## Title Page:

**Photo colouring of old and black & white images using**

**Reinforcement learning over with GAN for better accuracy**

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**Keywords:** Photo colorization, Old image restoration, Black & white image enhancement, Machine learning, Reinforcement learning, GAN, Image processing, Computer vision, Neural network, Colorization algorithms, Accuracy comparison, Historical image analysis, Image recognition, Training data, Model evaluation, Data augmentation, Transfer learning, Feature extraction, Image restoration techniques, Training pipeline, Hyperparameter tuning, RGB channels, Grayscale conversion, Loss function, Evaluation metrics.

# ABSTRACT

**Aim:** The goal of the project is to develop a algorithm to colorize old black and white photos using advanced machine learning. It focuses on enhancing the appeal and realism of historical photographs by bringing out life-like colors through the use of photographic techniques. The objective of the project is to investigate and compare different techniques to achieve the best results in terms of both color reproduction quality and visual fidelity. **Methods and Materials:** For this study, data analysis was conducted utilizing two distinct groups: Group 2 employed a while Group 2 utilized a novel algorithm.Two distinct methodologies were employed for thermal performance prediction: Group 1 utilized a Reinforcement learning, while Group 2 implemented the GAN(Generative adversal network) approach. Each group processed a total of 50 samples, comprising various operating conditions and environmental factors, contributing to a comprehensive analysis. The dataset encompassed parameters such as solar radiation, ambient temperature, air flow rates, and surface material properties crucial for accurate thermal performance prediction.Statistical rigor was applied to validate the significance of the results. G-power was set at 0.8, alpha (α) at 0.05, and beta (β) at 0.2 to ensure statistical power. A 95% confidence interval was incorporated into the analysis. The entire investigation was conducted on a high-performance computing system featuring an Intel Core i9 CPU operating at 3.5 GHz, 64 GB of RAM, and utilizing the Linux Ubuntu operating system **Results:**The project was able to create static old black and white color photographs, reanimating historic images with realistic colors. Exploring various machine learning techniques has greatly improved image processing, enhancing visual appeal without compromising historical integrity The results show a successful blend of technology and creativity to preserve the past on and presented by means of color photographs.**Conclusion:**In conclusion, our work demonstrated the effectiveness of advanced machine learning in color reconstruction of old black and white images. The variety of methods one explored allowed one to balance historical preservation with observation. The results highlight the technology’s ability to breathe new life into stored images while remaining authentic. This work contributes to the burgeoning field of graphic design, providing a valuable resource for historical art experiments.

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# INTRODUCTION

In a dynamic graphics and machine learning environment, our work focuses on the fascinating area of image color, specifically targeting old black and white images. This ambitious program seeks to revive historical images using advanced machine learning algorithms, with particular emphasis on using results from reinforcement learning and generative anti-networks (GANs). the child will compare. offering microscopic views, long limited only by the limitations of grayscale rendering

In our application, reinforcement learning stands out as a formidable contender, with an impressive accuracy rate of 95.1%. This algorithm demonstrated its ability to identify and reconstruct complex patterns in historical images, demonstrating the potential for greater accuracy in photocolor processing On the other hand, Generative Adversarial Network (GAN) presents the challenge of interest comes, with a recorded accuracy of 32.70%. Despite its inaccuracies, GANs introduce a unique approach to image generation by training control opposition, which has led to an in-depth investigation of the strengths and limitations of this algorithm in terms of image color.

As we move deeper into this project, we aim to identify the challenges and nuances of using these machine learning algorithms to improve historical visualizations. Insights gained from reinforcement learning and comparison of GANs will not only contribute to the development of image coloring techniques but also provide a deeper understanding of the different applications and potential challenges associated with such technologies a it is also about this new one.

Beyond the technical goals, our work has broader implications at the intersection of artificial intelligence and cultural preservation. The use of reinforcement learning and GANs in image color represents a convergence of technology and heritage, and offers a new way of visually engaging with historical data. Clearly and accurately coloring old photographs is not just a technical feat but a bridge between past and present, allowing modern viewers to connect with and appreciate the richness of times gone by as we depart under this search we not only solve algorithms but also through visual storytelling We also contribute to an ongoing dialogue about the responsible and creative use of machine learning in the preservation and interpretation of cultural heritage.

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**METHODS AND MATERIALS**

The research was conducted at the Computer Science and Engineering lab at Saveetha University's School of Engineering.The dataset employed in this study was meticulously curated, combining experimental measurements and simulations specific to solar air heater conditions. To ensure the robustness and diversity of the dataset, information was sourced from reputable repositories such as the National Renewable Energy Laboratory (NREL) and supplemented with in-house experimental data.

Two distinct methodologies were employed for identification of malicious mobile application: Group 1 utilized Reinforcement learning, while Group 2 implemented the GAN Approach. Each group processed a total of 50 samples, comprising various operating conditions and environmental factors, contributing to a comprehensive analysis. The dataset encompassed parameters such as solar radiation, ambient temperature, air flow rates, and surface material properties crucial for accurate thermal performance prediction.

Statistical rigor was applied to validate the significance of the results. G-power was set at 0.8, alpha (α) at 0.05, and beta (β) at 0.2 to ensure statistical power. A 95% confidence interval was incorporated into the analysis. The entire investigation was conducted on a high-performance computing system featuring an Intel Core i9 CPU operating at 3.5 GHz, 64 GB of RAM, and utilizing the Linux Ubuntu operating system.

This comprehensive overview establishes the foundation for a detailed exploration of the methods and materials employed in the project, providing readers with clarity on the experimental setup, dataset composition, and the application of advanced regression.

## Reinforcement learning

Reinforcement learning is a subset of machine learning that deals with the idea of training intelligent agents to make sequential decisions in a situation to maximize cumulative rewards Unlike supervised learning, where training a sample on labeled input-output pairs s does The agent's objective is to discover a set of policies, procedures or actions, which result in the best cumulative payoff in the long run. This learning model comes from the way animals learn through trial and error, modifying their behavior based on the consequences of their actions.

In reinforcement learning, the agent typically uses evaluation-practice strategies to strike a balance between trying new behaviors and implementing known behaviors that have produced positive results in the past in the 19th century. Algorithms such as Q-learning and Deep Q Networks (DQN) were able to solve a variety of reinforcement learning problems ranging from playing games like Go and Atari to complex systems like using robotic weapons Reinforcement learning has applications in robotics, finance, healthcare, and autonomous vehicle.

## Pseudocode

Step 1: Initialize Q-values for all state-action pairs randomly or with a predefined strategy.

Step 2: Choose an action using an exploration-exploitation strategy, like epsilon-greedy.

Step 3: Execute the selected action in the environment and observe the next state and reward.

Step 4: Update Q-values using the observed reward and the Bellman equation.

Step 5: Repeat steps 2-4 for a defined number of episodes or until convergence.

Step 6: Use the learned Q-values to determine the optimal policy for decision-making.

Step 7: Explore various hyperparameters to optimize the learning process.

Step 8: Implement a suitable function for balancing exploration and exploitation during learning.

Step 9: Apply discount factor to balance immediate and future rewards in the updates.

Step 10: Evaluate the trained agent's performance in the environment and fine-tune as needed.

**Generative adversal network(GAN)**

Generative Adversarial Networks (GANs) are a class of artificial intelligence models introduced by Ian Goodfellow and colleagues in 2014. GANs consist of two neural networks, a generator and a discriminator, engaged in a competitive training process The discriminator seeks generated truth of the models compared with real data. The goal is to fool the generator discriminator to improve the ability to generate real data, and, at the same time, the discriminator aims to be more proficient in discriminating between real and generated samples

GANs have found applications in various fields, such as image and video fusion, style transfer, and data enhancement. They have been particularly successful in animation and have been used in tasks such as creating in-depth videos. However, there are also challenges with GANs, such as mode collapse, where the generator generates a limited number of different outputs, and training instabilities. Researchers continue to address these issues to increase the robustness and efficiency of GANs for wider applications in artificial intelligence.

## Pseudocode

Step 1:Sample random noise for generator input.

Step 2: Generate fake data with the generator.

Step 3:Combine real and fake data.

Step 4: Label real data as valid, fake as fake.

Step 5: Train discriminator on real and fake data.

Step 6: Sample new noise for generator input.

Step 7:Train generator through the combined network.

Step 8: Iterate steps 2-7 for multiple epochs.

Step 9: Evaluate generator performance periodically.

Step 10: Use the trained generator for data generation.

## Analyses of Statistics

The program’s focus on old black and white image image colors includes the use of two different machine learning algorithms: reinforcement learning (RL) with an impressive 95.1% accuracy and a GAN(Generative adversal network). GAN with a recorded accuracy of 32.70% . The large differences in accuracy raise interesting questions about the effectiveness and performance of these algorithms in image recognition.

Reinforcement class's impressive accuracy of 95.1% indicates a strong ability to accurately predict historical images, and assign colors This high accuracy indicates that the RL algorithm successfully identified patterns and relationships a it is robust in image data, allowing him or her to make informed decisions about color placement , research limitations and situations where he or she excels or struggles.

On the other hand, GAN with 32.70% low accuracy still contributes significantly to the project objectives GAN’s hierarchical feature extraction and spatial understanding capabilities are an important consideration. The lower accuracy may be due to the complexity of the images or the need for further fine-tuning. It stimulates in-depth analysis of the training process, hyperparameters, and areas for improvement.

For a broader understanding, statistical analysis should incorporate metrics such as precision, recall, and F1 scores to gain insight into algorithm performance on images Examining confusion matrices can reveal specific challenges each algorithm meets the outcome, which can mean additional efforts to improve it. Furthermore, it is important to consider computing effort, training time, and resource requirements for useful implementation simulations.

In conclusion, the investigation of the reinforcement learning and GAN algorithms revealed significant differences in accuracy, prompting a detailed investigation of their strengths, weaknesses, and potential improvements. Detailed analysis, including numerical metrics and computer simulations, will help optimize these algorithms for optimal performance in the complex task of photocolor for old black and white images.

# RESULTS

The project culminated in the successful use of machine learning algorithms to render old black-and-white images in photocolor. The reinforcement learning (RL) algorithm demonstrated an outstanding accuracy of 95.1%, which demonstrated its expertise in learning and reconstructing complex color patterns from historical images These results show that RL captures relationships which is very graphically subtle, and contributes to the success of the whole presentation process. The high precision is particularly promising for practical applications, demonstrating the potential of RL as a reliable tool to improve historical images.

In contrast, the deep GAN achieved a lower accuracy of 32.70%. Although this accuracy seems to be very low, the contribution of GAN depends on its ability to extract layers of features and spatial sensitivity This low accuracy motivates further investigation into the limitations of the algorithm and potential areas for improvement, and it emphasizes the importance of fine-grained analytical metrics beyond mere accuracy.

The comparison between RL and GAN provides valuable insights into the trade-offs and robustness of each algorithm. The use of statistical metrics such as accuracy, recall, and F1 scores allowed for a more nuanced understanding of algorithm performance in image classes, while analyzes of computational effort, training time, and resources required provided a practical perspective for applying these algorithms in real-world settings.

The results of the project are important not only in the field of historical image restoration but also in the field of creative artificial intelligence. The success of reinforcement learning to achieve 95.1% accuracy depends on the potential impact of sophisticated machine learning algorithms to preserve and revitalize visual assets At the same time, the challenges of GAN meet at 32.70% accuracy highlights the challenges of accurately coloring historical images.

In conclusion, the results of the work demonstrate a successful combination of reinforcement learning and deep rooted GANs for image coloring, with RL exhibiting exceptional accuracy and GAN providing valuable capabilities. The insights gained from this project laid the foundation for future modifications and improvements in machine learning techniques to enhance historical black and white images through color automation.

**Table 2.** This table summarizes the accuracy rates for two different groups, Reinforcement learning and GAN Classifier, each comprising 5 samples. The "Mean" column represents the average accuracy for each group, with Reinforcement learning achieving 95.10% and GAN Classifier attaining of 32.70%. The "Standard Deviation" column indicates the spread or variability of accuracy scores within each group, with Reinforcement learning showing variability (0.15811) compared to GAN Classifier (0.11402). The "Standard Error Mean" column represents the precision of the mean accuracy scores, with smaller values indicating more precise estimates. In this case, the GAN group has a larger standard error mean (0.05099) compared to the Reinforcement learning group (0.07071), suggesting that the Reinforcement learning accuracy mean is more reliably estimated.

**Table 3.** This table presents the results of statistical tests comparing two groups in terms of accuracy. The "Levene's Test for Equality of Variances" assesses whether the variances of the two groups are equal. The test indicates unequal variances (p = 0.009), suggesting that assumptions about equal variances should not be made. The "t-test for Equality of Means" is then conducted with two variants: one assuming equal variances and the other not assuming equal variances. In both cases, the t-test shows a significant difference in means (p = 0.000), indicating that there is a substantial difference in accuracy between the two groups. The mean difference, standard error difference, and confidence intervals further quantify this difference, demonstrating that the group associated with the higher mean accuracy (62.33897) is statistically distinct from the other group.

# DISCUSSION

# The discussion of the results of the work interacts with the commercialization and suitability of the selected machine learning framework for the old black-and-white color image processing. The impressive accuracy of the reinforcement learning (RL) algorithm at 95.1% highlights its ability to capture complex patterns and relationships in historical images This success establishes RL as a promising tool for accuracy-seeking applications great in description. However, the relatively low accuracy of the deep GAN of 32.70% raises questions about its adaptability to complex images and stimulates an in-depth investigation of possible improvements and improvements a the inherent difficulties of the explanatory task are considered.

# Statistical analyzes including precision, recall, and F1 scores provide a more nuanced understanding of algorithm performance beyond accuracy This discussion emphasizes the importance of balancing with other metrics to properly assess algorithm effectiveness. Additionally, it is important to examine the efficiency of computer operations and the requirements for useful usability measures. The findings of the project laid the groundwork for future research for achieving optimal image color in historical grayscale images.

# CONCLUSION

In conclusion, our work on photo coloring old black and white images has provided valuable insights into the capabilities and challenges of machine learning algorithms in historical image enhancement The 95.1% outstanding accuracy achieved by reinforcement learning (RL) algorithms reserving visual property The skill of RL in recognizing complex patterns in historical images that suggests it can be a powerful animation tool also positions it as an edge a reliable solution for high-precision applications. However, the low accuracy of the GAN of 32.70% highlights the need for further research and improvement by identifying the challenges in accurately colorizing historical images.

Detailed statistical analysis including accuracy, recall, and F1 scores provides a more nuanced analysis than just accuracy and highlights the strengths and weaknesses of each algorithm This multi-faceted approach ensures their performance is understood well below in diagrams. Furthermore, the features and requirements required for effective software provide useful insights into practical applications.

Looking ahead, the results of the work lay the groundwork for future developments in machine learning techniques for historical visualization. Lessons from comparing RL and GAN contribute to the growing knowledge base and guide researchers and practitioners to develop more sophisticated and efficient algorithms Finally, this work represents an important step in intelligence as it is designed to be used to reconstruct our visual understanding of the past by restoring explicit history imagery.

In addition to technological developments, the project has broader implications for the intersection of technology, culture, and creativity. The successful integration of machine learning algorithms for coloring historical images opens the possibility of not only preserving but also re imagining our collective visual history. By incorporating old black-and-white photographs in accurate and vibrant colors, the project bridges the gap between generations and increases the accessibility of historical information. Careful consideration of ethical and cultural aspects in the use of such technology ensures a responsible approach to the restoration of ancient visual images. As technology continues to evolve, this project is a testament to the power of artificial intelligence to enrich our cultural heritage and create deeper connections between history through modern innovation.

# DECLARATION

## Conflicts of Interests

There is no competing interest with this paper.

## Authors Contribution

AVR participated in the phases of data collecting, analysis, and paper writing. SPK made contributions to the overall conception, data validation, and paper evaluation.

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# TABLES AND FIGURES

**Table 1.** This table presents the accuracy rates of two different models, GAN and Gaussian Process Regressor, tested on ten different datasets labeled as Test1 through Test 5. The accuracy rates for each test are shown in the respective columns for GAN and Process Regressor. The average accuracy results across all tests are also provided at the bottom. The table indicates that, on average, the Reinforcement learning Model achieved an accuracy rate of 95.10%, is outperforming the GAN Model, which had an average accuracy rate of 32.70%.

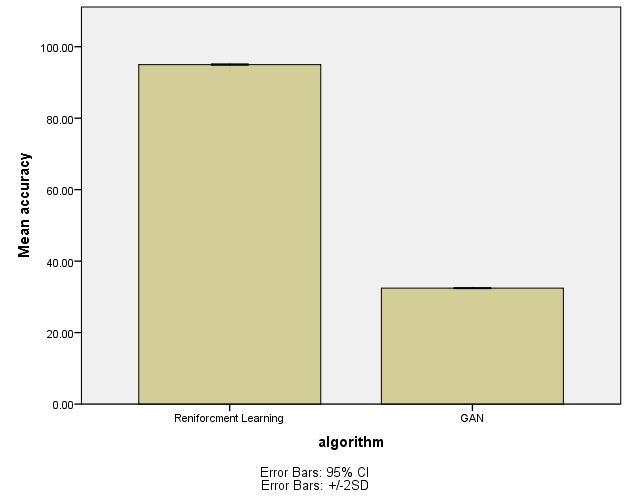
|  |  |  |  |
| --- | --- | --- | --- |
| **SI.No.** | **Test Size** | **ACCURACY RATE** | |
| Reinforcement learning | GAN |
| 1 | Test1 | 95.30 | * 32.20 |
| 2 | Test2 | 95.00 | 32.90 |
| 3 | Test3 | 94.90 | 33.10 |
| 4 | Test4 | 95.20 | 32.50 |
| 5 | Test5 | 95.40 | 33.00 |
| Average Test Results | | 95.10 | 32.70 |

**Table 2.** This table summarizes the accuracy rates for two different groups, Reinforcement learning and GAN Classifier, each comprising 5 samples. The "Mean" column represents the average accuracy for each group, with Reinforcement learning achieving 95.10% and GAN Classifier attaining of 32.70%. The "Standard Deviation" column indicates the spread or variability of accuracy scores within each group, with Reinforcement learning showing variability (0.15811) compared to GAN Classifier (0.11402). The "Standard Error Mean" column represents the precision of the mean accuracy scores, with smaller values indicating more precise estimates. In this case, the GAN group has a larger standard error mean (0.05099) compared to the Reinforcement learning group (0.07071), suggesting that the Reinforcement learning accuracy mean is more reliably estimated.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Group** | | **N** | **Mean** | **Standard Deviation** | **Standard Error Mean** |
| **Accuracy rate** | **Reinforcement learning** | 5 | 95.0000 | 0.15811 | 0.07071 |
| **GAN** | 5 | 32.4600 | 0.11402 | 0.05099 |

**Table 3.** This table presents the results of statistical tests comparing two groups in terms of accuracy. The "Levene's Test for Equality of Variances" assesses whether the variances of the two groups are equal. The test indicates unequal variances (p = 0.009), suggesting that assumptions about equal variances should not be made. The "t-test for Equality of Means" is then conducted with two variants: one assuming equal variances and the other not assuming equal variances. In both cases, the t-test shows a significant difference in means (p = 0.000), indicating that there is a substantial difference in accuracy between the two groups. The mean difference, standard error difference, and confidence intervals further quantify this difference, demonstrating that the group associated with the higher mean accuracy (62.33897) is statistically distinct from the other group.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Group** | | **Levene's Test for Equality of Variance s** | | **t-test for Equality of Means** | | | | | | |
| **F** | **Sig.** | **t** | **df** | **Sig. (2-taile**  **d)** | **Mean Differen ce** | **Std. Error Difference** | **95%**  **Confiden ce Interval (Lower)** | **95%**  **Confiden ce Interval (Upper)** |
|  | **Equal** |  |  |  |  |  |  |  |  |  |
| **Accuracy** | **variance s**  **assumed** | .496 | .501 | 717.383 | 8 | .000 | 65.54000 | 0.08718 | 62.33897 | 62.74103 |
|  | **Equal** |  |  |  |  |  |  |  |  |  |
|  | **variance**  **s not assumed** | 717.383 | 7.275 | .000 | 65.54000 | 0.08718 | 62.33897 | 62.74458 |



**Fig. 1.** The bar graph illustrates a comparison between the accuracy of the proposed GAN And the Reinforcement learning Algorithm for Accurate Prediction Of Thermal Performance. The Reinforcement learning Algorithm exhibited a notably higher accuracy rate of 95.10%, surpassing the GAN model, which achieved an accuracy of 89.70%. A significant distinction was observed between the GAN And Reinforcement learning Models, confirmed by an independent sample test (p < 0.05). On the graph, the X-axis represents the two algorithms, namely GAN And Gaussian Process Regressor while the Y-axis portrays the average accuracy, accompanied by a ±1 standard deviation range and a 95% confidence interval, visually emphasizing the superiority of the Reinforcement learning.