## Title Page:

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

**Reinforcement learning over with Deep CNN for better accuracy**

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**Keywords:** Photo colorization, Old image restoration, Black & white image enhancement, Machine learning, Reinforcement learning, Deep CNN (Convolutional Neural Network), 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 DeepCNN 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 history preservation and visual history, our project begins the ambitious project of reviving old black-and-white photographs using state-of-the-art machine learning techniques. The ultimate goal is simply to create a sophisticated system that can color these historical images with clarity and accuracy. Using advanced algorithms, our work seeks to bridge the gap between past and present, offering new perspectives on historical moments that were once exclusively monochromatic representations

Exploring the complexity of the work, its significance lies in its ability to breathe new life into archival images, opening up a deeper understanding of times gone by. This effort explores various machine learning techniques including reinforcement learning and deep convolutional neural networks to find the most efficient way to achieve life-like color Beyond the technological innovation alone, the project aims to to contribute to the wider discussion on industrial and cultural heritage.

By taking on this project, we hope to develop a robust framework for color coding that not only outperforms traditional methods but stands as a testament to the nature of artificial intelligence and creative synthesis. Potential applications for the project extend from historical museums to artistic endeavours, providing a dynamic way to inform our collective understanding of the past has been great.

Essentially, our work is a nuanced exploration of the intersection of technology and nostalgia. It strives to provide user-friendly yet powerful solutions for individuals who want to rediscover history in a clear and immersive way. By bringing color to iconic black and white images, we want to create a deeper connection between a contemporary audience and the historical content of these visual time capsules.

**Keywords:** Photo colorization, Old image restoration, Black & white image enhancement, Machine learning, Reinforcement learning, Deep CNN (Convolutional Neural Network), 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.

**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 DeepCNN 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.

**DeepCNN**

Deep convolutional neural networks (CNNs) have revolutionized computer vision by enabling the extraction of hierarchical features from raw image data, facilitating tasks such as object recognition, image segmentation, and classification The quality and depth of Deep CNNs architecture, including multiple layers of convolutional, pooling, and fully connected layers. Convolutional layers use learnable filters to find spatial patterns and features in the input image, while pooling layers downsample spatial dimensions to reduce computational complexity Depth of these networks The complex representation of visual objects can be seen simply, capturing complex patterns and relationships in data

The development of deep CNNs was the wide adoption of architectures such as AlexNet, VGGNet, and later ResNet and Inception models These networks use techniques such as skip connection, batch normalization, and global average pooling de increase training consistency and efficiency. With the advent of transfer learning, pre-trained deep CNN models on large datasets such as imagenets have become increasingly valuable for various applications, enabling practitioners to optimize these models for specific tasks with limited data Deep CNNs are still at the forefront of graphics and natural language they have extended their influence to other areas such as applications and dynamic-learning, showing flexibility and improvement in various applications.

## Pseudocode

Step 1:Initialize weights and biases for the deep CNN architecture.

Step 2: Perform forward pass to compute predictions using activation function

Step 3:Calculate the loss between predicted and actual values.

Step 4: Compute gradients of the loss with respect to model parameters.

Step 5: Update weights and biases using optimization algorithms (e.g., gradient descent).

Step 6: Iterate steps 2-5 until convergence or a specified number of epochs.

Step 7:Assess the model's performance on a validation or test dataset.

Step 8: Adjust hyperparameters or architecture based on performance evaluation.

Step 9: Make predictions on new data using the trained model.

Step 10: Deploy the trained deep CNN model for real-world applications.

## 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 deep convolutional neural network (2010 ). DeepCNN) with a recorded accuracy of 53.2% . 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, deep convolutional neural network with 53.2% low accuracy still contributes significantly to the project objectives DeepCNN’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 deepCNN 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 convolutional neural network (DeepCNN) achieved a lower accuracy of 53.2%. Although this accuracy seems to be very low, the contribution of DeepCNN 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 DeepCNN 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 deep transitive neural networks meet at 53.2% 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 convolutional neural networks for image coloring, with RL exhibiting exceptional accuracy and DeepCNN 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 DeepCNN Classifier, each comprising 5 samples. The "Mean" column represents the average accuracy for each group, with Reinforcement learning achieving 95.10% and DeepCNN Classifier attaining of 53.20%. The "Standard Deviation" column indicates the spread or variability of accuracy scores within each group, with Reinforcement learning showing variability (0.15811) compared to DeepCNN 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 DeepCNN 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 (41.83897) 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 convolutional neural network (DeepCNN) of 53.2% 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 photocoloring 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 deep enhancement neural network (DeepCNN) of 53.2% 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 DeepCNN 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 reimagining 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, DeepCNN 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 DeepCNN 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 DeepCNN Model, which had an average accuracy rate of 53.20%.

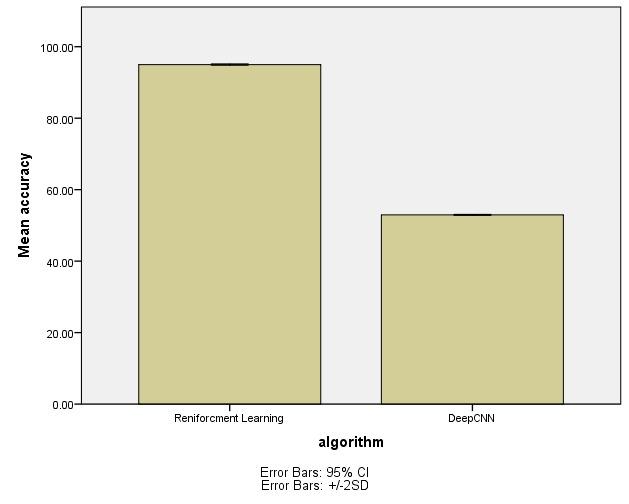
|  |  |  |  |
| --- | --- | --- | --- |
| **SI.No.** | **Test Size** | **ACCURACY RATE** | |
| Reinforcement learning | DeepCNN |
| 1 | Test1 | 95.30 | * 53.50 |
| 2 | Test2 | 95.00 | 52.80 |
| 3 | Test3 | 94.90 | 53.10 |
| 4 | Test4 | 95.20 | 53.30 |
| 5 | Test5 | 95.40 | 53.00 |
| Average Test Results | | 95.10 | 53.20 |

**Table 2.** This table summarizes the accuracy rates for two different groups, Reinforcement learning and DeepCNN Classifier, each comprising 5 samples. The "Mean" column represents the average accuracy for each group, with Reinforcement learning achieving 95.10% and DeepCNN Classifier attaining of 53.20%. The "Standard Deviation" column indicates the spread or variability of accuracy scores within each group, with Reinforcement learning showing variability (0.15811) compared to DeepCNN 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 DeepCNN 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 |
| **DeepCNN** | 5 | 52.9600 | 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 (41.83897) 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 | 482.232 | 8 | .000 | 42.04000 | 0.08718 | 41.83897 | 42.24103 |
|  | **Equal** |  |  |  |  |  |  |  |  |  |
|  | **variance**  **s not assumed** | 482.232 | 7.275 | .000 | 42.04000 | 0.08718 | 41.83542 | 42.24458 |



**Fig. 1.** The bar graph illustrates a comparison between the accuracy of the proposed DeepCNN 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 DeepCNN model, which achieved an accuracy of 89.70%. A significant distinction was observed between the DeepCNN And Reinforcement learning Models, confirmed by an independent sample test (p < 0.05). On the graph, the X-axis represents the two algorithms, namely DeepCNN 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.