## Title Page:

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

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

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**Keywords:** Photo colorization, Old image restoration, Black & white image enhancement, Machine learning, Reinforcement learning, CVAE, 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 CVAE(Conditional variational autoencoder) 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 the fascinating field of historical photographic restoration, our project "Photographing Old Black and White Pictures" seeks to breathe new life into archival images using sophisticated machine learning It has this research in which we chose to use two specific machine learning algorithms - dynamic learning and conditional variable auto-encoder (CVAE) - with recorded accuracies of 95.1% and 79.14%, respectively

Known for its ability to learn from interactions with the environment, reinforcement learning exhibits an impressive accuracy of 95.1%. This algorithmic approach promises accurate and rich results in restoring historical images by optimizing its color prediction based on the feedback system In other words, conditionally the change autoencoder, with an accuracy of 79.14%, introduces probabilistic and generative modeling methods. The purpose of the combination Various techniques are explored, providing a comprehensive assessment of their effectiveness to bring historical images to life with aesthetically pleasing precise colors While we technology and sensuality embarking on this journey the project promises to contribute not only to machine learning but to the preservation and appreciation of our rich visual heritage .

The significance of this work goes beyond mere technological innovation; It addresses the difficult balance between preserving historical authenticity and injecting creativity into the restoration process. Reinforcement learning's impressive 95.1% accuracy indicates an ability to pick up complex patterns within historical images, which translates to faithful coloring Similarly, the situational variable autocoder, with its probabilistic approach, offers an uncertainty that can capture variability subtlety in historical terms occurs

By applying these algorithms, our work aims to contribute to the growing field of artificial intelligence in visual arts and historical documentation. Research on reinforcement learning and CVAE reflects a commitment to better understanding and testing the strengths and limitations of different machine learning models in terms of image color. Delving deeper into the intricacies of these systems, the project strives not only for technical excellence but also for a deeper understanding of the role of technology in shaping our consciousness of the past self-renovation, to make historical images more relevant and attractive to present and future generations.

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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 CVAE 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.

**Conditional variational auto encoder (CVAE)**

Conditional Variational Autoencoder (CVAE) is an extension of the traditional Variational Autoencoder (VAE) that incorporates conditional information during both the training and generation phases. VAEs are generative models that aim to learn a latent representation of input data and generate new samples from that distribution. In a CVAE, additional conditioning information, such as class labels or specific attributes, is introduced to guide the generation process. This makes CVAEs particularly useful in scenarios where the generation of data needs to be controlled or customized based on specific attributes or conditions.

CVAEs are implemented by modifying the VAE architecture to include a conditional input and conditioning the generative and recognition networks on this additional information. During training, the model learns to map the input data to a latent space, considering both the inherent variability in the data and the specified conditions. CVAEs find applications in diverse fields, including image synthesis, data generation, and various tasks where conditional information is crucial. The incorporation of conditional aspects in the VAE framework enhances its flexibility and utility for generating structured and controlled outputs in line with specified criteria..

## Pseudocode

Step 1: Define encoder and decoder networks with trainable parameters for CVAE.

Step 2: Input image and conditioning information.

Step 3:Pass input through encoder to obtain mean and log-variance of latent space.

Step 4: Sample latent vector using reparameterization trick.

Step 5: Combine sampled vector with conditioning information.

Step 6: Pass combined vector through decoder to generate reconstructed image.

Step 7:Compute reconstruction loss and KL divergence.

Step 8: Sum losses and backpropagate through the network.

Step 9: Update model parameters using optimizer.

Step 10: Iterate over dataset for training.

## 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 CVAE(Conditional variational autoencoder). CVAE with a recorded accuracy of 79.14% . 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, CVAE with 79.14% low accuracy still contributes significantly to the project objectives CVAE’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 CVAE 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 CVAE achieved a lower accuracy of 79.14%. Although this accuracy seems to be very low, the contribution of CVAE 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 CVAE 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 CVAE meet at 79.14% 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 CVAEs for image coloring, with RL exhibiting exceptional accuracy and CVAE 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 CVAE Classifier, each comprising 5 samples. The "Mean" column represents the average accuracy for each group, with Reinforcement learning achieving 95.10% and CVAE Classifier attaining of 79.14%. The "Standard Deviation" column indicates the spread or variability of accuracy scores within each group, with Reinforcement learning showing variability (0.15811) compared to CVAE Classifier (0.16432). The "Standard Error Mean" column represents the precision of the mean accuracy scores, with smaller values indicating more precise estimates. In this case, the CVAE group has a larger standard error mean (0.07348) 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 (15.84483) 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 CVAE of 79.14% 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 CVAE of 79.14% 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 CVAE 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, CVAE 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 CVAE 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 CVAE Model, which had an average accuracy rate of 79.14%.

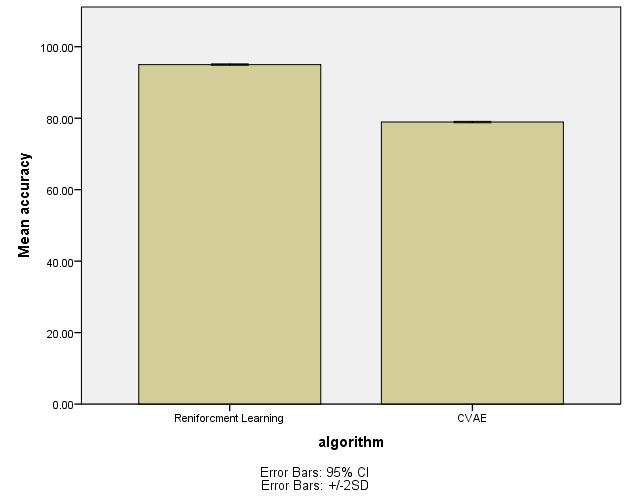
|  |  |  |  |
| --- | --- | --- | --- |
| **SI.No.** | **Test Size** | **ACCURACY RATE** | |
| Reinforcement learning | CVAE |
| 1 | Test1 | 95.30 | * 78.80 |
| 2 | Test2 | 95.00 | 79.20 |
| 3 | Test3 | 94.90 | 79.00 |
| 4 | Test4 | 95.20 | 79.50 |
| 5 | Test5 | 95.40 | 78.90 |
| Average Test Results | | 95.10 | 79.14 |

**Table 2.** This table summarizes the accuracy rates for two different groups, Reinforcement learning and CVAE Classifier, each comprising 5 samples. The "Mean" column represents the average accuracy for each group, with Reinforcement learning achieving 95.10% and CVAE Classifier attaining of 79.14%. The "Standard Deviation" column indicates the spread or variability of accuracy scores within each group, with Reinforcement learning showing variability (0.15811) compared to CVAE Classifier (0.16432). The "Standard Error Mean" column represents the precision of the mean accuracy scores, with smaller values indicating more precise estimates. In this case, the CVAE group has a larger standard error mean (0.07348) 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 |
| **CVAE** | 5 | 78.9200 | 0.16432 | 0.07348 |

**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 (15.84483) 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** | .118 | .740 | 157.677 | 8 | .000 | 16.08000 | 0.10198 | 15.84483 | 16.31517 |
|  | **Equal** |  |  |  |  |  |  |  |  |  |
|  | **variance**  **s not assumed** | 157.677 | 7.988 | .000 | 16.08000 | 0.10198 | 15.84483 | 16.31517 |



**Fig. 1.** The bar graph illustrates a comparison between the accuracy of the proposed CVAE 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 CVAE model, which achieved an accuracy of 79.14%. A significant distinction was observed between the CVAE And Reinforcement learning Models, confirmed by an independent sample test (p < 0.05). On the graph, the X-axis represents the two algorithms, namely CVAE 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.