoration results are evaluated, and the model is refined as needed to improve the quality of the output.

This process is facilitated by software like Nukex (The Foundry), which allows for the creation and training of custom ML models. Custom ML models can be designed to tackle restoration problems that are difficult or impossible to solve with conventional tools.

Color Recovery

The transition from Technicolor dye-transfer prints to Eastman Color Negative and Print in 1950 shifted cinematography to color and introduced new preservation challenges. Chromogenic films degrade over time, with dye fading [5] necessitating color recovery.

Figure 2. *Example of color recovery using ML in the film Friends (2001)*

Color recovery can utilize references like DVDs or telecines, even with resolution or compression issues. A small ML model trained on a subset of frames can replicate colors across shots, scenes, or reels. This method was applied to Candy Candy (Hiroshi Shidara, 1976). The original 16mm film (Figure 3, top left) exhibited severe magenta dominance. Using 33 degraded frames and 33 DVD reference frames (Figure 3, bottom left), tools like Phoenix and Loki (Filmworkz) cleaned the material, while Nukex (The Foundry) and its Copycat tool trained the ML model. This process successfully replicated colors while preserving resolution (Figure 3, bottom right).

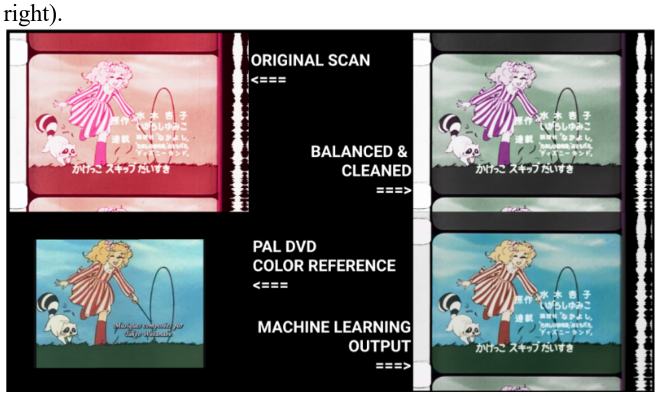

Figure 3. *Reference-based color recovery in Candy Candy (1976) using ML)*

When references are unavailable, color can be inferred from similar images (paintings, photos) or manually painted in Photoshop. This capability to "learn" color information from external sources is a significant advantage of ML over traditional color correction methods, which are limited to manipulating existing color channels. For the short film Rebelión de las tapadas (Nelson García Miranda, 1943), colonial-era paintings trained the ML model to emulate colors and artistic styles.

Figure 4. *Encuentro en la Alameda Nueva Watercolor painting by Johann Moritz Rugendas (1843), Lima, Peru. Source: Wikimedia Commons*

Figure 5. Non-reference color recovery in Rebelión de las tapadas (1943) using ML

Spatial Recovery

Spatial recovery restores details lost to damage or generational loss. ML models trained on secondary references (telecines, alternate copies) recover original spatial features. Techniques include gauge recovery, generation recovery, and analog video reference recovery. Gauge and generation recovery models trained on overlapping data from different gauges or generations adapt to variations, aligning film quality with the best available source. In Mission Kill (1990), a 16mm film was enhanced to match 35mm internegative quality.

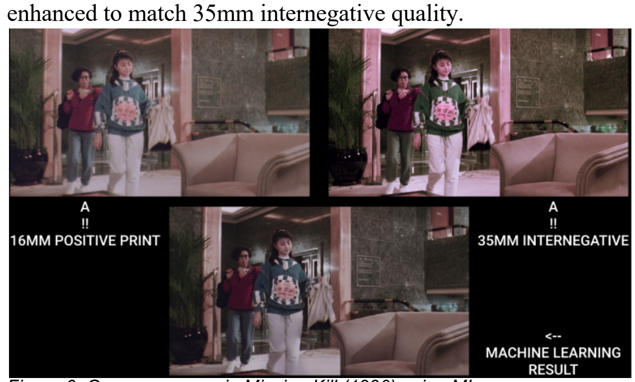

Figure 6. Gauge recovery in Mission Kill (1990) using ML

Analog video reference recovery uses telecines in a two-step process: training a model on less-damaged sections to capture uncontaminated spatial features, then applying this to full-frame recovery. This method addressed cropping and limited spatial data in El gran tinterillo (1975). This ability of ML models to "learn" spatial details from different sources to reconstruct missing information surpasses the limitations of traditional spatial filters that can only interpolate or sharpen within the same or neighboring frames.

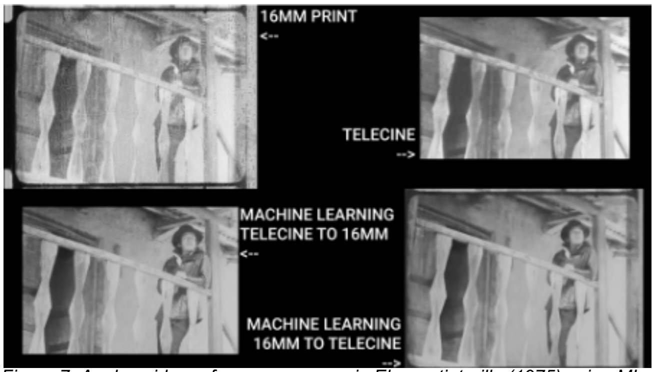

Figure 7. Analog video reference recovery in El gran tinterillo (1975) using ML

Conclusion

While the case studies presented demonstrate the feasibility of using ML for specific restoration tasks, the scalability of this approach to full-length films or entire collections remains a major consideration.

Machine learning offers a powerful and versatile toolkit for addressing the challenges of film restoration, demonstrating significant potential in recovering both color and spatial features from damaged film materials. The case studies presented highlight the adaptability of custom-trained ML models, capable of producing compelling results even when direct reference materials are limited or unavailable. A key advantage of ML-based restoration is its ability to overcome the limitations of traditional spatial and temporal filters by "learning" information from external references and applying that knowledge to the restoration process. This enables the recovery of information in scenarios where traditional methods fail, such as inferring color from paintings or reconstructing spatial detail from severely degraded film. However, the development and application of more specialized models are crucial to achieve optimal restoration outcomes. Furthermore, the ethical sourcing of training data and the use of locally run models are paramount considerations for responsible practice.

While the presented research showcases the promise of ML for targeted film restoration tasks, several factors must be carefully considered for broader implementation. The scalability of this approach to restore entire films or large archival collections presents a significant hurdle. Training individual ML models for each restoration project can be computationally intensive, requiring substantial processing power and time. The associated costs, including hardware, software, and specialized personnel, must be weighed against the potential benefits.

A thorough cost-benefit analysis is essential to determine the feasibility of ML-based restoration on a larger scale. While ML can offer increased efficiency in certain tasks, such as automated damage removal, the initial investment in training and deploying models can be considerable. It is crucial to compare the long-term costs and benefits of ML-based restoration with those of traditional, manual restoration methods, considering factors such as:

- Time efficiency: Can ML significantly reduce the time required for restoration?
- Quality of results: Does ML consistently produce superior restoration outcomes?
- Preservation of authenticity: Does ML preserve or enhance the original aesthetic qualities of the film?
- Archival sustainability: Is ML a sustainable solution for long-term film preservation?

Future research should focus on addressing the scalability and cost-effectiveness of ML for film restoration. Key areas of investigation include:

- Developing more generalized models: Research should explore the possibility of creating more generalized ML models that can be adapted to a wider range of restoration tasks, reducing the need for training individual models for each film.
- Optimizing workflows: Streamlining the restoration workflow, from data preparation to model deployment, is crucial to improve efficiency and reduce costs.
- Leveraging cloud computing: Cloud-based computing platforms can provide the necessary computational resources for large-scale ML-based restoration projects.
- Exploring hybrid approaches: Combining ML with traditional restoration techniques may offer the most effective and efficient solution.
- Expanding ML applications: Investigating the use of ML for other film preservation tasks, such as print alignment recovery, grain reconstruction, damage detection, and dynamic range recovery, could further enhance archival practices.

Ultimately, realizing the full potential of ML in film restoration requires a concerted effort from researchers, archivists, and policymakers to address the technical, ethical, and economic challenges involved.

References:

[1] E. Alpaydin, *Introduction to Machine Learning*, Cambridge, MA: MIT Press, 2004.

[2] R. Bellman, *An Introduction to Artificial Intelligence: Can Computers Think?*, San Francisco, CA: Boyd & Fraser, 1978.

[3] J. James, *Digital Intermediates for Film and Video*, Burlington, MA: Elsevier, 2006.

[4] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, Upper Saddle River, NJ: Prentice-Hall, 1995.

[5] H. Wilhelm, *The Permanence and Care of Color Photographs: Traditional and Digital Color Prints, Color Negatives, Slides, and Motion Pictures*, Grinnell, IA: Preservation Publishing, 1993.

[6] G. Vincent, *AI Ethics in Digital Humanities: Practices, Pitfalls, and Possibilities*, London, UK: Routledge, 2021.

Author Biography

Fabio Paul Bedoya Huerta is a film restoration technician at Duplitech and a master trainer at Filmworkz, where he provides instruction on Phoenix software for post-production facilities and individuals. His research focuses on integrating machine learning and artificial intelligence into film restoration workflows, addressing complex and unconventional restoration scenarios. His work bridges commercial restoration practices with experimental research in advanced digital restoration methods.