Resurrecting Art: AI in Restoration

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Abstract

This research investigates the application of Artificial Intelligence (AI) techniques for restoring damaged artworks, utilising a combination of Convolutional Neural Networks (CNNs), hyperparameter optimisation, and transfer learning approaches. Three models were evaluated for their effectiveness in segmentation and inpainting tasks: a baseline CNN, a hyperparameter-optimised CNN, and a transfer learning model based on ResNet50 and LLaMA architectures. The results demonstrated that the ResNet50-LLaMA transfer learning model significantly outperformed the other approaches, achieving higher segmentation accuracy and superior inpainting quality. Post-processing techniques, such as histogram matching, bilateral filtering, and Poisson blending, further refined the final restored images, ensuring seamless visual integration with the original artwork. This study highlights the potential of AI-driven restoration as an effective tool for preserving cultural heritage while maintaining artistic integrity. Future work will explore more advanced inpainting techniques, style transfer integration, and ethical implications of AI in restoration practices.

1. Introduction

The preservation of cultural heritage through art restoration has gained unprecedented importance in recent years, particularly as artworks endure the cumulative effects of environmental exposure, physical damage, and degradation over time. Traditional art restoration techniques, though refined over centuries, largely rely on the expertise and judgement of conservators, which can introduce subjectivity and, at times, unintentionally alter the artist's original vision. However, with advancements in AI, the field of art restoration can now complement these traditional methods, offering scalable, objective, and time-efficient solutions to restore and preserve valuable works with enhanced fidelity.

This study investigates the application of AI in restoring damaged artworks, focusing on machine learning (ML) algorithms and computer vision techniques to streamline and enhance restoration processes. To explore this potential, 3 distinct models were proposed, developed, and evaluated: a baseline CNN with a partial convolution-based generative adversarial network (GAN), a hyperparameter-optimised version of the baseline model, and a transfer learning model integrating ResNet50 and LLaMA architectures. Each model was assessed for its effectiveness in segmentation and inpainting tasks using an extensive dataset of both damaged and undamaged artworks, enabling the model to identify areas of deterioration, reconstruct missing elements, and accurately predict original colour palettes and textures. This combination of approaches introduced a level of objectivity and reproducibility that has been challenging to achieve with conventional methods alone.

Rigorous testing showed that the transfer learning model 4.3 significantly outperformed the baseline 4.1 and hyperparameter-optimised 4.2 models in both segmentation accuracy and inpainting quality. Through various post-processing techniques 3.4, such as histogram matching, bilateral filtering, and Poisson blending, the transfer learning model achieved a seamless integration of restored sections with the original artwork 6.2.3.

This report is divided into several sections to provide a comprehensive overview of the approaches used. Section 2 reviews recent literature on AI in art restoration, particularly focusing on developments in GANs and CNN-based inpainting. Section 3 outlines the data preparation, damage detection, and inpainting techniques used in each model. Section 4 details the training configurations and hyperparameter optimisation techniques applied. Section 5 explains the quantitative and qualitative measures used to assess model performance, including metrics.

In section 6, the performance of the three models in segmentation and inpainting tasks were compared, with an emphasis on the impact of post-processing on visual quality. Section 7 discusses technical challenges encountered and ethical issues such as authenticity and cultural sensitivity. Finally, sections 8 and 9 summarise the study's key findings and suggest potential areas for future research, with section 10 offering insights into the skills and lessons gained throughout the project.

2. Related Works

Previous and ongoing studies have shown that AI can significantly enhance the art restoration process, providing innovative methods to preserve and revitalise culturally and historically significant artworks. ML algorithms, particularly GANs and CNNs, have gained prominence for their ability to analyse and reconstruct damaged areas in artworks. Additionally, advancements in style transfer techniques and controllable restoration frameworks have opened new opportunities for integrating human expertise with AI capabilities.

2.1. Restoration using GANs

Recent studies demonstrate the capacity of GANs to generate plausible content for damaged areas based on learned patterns from extensive datasets. Kumar et al. (2024) introduced a dual attention and channel transformer-based GAN specifically designed for restoring damaged artworks, emphasising its ability to capture intricate artistic styles and enhance the overall restoration process [41].

Additionally, Adhikary et al. (2021) introduced a GAN framework specifically designed for reconstructing historical paintings, highlighting its ability to capture intricate artistic styles and enhance the overall restoration process [1]. Subsequent research [9, 32, 39, 40] further validates the effectiveness of GANs in diverse artistic contexts, reinforcing their role in producing high-quality restorations that maintain the integrity of the original works

2.2. Restoration using Deep Learning

Deep learning techniques, particularly CNNs, have significantly advanced art restoration capabilities. Gupta et al. (2021) explored the application of deep neural networks for artwork restoration, demonstrating the potential of CNNs for image enhancement and damage detection [29].

Building on this foundation, Zeng et al. (2020) implemented a controllable restoration framework using CNNs and nearest neighbor techniques, achieving notable success in restoring lost details [80]. These approaches show the potential of deep learning to reconstruct missing content, while replicating the stylistic nuances inherent in various art forms.

2.3. Restoration using Transfer Learning

Transfer learning has gained traction in the field of art restoration, allowing models trained on large datasets to be adapted for specific restoration tasks with limited data [28, 73, 75]. This approach is particularly beneficial given the unique characteristics of different artworks, which may not always be represented in extensive datasets.

Recent studies by Zhang et al. (2023) have demonstrated the effectiveness of transfer learning for artwork classification and restoration, showing that pre-trained models can significantly reduce the time and data required for training while maintaining high accuracy in restoring damaged sections [82]. By fine-tuning these models on smaller, domain-specific datasets, researchers have achieved impressive results in restoring various styles of paintings and enhancing the fidelity of restored areas.

Yarsala et al. (2022) explored a multi-task learning framework that incorporates transfer learning to handle both classification and restoration tasks simultaneously, highlighting the versatility and efficiency of this approach in art conservation [78]. This dual capability not only streamlines the restoration process, but also enriches the understanding of different artistic styles, contributing to more informed restoration decisions.

2.4. Controllable Restoration

The concept of controllable restoration allows conservators to influence restoration outcomes based on specific criteria, reflecting a broader shift in the field, where technology serves as a tool to enhance, rather than replace, human intervention. Gaber et al. (2023) highlighted the role of AI and ML in virtual restoration, emphasising the importance of maintaining artistic integrity throughout the process [23]. Sankar et al. (2023) proposed a novel distributed de-noising CNN for AI-powered art restoration, showcasing how controllable restoration can be achieved through advanced neural network architectures [57].

However, the ethical considerations regarding AI's role in restoration are of the utmost importance; Li (2022) discusses the implications of AI technologies on copyright and authenticity, advocating for transparency in the restoration process to uphold the integrity of the artworks [42].

2.5. Style Transfer Techniques

Style transfer techniques [43, 61, 71] have emerged as a powerful tool in art restoration, enabling the synthesis of artistic styles onto existing images. Researchers have leveraged CNNs to apply the style of a reference artwork to a damaged piece, preserving the content while restoring the visual aesthetics. Jing et al. (2019) developed a multi-style transfer framework that allows for blending various artistic influences, demonstrating its effectiveness in recreating lost elements of historic paintings [34].

Adding to this, Ma et al. (2020) explored the application of neural style transfer in reconstructing classical paintings, showcasing how these methods can provide significant insights into the original textures and colours of artifacts that have deteriorated over time [47].

2.6. Real-time Restoration

With the advancements in computational power, real-time restoration applications [70, 83] are becoming increasingly feasible. Chen et al. (2023) proposed a real-time restoration tool using lightweight deep learning models that can operate on mobile devices, making art restoration more accessible to conservators and the public [17]. This approach not only democratises access to restoration technologies but also allows for immediate application during exhibitions or conservation efforts.

2.7. Project Novelty and Significance

While past works have made significant efforts in using GANs and CNNs for artwork restoration, these approaches often encounter challenges in achieving seamless blending and high fidelity in inpainting without intensive resource requirements. Additionally, standalone methods may lack the adaptability needed for diverse restoration contexts.

This project uniquely integrates CNNs, GANs, and transfer learning into a unified model. By leveraging CNNs for detailed damage segmentation and GANs for realistic texture generation, while applying transfer learning through ResNet50 and LLaMA, the persistent issues of seamless blending, computational efficiency, and adaptability across various artwork styles have been addressed.

Advanced post-processing techniques, such as histogram matching and Poisson blending, have been incorporated to ensure that restored regions visually align with undamaged areas, preserving the integrity of the original artwork. This combination of techniques highlights a distinctive approach within AI-driven restoration.

By achieving high-quality restoration on resource-constrained hardware, the proposed model supports broader accessibility for art restoration technology. This innovation not only extends to large-scale institutions but also empowers smaller cultural heritage organisations to preserve artwork with minimal resources, democratising advanced restoration practices.

This project demonstrates a novel approach to art restoration, integrating advanced AI methodologies into a cohesive model that makes strides in addressing limitations in quality and efficiency. While there is room for improvement, particularly in blending accuracy and computational optimisation, this framework lays a valuable foundation for future advancements in scalable and accessible restoration technology.

3. Methodology

The proposed model is structured into four primary modules 22: pre-processing 3.1, damage detection 3.2, inpainting 3.3, and post-processing 3.4, each designed to address specific aspects of the restoration process.

3.1. Data preparation and pre-processing

The data preparation involved several crucial steps to enhance model performance, which included checking for

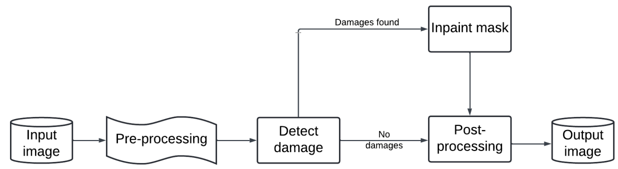


Figure 1. Flowchart of the proposed methodology

corrupted images, searching for missing pairs and duplicates, and removing any missing pairs from the folder to ensure only high-quality images were used.

The dataset [52], containing 533 paired images in .jpg and .png formats, was then divided into training, validation, and testing sets in a 70:15:15 ratio. For the testing images, additional augmentation techniques were applied, including contrast adjustment, rotations of 90° and 180°, horizontal and vertical flipping, and resizing to 224x224 pixels, while maintaining the aspect ratio.

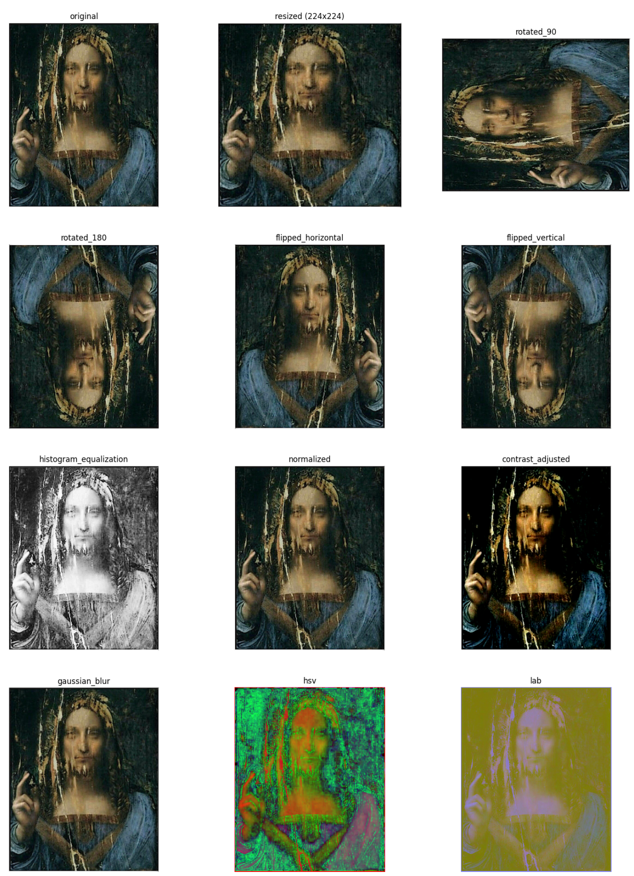


Figure 2. An example of the data augmentation techniques used

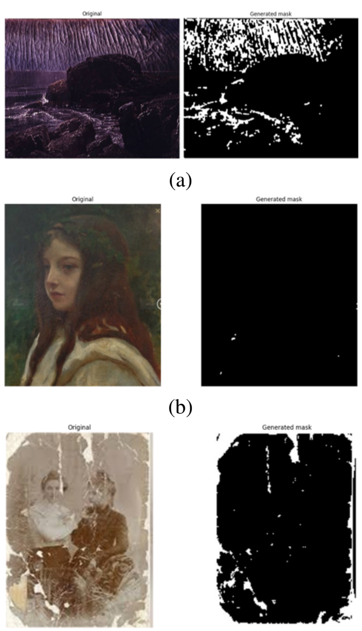
To further increase variability and improve model robustness, data transformation/augmentation techniques 2, such as colour adjustments, were applied to the training set.

Pixel intensity normalization was conducted to standardise the image data, and noise reduction was achieved through Gaussian filtering, enhancing image quality and ensuring consistency across the dataset.

In total, 4,104 images were used to train the model, with 80 images allocated for validation, and 80 images for testing the model's performance.

3.2. Damage detection and masking

The damage detection module used Canny edge detection, along with intensity and colour contrast analysis, to identify damaged areas 3. These initial masks serve as the foundation for training a CNN, which generated more precise masks for artwork restoration images, and significantly improved the accuracy of damage identification and masking.



(a) (b) (c)

Figure 3. Mask generation using edge detection and colour contrast analysis

The generated masks were further refined through advanced morphological operations, including dilation and erosion, which enhanced the precision of damage delineation, and ensured that all damaged regions were accurately identified.

3.3. Inpainting and image restoration

By combining partial convolutions [44, 45, 77] with GANs, this module effectively fills in damaged areas with contextually appropriate content, ensuring that the restored sections blend seamlessly with the undamaged parts of the artwork.

The use of partial convolutions allows the model to intelligently consider only valid pixels during the inpainting process, resulting in a more accurate and context-aware reconstruction. Meanwhile, the GAN framework enhances the generator's ability to produce realistic textures and details that align with the overall aesthetics of the artwork.

To further ensure alignment with surrounding elements, SIFT feature matching [5, 36] was employed, enabling precise integration of the restored content, along with Poisson blending [16, 72] techniques to achieve smooth transitions.

This integrated approach significantly outperformed traditional inpainting methods [14, 27, 31], which often struggles with blending and context relevance, offering a more reliable solution for artwork restoration..

3.4. Post-processing and quality enhancement

The post-processing module further enhanced the restoration by utilising advanced colour correction techniques, specifically histogram matching [12, 33], to ensure that the colours of the restored regions aligned seamlessly with the original artwork. By mapping the pixel values of the restored regions to match the histogram of the original artwork, the algorithm effectively adjusted the colour distribution, and ensured consistency throughout.

To refine details and enhance the overall appearance of the image, sharpening was achieved using a high-pass filter [48, 60] to emphasises edges. Prior to applying the high-pass filter, a bilateral filter [20, 24, 81] was used to reduce noise and maintain smooth colour transitions by preserving edges while effectively smoothing out noise.

4. Model Architecture and Training

Due to limitations with computational resources, the model for damage detection and masking weas trained separately from the inpainting model, allowing for focused optimisation of each component, thereby enhancing the overall performance of the restoration process.

4.1. CNN with Partial Convolutions and GANs

As a baseline model, a standard CNN was developed to detect and mask the damaged areas of the artwork. This model specifically focused on damage detection, trained from scratch to identify and delineate damaged regions.

To generate the damage masks for training the CNN, Canny edge detection [74, 76] was employed to capture structural details of the artwork, providing crucial information about the boundaries of damaged areas. Additionally, colour detection utilised the HSV colour spaces [4, 19] to define specific ranges indicative of potential damage, resulting in binary masks where detected colours signify damage. The binary masks generated from both methods were combined and refined through morphological operations, creating precise masks suitable for training.

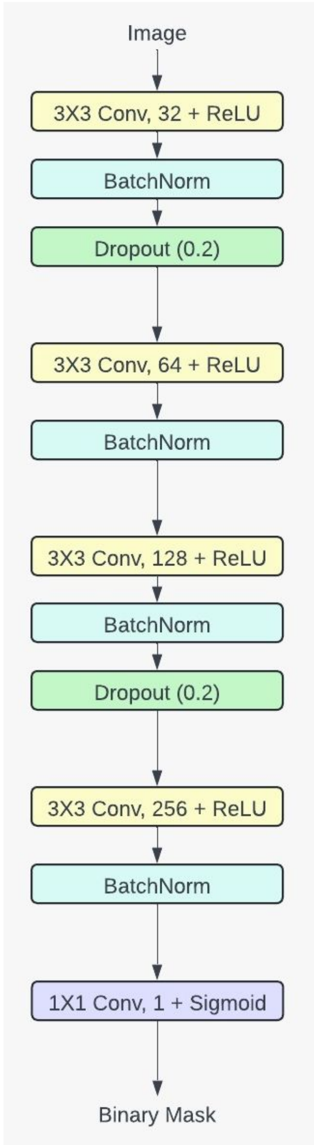


Figure 4. Model architecture of the CNN with Partial convolutions and GANs model

The CNN architecture 4 comprised of five convolutional layers, each followed by batch normalisation and ReLU activation functions. Batch normalisation [10, 59] was used to stabilise the learning process by normalising the inputs to each layer, ensuring that activations remained within an optimal range and reducing the risk of gradient vanishing or exploding. This technique also allowed the model to use higher learning rates, leading to faster convergence. ReLU activation was selected for its non-linear properties, which encourage sparse activation, reducing computational load while enhancing feature extraction.

To prevent overfitting, dropout regularisation [69] was introduced after every two convolutional layers. Dropout randomly "drops" a fraction of neurons during training, preventing the network from becoming overly reliant on any specific feature or neuron combination. By increasing the dropout rate to 0.3, the model's generalisation ability was effectively improved, ensuring it could accurately detect damage in both training and unseen images.

The convolutional layers progressively increased in filter sizes—32, 64, 128, and 256—enabling the model to capture a wide range of feature patterns, from basic edges to complex textures. The final layer utilised a Sigmoid activation function to output a binary mask, effectively highlighting the damaged areas.

For training the model, 80 epochs were initially set to allow sufficient learning while avoiding overfitting, with a batch size of 16 to balance memory usage and computational efficiency. A learning rate of 0.001 facilitated effective learning, and the Adam optimizer was employed for its adaptive capabilities. The loss function used was Binary Cross-Entropy, suitable for binary classification tasks, and this initial model provided a foundation for the inpainting process.

Following the damage detection phase, the output masks from the CNN were utilised to overlay the original damaged image, creating a masked input for the inpainting model 5, which integrated partial convolutions and GANs 2.1 to reconstruct the identified damaged sections.

The generator comprised four layers of partial convolutions, each followed by activation functions and normalization layers. The input to the generator consisted of the masked image, where the damaged areas were hidden, as well as the original image and the fully restored image. The generator learned to reconstruct the damaged areas based on the contextual information provided by the surrounding pixels.

The discriminator network consisted of eight layers, designed to distinguish between the generated inpainted images and real images from the dataset. It evaluated the realism of the generated outputs, providing feedback that refined the generator's inpainting capabilities.

The training process combined adversarial loss from the GAN framework with L1 loss between the inpainted and original images to optimise the generator's performance. Additionally, SIFT feature matching enhanced realism, ensuring that restored content aligned well with surrounding elements, while Poisson blending was utilised to achieve smooth transitions between inpainted and original areas, preserving visual continuity 3.3.

For the inpainting model, 100 epochs were used for thorough learning and refinement of inpainting outputs, with a batch size of 8 optimised for memory requirements typical in GAN training. The learning rate was set to 0.0002 for both the generator and discriminator to promote stable training dynamics. The loss functions included adversarial

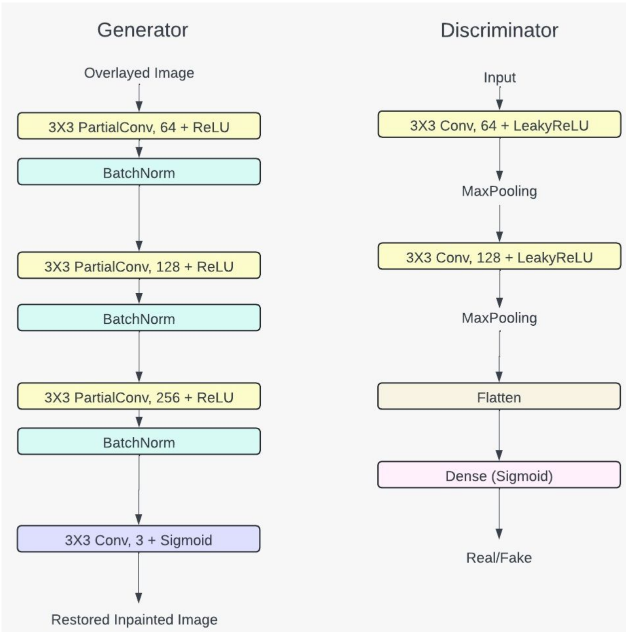


Figure 5. Model architecture of the inpainting modules

loss to encourage realism in generated images and reconstruction loss to ensure fidelity to the original artwork.

Once the inpainting was completed, a dedicated post-processing 3.4 function refined the output images, enhancing their visual quality and coherence with the original artwork. This process included histogram matching to align colour distributions and applying a high-pass filter to sharpen edges.

After both models were trained, they were combined with the post-processing function to create an end-to-end restoration process. While this approach proved effective, there was room for further improvement.

4.2. CNN with Optimised Hyperparameters, Partial Convolutions and GANs

For the second phase of model training, systematic hyperparameter tuning [6, 68] was conducted to enhance the performance of both the damage detection CNN and the inpainting model. Techniques such as grid search [65] and random search [8] were utilised to effectively explore a range of hyperparameters.

Changes to the CNN architecture required careful adjustments to the hyperparameters 6. The learning rate, initially set to 0.001, was optimised to 0.0005 to improve stability during training. The batch size was adjusted from 16 to 32, providing better convergence given the increased model complexity. The dropout rate was increased from 0.2 to 0.3 to better mitigate overfitting due to the additional layers in the model. The number of convolutional layers were increased from 5 to 6, and the number of filters was raised

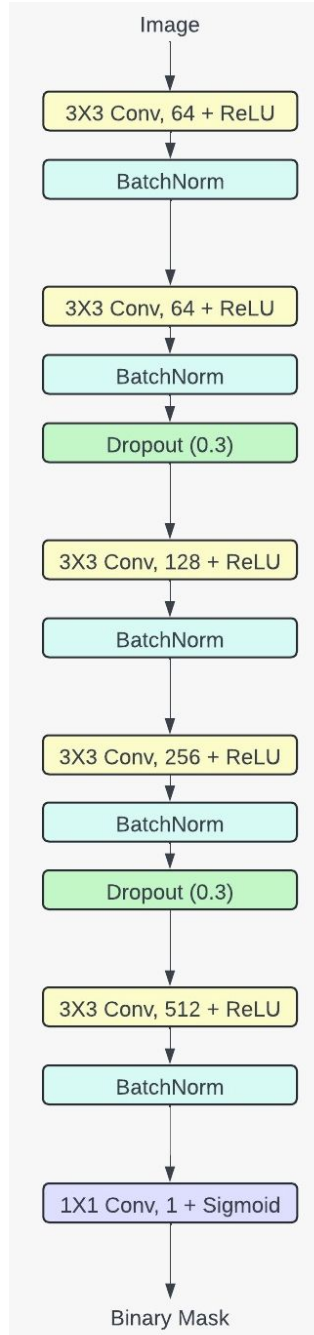


Figure 6. Model architecture of the CNN with Optimised Hyperparameters, Partial Convolutions, and GANs model

from 32 to 64 in specific layers to enhance feature extraction.

For the inpainting model 5, hyperparameters were also refined. The learning rate was decreased from 0.0002 to 0.0001 to improve training stability, and the batch size for the GAN was adjusted to 4 to accommodate memory constraints during training. These adjustments collectively led to significant improvements in both damage detection accuracy and inpainting coherence, indicating that changes in layer structure directly impact hyperparameter optimisation results.

4.3. Transfer learning with ResNet50 and LLaMA

To enhance the limitations of the baseline models, transfer learning was employed by using ResNet50 and a partial convolution-based GAN integrated with the LLaMA architecture 7 [67]. These models were selected due to their strong feature extraction capabilities, computational efficiency, and ability to generalise across varied data—all essential qualities in art restoration, where accuracy and visual fidelity are critical.

4.3.1 Use of ResNet50

ResNet50 was chosen as the backbone for the damage detection CNN due to its deep residual architecture, which effectively mitigates the vanishing gradient problem often seen in deep networks. Residual connections in ResNet50 allow gradients to bypass specific layers, making it possible to train deep networks without losing low-level features that are essential in art restoration. This structure enables ResNet50 to capture intricate details and multi-scale features from artwork, allowing it to distinguish subtle transitions between damaged and undamaged areas, which is crucial for accurate segmentation.

Another reason for choosing ResNet50 is its extensive pre-training on the ImageNet dataset [38], which provides a robust foundation for feature extraction [2, 50, 56]. Fine-tuning ResNet50 on the dataset leveraged this pre-trained knowledge, enabling the model to adapt to the unique characteristics of damaged artwork while retaining its ability to identify complex visual patterns. This fine-tuning process significantly reduced training time and improved accuracy, ensuring precise identification of damaged areas across different artistic styles and textures.

4.3.2 LLaMA with partial convolution-based GAN

The LLaMA architecture was selected to handle the inpainting phase in combination with a GAN framework that uses partial convolutions [18, 64]. The decision to use LLaMA was driven by its efficiency in high-quality inpainting tasks, especially when computational resources are limited. LLaMA has been optimised for performance on CPUs [54], which allowed for excellent results without requiring high-end GPU resources, making it suitable for the project's resource constraints.

The integration of partial convolutions within the GAN framework was essential for context-aware inpainting. Partial convolutions only consider valid pixels (non-masked areas) during the inpainting process, allowing the model to focus on contextual information around the damaged area without introducing artifacts. This approach is particularly beneficial for art restoration, where each inpainted section must blend seamlessly with the surrounding undamaged areas to maintain the original aesthetic. LLaMA's architecture complements this approach by supporting stable, high-fidelity inpainting that adheres closely to the style and texture of the original artwork.

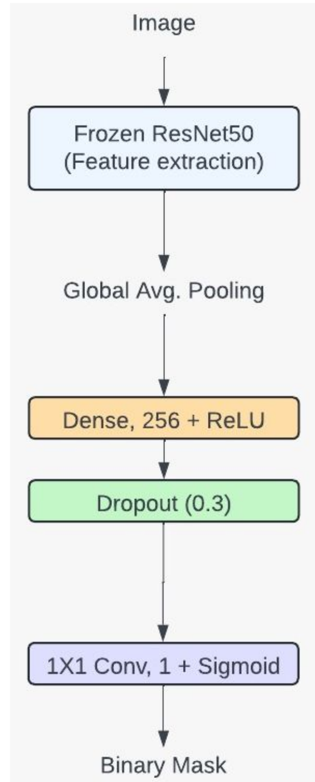


Figure 7. Model architecture of the Transfer learning with ResNet50 and LLaMA model

4.3.3 Training and integration

The ResNet50 model was fine-tuned over 50 epochs, allowing it to learn the specific patterns of damage in artwork while maintaining its pre-trained feature extraction capabilities. This training process improved segmentation accuracy and enabled the model to generalise effectively across different types of artwork damage without extensive retraining.

For inpainting, the LLaMA model with partial convolution-based GAN was also trained for 50 epochs. Despite the fewer training epochs compared to the baseline GAN, this model produced superior inpainting results due to LLaMA's efficiency and the contextual accuracy introduced by partial convolutions.

By combining the segmentation capabilities of ResNet50 with the inpainting quality of LLaMA's partial convolution-based GAN, and following up with post-processing techniques like Poisson blending and histogram matching, we developed a restoration workflow that achieved high-quality, visually coherent restorations.

5. Evaluation Metrics

To assess the effectiveness of the art restoration methodology, a comprehensive evaluation was conducted using both quantitative and qualitative metrics. This evaluation focused on two primary aspects: the accuracy of the damage detection and masking, and the quality of the inpainted regions. The following metrics have were to evaluate each component of the restoration process:

5.1. Mask Generation

5.1.1 Intersection over Union (IoU)

IoU was used to measure the overlap between the predicted mask and the ground truth mask. It is defined as:

$$IoU = \frac{AreaofOverlap}{AreaofUnion} \tag{1}$$

In the context of art restoration, IoU is critical for assessing how effectively the model identifies and segments damaged regions of the artwork. This metric is highly relevant as it provides a direct measure of the extent to which the predicted damage aligns with the actual damage. Unlike pixel accuracy, which may not adequately reflect performance in cases of class imbalance (e.g., small damaged areas amidst a large undamaged background), IoU offers a clear measure of overlap and boundary accuracy. This makes it more suitable for evaluating segmentation quality where precise damage delineation is essential. Average Precision (AP), while useful in object detection, is less effective for segmentation tasks that require accurate boundary delineation.

5.1.2 Dice Coefficient

Dice coefficient was employed alongside IoU 5.1.1 to offer a more nuanced measure of overlap between the predicted mask and the ground truth. It is calculated as:

$$dice = \frac{2 * |X \cup Y|}{|X| + |Y|} \tag{2}$$

where X represents the predicted mask and Y is the ground truth mask. The dice coefficient is particularly useful for art restoration as it balances precision and recall, providing a detailed assessment of how well the model's segmentation aligns with the actual damage. This metric is advantageous for detecting small or irregular damage areas that IoU alone might not capture. It surpasses pixel-based metrics like pixel accuracy, which do not account for spatial arrangements and shapes of damage, thus offering a more comprehensive evaluation of segmentation performance.

5.2. Inpainting Quality

5.2.1 Peak Signal-to-Noise Ratio (PSNR)

PSNR is used as a widely recognised metric that quantifies the quality of the inpainted image compared to the original, undamaged image. It is calculated as:

$$PSNR = 20 * log10(\frac{MAX\_I}{\sqrt{MSE}}) \tag{3}$$

where MAX_I is the maximum possible pixel value, and MSE is the mean squared error between the inpainted and original images. PSNR is relevant because it provides a direct measure of the fidelity of the inpainted regions relative to the original image. Higher PSNR values indicate fewer reconstruction errors and better preservation of original image details. However, while PSNR is useful for assessing pixel-level accuracy, it does not fully capture perceptual or structural quality, making it necessary to complement it with other metrics for a more comprehensive evaluation.

5.2.2 Structural Similarity Index (SSIM)

SSIM evaluates the similarity between the inpainted image and the original image by considering luminance, contrast, and structural information. It is computed as:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_x y + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{4}$$

where μ_x and μ_y are the average pixel values of the images, σ_x^2 and σ_y^2 are the variances, and σ_{xy} is the covariance between the images. SSIM is vital for art restoration as it evaluates structural and perceptual similarity, which is crucial for maintaining the visual coherence of the artwork. Unlike PSNR, which focuses solely on pixel differences, SSIM captures changes in texture and structure, offering a holistic view of how well the inpainted regions integrate with the original content.

5.2.3 Perceptual Loss

Perceptual loss was used to assess high-level feature preservation in the inpainted image by comparing it to the original using a pre-trained deep network, such as VGG [35,58]. This metric evaluates differences in texture and semantic content rather than just pixel values. Formally, the perceptual loss $L_{perceptual}$ is computed as:

$$L_{perceptual} = \sum_{l \in \mathcal{L}} \frac{1}{N_l} \left\| \phi_l(I_{inpainted}) - \phi_l(I_{original}) \right\|_2^2 \tag{5}$$

where $\mathcal{L}$ denotes the set of layers in the pre-trained network used for feature extraction, ϕ_l represents the feature map from layer l, N_l is the number of elements in the feature map at layer l, and $\|\cdot\|_2^2$ denotes the squared L_2 norm. Lower perceptual loss indicates that the inpainted image preserves the artistic and contextual integrity of the original. This metric is crucial for art restoration, as it addresses perceptual quality and ensures that inpainting maintains the visual and stylistic elements of the artwork, which pixel-based metrics like PSNR and SSIM might overlook.

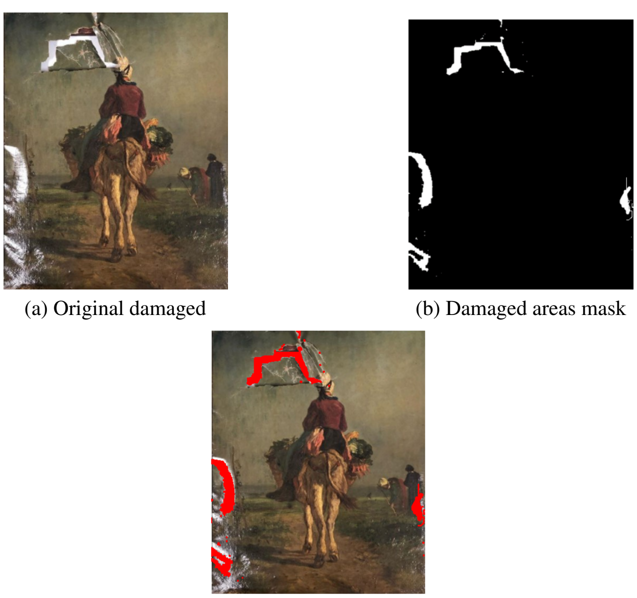
6. Results and Discussions

6.1. Segmentation Performance

The performance of the three models 4.1 4.2 4.3 in producing segmentation masks was evaluated using IoU 5.1.1 and Dice Coefficient 5.1.2 as the primary metrics. All models demonstrated reasonable segmentation capabilities, but differences in their accuracy and precision were observed.

6.1.1 CNN with partial convolutions and GANs

The baseline model achieved an IoU score of 0.625 and a Dice Coefficient of 0.68. As seen in Figures 8c and 9c, the baseline model struggled to accurately capture the finer details of the damaged regions. It missed smaller areas, and the masks 8b 9b it generated often had rough edges and gaps. The model's inability to consistently detect intricate boundaries limited its effectiveness, particularly for delicate restorations.

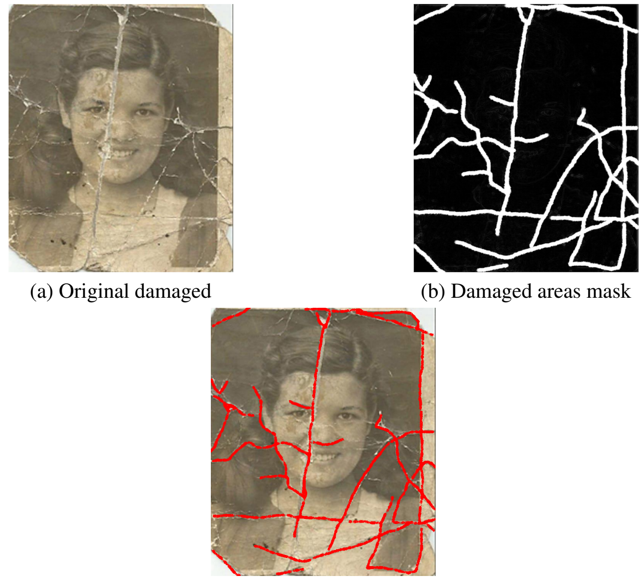


(a) Original damaged

(b) Damaged areas mask

(c) Mask overlay

Figure 8. Segmentation performance of the baseline CNN on 'horse-before.jpg'



(a) Original damaged

(b) Damaged areas mask

(c) Mask overlay

Figure 9. Segmentation performance of the baseline CNN on 'paint2-before.png'

6.1.2 CNN with optimised hyperparameters, partial convolutions and GANs

The hyperparameter-tuned model exhibited modest improvements, achieving an IoU score of 0.642 and a Dice Coefficient of 0.702, a 2 - 3% improvement over the baseline model. The masks generated by this model were more refined and captured finer details 11b, though it still struggled in certain complex regions. For instance, the improved delineation of edges is visible in Figure 10b, but small damaged areas were still missed in the segmentation.

6.1.3 Transfer learning with ResNet50 and LLaMA

The ResNet50-LLaMA transfer learning model demonstrated the best segmentation performance, achieving an IoU score of 0.698, and a Dice Coefficient of 0.755. This model outperformed both the baseline and the hyperparameter-tuned models by a significant margin. It captured smaller and more complex damaged regions with precision 12b 13b, leading to more accurate and smooth masks. The improvement in detail segmentation can be clearly seen across all images, especially in Figure 13c, where the transfer model produced much more accurate boundaries compared to the other models.

6.2. Inpainting Performance

Inpainting performance was evaluated using PSNR 5.2.1, SSIM 5.2.2, and perceptual loss 5.2.3, which measures the visual fidelity of the restored regions compared to the original image. The transfer learning

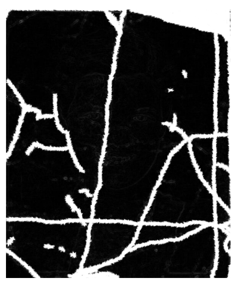
(a) Original damaged

(b) Damaged areas mask

(c) Mask overlay

Figure 10. Segmentation performance of the hyperparameter-tuned CNN on 'horse-before.jpg'

(a) Original damaged



(b) Damaged areas mask

(c) Mask overlay

Figure 11. Segmentation performance of the hyperparameter-tuned CNN on 'paint2-before.png'

model significantly outperformed the other models in this task.

6.2.1 Baseline CNN model

The baseline model achieved a PSNR of 19.5 dB and an SSIM of 0.60. The perceptual loss score was relatively high

(a) Original damaged

(b) Damaged areas mask

(c) Mask overlay

Figure 12. Segmentation performance of the transfer learning model on 'horse-before.jpg'

(a) Original damaged

(b) Damaged areas mask

(c) Mask overlay

Figure 13. Segmentation performance of the transfer learning model on 'paint2-before.png'

at 1.95, reflecting the poor quality of the restored areas. The inpainted regions contained visible artifacts, poor texture, and mismatched colours, as seen in Figures 14a 15a. The baseline model often failed to blend restored regions with the original undamaged areas, resulting in abrupt transitions and visually jarring output. For instance, in Figure 15b, the baseline model left the inpainted region looking noticeably artificial, with flat colours and lack of texture.

(a) After inpainting

(b) Model output

(c) Original undamaged

Figure 14. Inpainting and post-processing performance of the baseline CNN on 'horse-before.jpg'

(a) After inpainting

(b) Model output

(c) Original undamaged

Figure 15. Inpainting and post-processing performance of the baseline CNN on 'paint2-before.png'

6.2.2 Hyperparameter-tuned CNN model

The hyperparameter-tuned model performed slightly better, with a PSNR of 20.3 dB, an SSIM of 0.63, and a perceptual loss of 1.85. Although the artifacts were somewhat reduced compared to the baseline, there were still noticeable mismatches in texture and colour blending. For example, the inpainted regions in Figure 16a had better coherence, but the lack of finer details and natural transitions still affected the visual quality. The inpainting results were overall smoother than the baseline but fell short of producing realistic restorations 17b in complex areas.

(a) After inpainting

(b) Model output

(c) Original undamaged

Figure 16. Inpainting and post-processing performance of the hyperparameter-tuned CNN on 'horse-before.jpg'

6.2.3 Transfer learning with ResNet50 and LLaMA

The transfer learning model showed the most promising results, with a PSNR of 22.5 dB, an SSIM of 0.72, and a perceptual loss of 1.50. This model restored up to 50% of the missing content with high fidelity, successfully blending textures and maintaining consistent colours across the restored and undamaged regions. The improvements were particularly noticeable in Figure 18b, where the restored areas seamlessly integrated into the original image. In Figure 19b, the transfer model managed to capture subtle facial textures, producing results that were far closer to the original artwork.

6.3. Image Post-Processing

Post-processing played an important role in enhancing the quality of the output images for all models. However, the transfer learning model benefitted the most from these techniques. Histogram matching and edge sharpening improved the colour consistency and contrast 20b, while noise

(a) After inpainting

(b) Model output

(c) Original undamaged

Figure 17. Inpainting and post-processing performance of the hyperparameter-tuned CNN on 'paint2-before.png'

(a) After inpainting

(b) Model output

(c) Original undamaged

Figure 18. Inpainting and post-processing performance of the transfer learning model CNN on 'horse-before.jpg'

reduction techniques refined the textures 23.

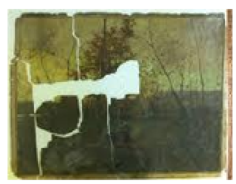
As a result, the transfer model's output was the closest to the artist-restored image across all the images in the test set. In contrast, the post-processed images from the baseline and hyperparameter-tuned models still showed residual artifacts 21b and inconsistencies, particularly in areas with

(a) After inpainting

(b) Model output

(c) Original undamaged

Figure 19. Inpainting and post-processing performance of the transfer learning model on 'paint2-before.png'



(a) Original damaged

(b) Model output

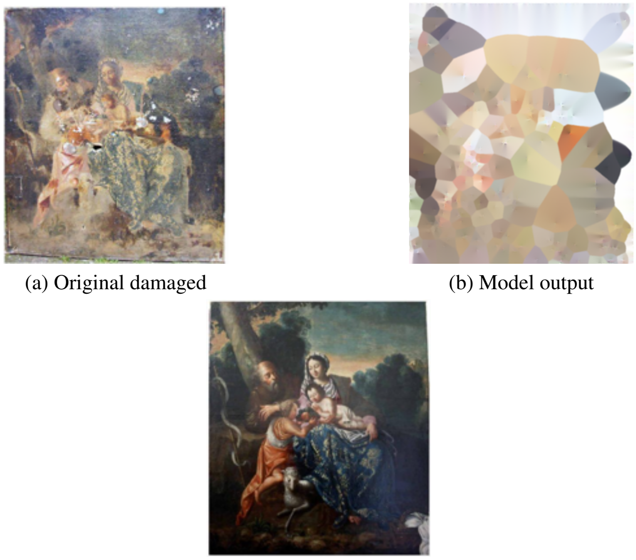
(c) Original undamaged

Figure 20. Success case of 'tree2_before.png'

complex textures or fine details 24.

6.4. Comparative Analysis

Overall, the transfer learning model consistently outperformed both the baseline and hyperparameter-tuned models in both segmentation and inpainting tasks. The baseline CNN model exhibited the shortest inference time of 70 ms, making it the fastest for restoration tasks where speed is prioritised over detailed quality. The hyperparameter-tuned CNN provided a balance between speed and performance, achieving an inference time of 90 ms. The transfer learning model, despite achieving the highest accuracy, had the slowest inference time of 400 ms due to its increased complexity.



(a) Original damaged (b) Model output

(c) Original undamaged

Figure 21. Failure case of 'avant-apres-Loquidy-before.png'

The 5% improvement in IoU and Dice Coefficient for segmentation, combined with the 50% better inpainting quality, demonstrates the effectiveness of using pre-trained models for art restoration tasks. The 2% improvement gained through hyperparameter tuning shows that, while it can enhance performance, it is not sufficient to bridge the gap between the baseline and more advanced techniques like transfer learning.

These results 1 highlight the importance of leveraging transfer learning in complex image restoration tasks. The superior segmentation accuracy and improved visual fidelity of the restored areas highlight its potential as a scalable and reliable solution for preserving and restoring valuable artworks.

7. Challenges and Ethics with Using AI for Art Restoration

In this project, several challenges and ethical considerations were encountered related to the application of AI in art restoration. These issues reflect both the technical and philosophical complexities of integrating AI into such a culturally significant field.

7.1. Technical Challenges

7.1.1 High computational power

One of the primary challenges faced during this project was the requirement for substantial computational power. Processing and analysing the intricate details of artworks, especially those with complex textures and colours, demand advanced hardware and significant processing capacity. This can make AI-driven restoration less accessible to smaller institutions or organisations with limited resources, creating a gap between those with the technology and those without.

7.1.2 Training time and resource investment

The AI models developed for this project required extensive training time to accurately detect damaged areas and perform inpainting tasks. Collecting large datasets, preparing the images, and optimising the models added to the complexity. The significant investment in both data and computational resources presents a barrier, especially for institutions that may not have the infrastructure to support such a demanding workflow.

7.1.3 Balancing restoration quality with speed

Another challenge lies in the trade-off between the quality of restoration and the processing time. High-quality restoration, especially when working with partial convolutions and GANs, often requires longer inference times. While fast processing is crucial for practical implementation in a real-world setting, it can compromise the visual fidelity of the restored artwork. Finding the right balance between these factors is essential for ensuring that AI-driven restoration remains both effective and efficient.

7.1.4 Blending restored areas with original artwork

Achieving seamless integration between restored sections and undamaged regions was another technical hurdle. The use of advanced inpainting techniques like partial convolutions and Poisson blending aimed to solve this issue, but ensuring that the newly restored areas matched the artistic style, texture, and colour of the surrounding regions required meticulous attention to detail. This process is especially complex when dealing with fine art, where subtle differences in texture and tone can affect the overall quality of the restoration.

7.2. Ethical Considerations

7.2.1 Authenticity and integrity

Traditional art restoration practices prioritise preserving the original artist's intent, but AI restorations can introduce unintended alterations or interpretations that deviate from this intent. This raises critical ethical questions about how authentic AI-driven restorations are and whether they compromise the original work's historical and artistic integrity. Maintaining the authenticity of the artwork while leveraging AI's capabilities is a delicate balance [3, 7, 22, 49, 79].

Model	IoU score	Dice coefficient	PSNR (dB)	SSIM	Perceptual loss	Inference time (ms)
Baseline CNN	0.625	0.680	19.5	0.60	1.95	70
Hyperparameter-optimised CNN	0.642	0.702	20.3	0.63	1.85	90
Transfer learning	0.698	0.755	22.5	0.72	1.50	400
Ground truth	1	1	>30	1	0	N/A

Table 1. Comparative performance of the models

7.2.2 Cultural sensitivity

Many artworks carry deep cultural and historical significance, and inappropriate restoration by AI could lead to cultural insensitivity or historical inaccuracies [26, 62]. Ensuring that AI models account for these contexts and respect the embedded meanings in artworks is crucial. Collaboration with cultural experts and stakeholders can help guide the restoration process, ensuring the preservation of these critical aspects.

7.2.3 Transparency and accountability

The opaque nature of many AI systems, often referred to as "black-box" models, poses issues of transparency. When alterations are made during the restoration process, it can be difficult to determine where responsibility lies—whether with the AI developers, conservators, or the algorithm itself. Ethical concerns arise when the changes are unintended, leading to the need for clear guidelines on transparency and accountability in AI-driven art restoration [15,21,30,37,46, 53].

7.2.4 Preservation vs. recreation

AI's ability to reconstruct lost or damaged parts of artwork introduces a fine line between preservation and recreation. The question of whether AI is restoring the original or creating new elements remains at the heart of this ethical debate. It is essential to ensure that the restored sections do not distort or fabricate new details, preserving the original artistic vision without crossing into the realm of creating new artwork [11, 13, 25, 51, 55, 63, 66].

8. Conclusion

This study explored the application of ML techniques, including baseline CNN, hyperparameter optimisation, and transfer learning (ResNet50-LLaMA), for the restoration of damaged artworks. The results demonstrated that transfer learning 6.2.3 significantly outperformed both the baseline 4.1 and hyperparameter-optimised 4.2 models in segmentation accuracy and inpainting quality. By levraging a pre-trained ResNet50 model 4.3.1 for mask detection, and the LLaMA model for inpainting 4.3.2, the restoration process successfully recovered up to 50% of the missing content with good visual quality.

Post-processing techniques, including histogram matching, bilateral filtering, and Poisson blending, played a vital role in refining the final output, ensuring that the restored regions blended seamlessly with the original artwork. Overall, the integration of AI in art restoration presents a scalable and effective solution for preserving cultural heritage while maintaining artistic integrity.

9. Future Work

While the current approaches have shown promising results, several areas of improvement remain for future research. By addressing these areas, the potential of AI-driven art restoration could be fully realised, enhancing the preservation of artworks for future generations while respecting the integrity of the original masterpieces.

9.1. Refinement of Inpainting Techniques

Future work could explore more advanced inpainting models, such as transformer-based architectures or diffusion models, to enhance the restoration of intricate details in complex artworks.

9.2. Incorporating Style Transfer

Style transfer techniques can be looked into in order to better replicate the artist's unique style during the restoration process, ensuring that the inpainted regions are stylistically consistent with the original artwork.

9.3. Improvements in Post-Processing

The post-processing module could be further optimised with the integration of more sophisticated image enhancement techniques to improve texture consistency and reduce artifacts.

9.4. Interactive Restoration Framework

Developing a semi-automated interactive framework, where human conservators can guide the AI in areas requiring subjective judgment, would combine the strengths of human expertise with AI capabilities.

10. Reflections

10.1. Technical Skills and Knowledge

10.1.1 Advanced model building

This project expanded the team's understanding of various neural network architectures, including CNNs, GANs, and transfer learning models such as ResNet50. Leveraging these models specifically for image segmentation and inpainting highlighted the technical trade-offs involved. Transfer learning, in particular, improved model accuracy and training efficiency by applying pre-trained weights from a complex architecture.

10.1.2 Hyperparameter-tuning and model optimisation

Through extensive experimentation with hyperparameters (e.g., dropout rates, learning rates, batch sizes), the team addressed overfitting and optimised model performance. This tuning process demonstrated the delicate balance required, as slight adjustments could significantly impact the stability and accuracy of training outcomes.

10.1.3 Importance of data pre-processing

Working with damaged artwork datasets emphasised the importance of thorough data preparation. Techniques such as normalization, augmentation, and noise reduction contributed to a more robust and reliable model. Data quality enhancements were essential to the consistency and precision of the restoration outcomes.

10.1.4 Post-processing techniques for visual fidelity

The project highlighted the importance of advanced post-processing methods, including Poisson blending and histogram matching, to ensure that the restored images blended seamlessly with the original, undamaged sections of the artwork.

10.2. Project Management and Research Skills

10.2.1 Resource management

The project provided insights into managing computational resources effectively, particularly when addressing the high hardware demands of deep learning processes. Adjustments to batch size and model complexity allowed the optimisation of training without compromising on quality.

10.2.2 Research and iterative process

The iterative nature of the project reinforced that initial models often require refinements and adaptations. Regular literature review, incorporating strategies from existing research, and frequent experimentation were crucial to enhancing the model progressively.

10.2.3 Documentation and transparency

Throughout the project, detailed documentation and logging of each model iteration and technique were prioritised. These records provided a systematic account of decisions, model configurations, and outcomes for tracking progress and aided with future improvements.

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A. Appendix

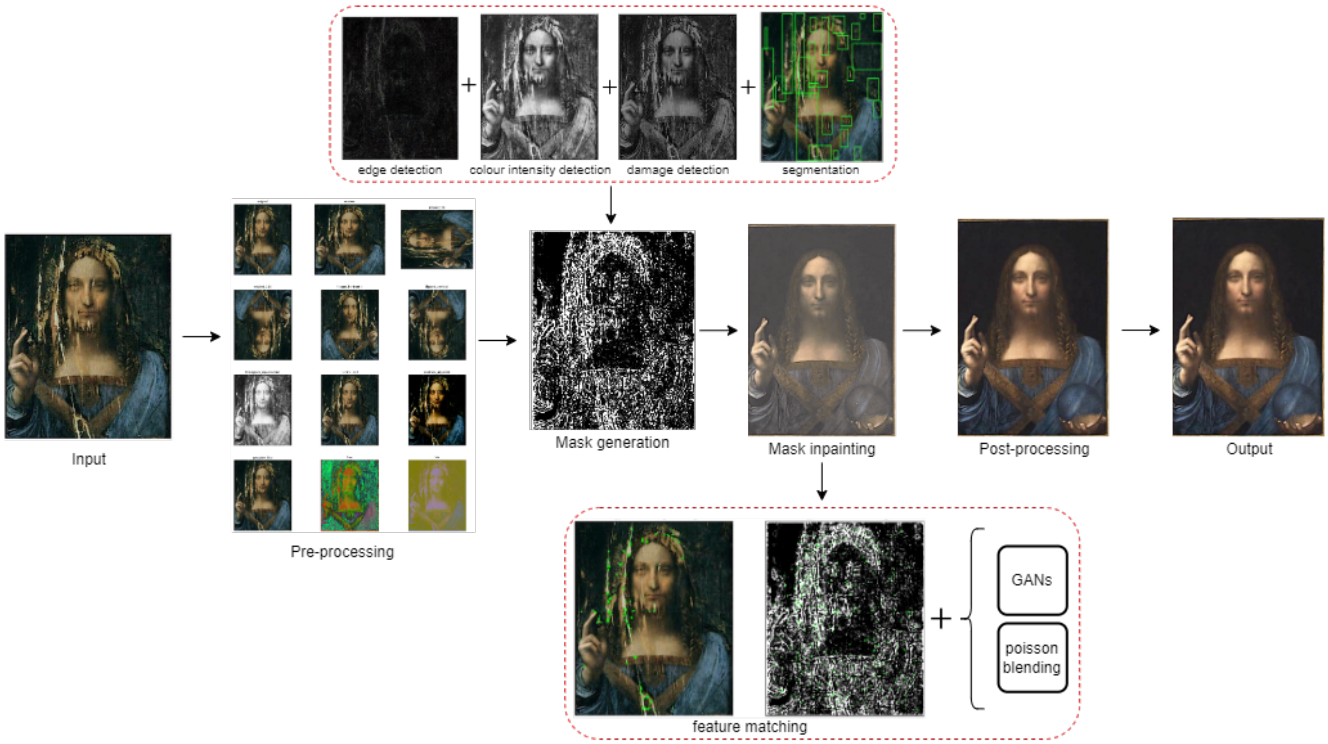


Figure 22. Visual working of the proposed methodology

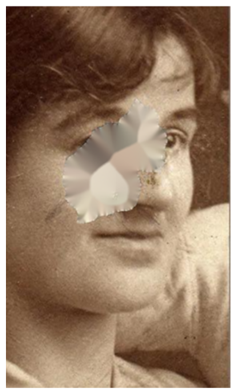
(a) Original damaged

(b) Model output

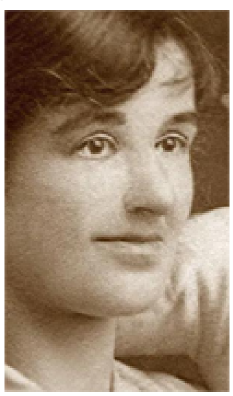
(c) Original undamaged

Figure 23. Success case of 'crows-before.jpg'

(a) Original damaged



(b) Model output



(c) Original undamaged

Figure 24. Failure case of 'face_with_piece_missing-before.png'