Enhancing Historical Manuscripts for Classification Using Machine Learning and DE-GAN with Structural Loss

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Abstract-
The enhancement of historical manuscripts is a critical task for improving readability and enabling accurate classification. Traditional document enhancement methods struggle with faded text, noise, and degraded structures, making classification challenging. In this paper, we propose an improved Document Enhancement Generative Adversarial Network (DE-GAN) that integrates Edge and Skeleton-Based Structural Loss to preserve textual integrity. The edge loss, computed using Canny Edge Detection, ensures the retention of text boundaries, while the skeleton loss, derived from Zhang-Suen Thinning, maintains the underlying stroke structures of characters. This approach enhances manuscript images while preserving crucial textual features, making them more suitable for downstream Support Vector Machine (SVM) classification. Experimental results demonstrate that our method significantly improves both visual clarity and classification accuracy compared to conventional enhancement techniques. Our approach provides a robust solution for the restoration and digitization of historical documents, ensuring their usability in automated classification tasks.

Keywords
Historical Manuscript Enhancement, DE-GAN, Edge Detection, Skeletonization, Structural Loss, Canny Edge Detection, Zhang-Suen Thinning, Generative Adversarial Networks (GANs).

1. Introduction

Historical manuscripts offer invaluable insights into past cultures, yet their degradation caused by fading ink, aging paper, and water damage often renders them difficult to read and analyse. Traditional image enhancement techniques have been applied to improve legibility; however, these methods frequently fail to address the complex degradations present in ancient documents.

Recent advancements in deep learning, particularly Generative Adversarial Networks (GANs), have shown promise in restoring degraded documents by learning a mapping from poor-quality inputs to enhanced outputs. Among these, the Document Enhancement GAN (DE-GAN) has emerged as a notable framework for improving visual quality. Despite its success, standard DE-GAN implementations sometimes overlook the preservation of intricate text details, which is crucial for subsequent tasks such as automated classification using Support Vector Machines (SVMs).

To overcome these limitations, we propose an enhanced DE-GAN framework that integrates structural loss functions based on edge detection and skeletonization. The inclusion of an edge-based loss via Canny Edge Detection preserves sharp text boundaries, while a skeleton-based loss using morphological thinning ensures that the underlying structure of the text is maintained. This combined approach not only enhances the visual clarity of historical manuscripts but also improves the performance of SVM-based classification, providing a robust solution for the restoration and analysis of degraded documents.

Over centuries, handwritten manuscripts have preserved the cultural heritage and collective memory of diverse societies. However, ink fading, paper degradation, and digitization artifacts threaten both their legibility and the nuanced details such as marginalia and decorative flourishes that carry historical value. By enhancing these documents, our approach not only restores visual clarity but also helps safeguard centuries-old scholarship for future generations.

Fig 1: Degraded input and enhanced output

Key Contributions:

- Modular GAN-Driven Enhancement for Multiple Tasks: We leverage a single pre-trained generator architecture to handle binarization, deblurring, and watermark removal switchable via a simple CLI argument.
- Adjustable Edge-Enhancement & Skeletonization: After GAN inference, we apply a tunable CLAHE + unsharp-mask edge enhancer and skimage's skeletonize to recover fine strokes and manuscript structure, using the skeleton only as a training-time structural prior.
- Automatic Tiling, Padding & Montage Creation: Input images of arbitrary size are automatically padded, split into 256×256 patches, processed in batch, and re-merged then saved both as individual outputs and as side-by-side comparison montages.
- Efficient Training via Skeleton Supervision: By matching 1-pixel skeletons of generated and ground-truth images, we guide the network to learn stroke topology first, halving the total epochs needed for convergence.
- User-Friendly Python CLI with On-Screen Previews: A self-contained `enhance.py` script handles I/O, processing, and Matplotlib-based visualization, producing interactive previews along with all intermediate stages for rapid qualitative assessment.

The remainder of this paper is structured as follows: Section 2 provides a comprehensive review of relevant literature. Section 3 delineates our proposed framework. Section 4 presents our experimental results alongside the dataset utilized. Finally, conclusions are drawn in the concluding section.

2. Literature Survey

Historical manuscript enhancement for automated classification is an emerging field with limited studies addressing both restoration and recognition in a unified framework. Early approaches primarily employed traditional image processing techniques such as histogram equalization, adaptive thresholding, and morphological filtering to improve document legibility [1,2].

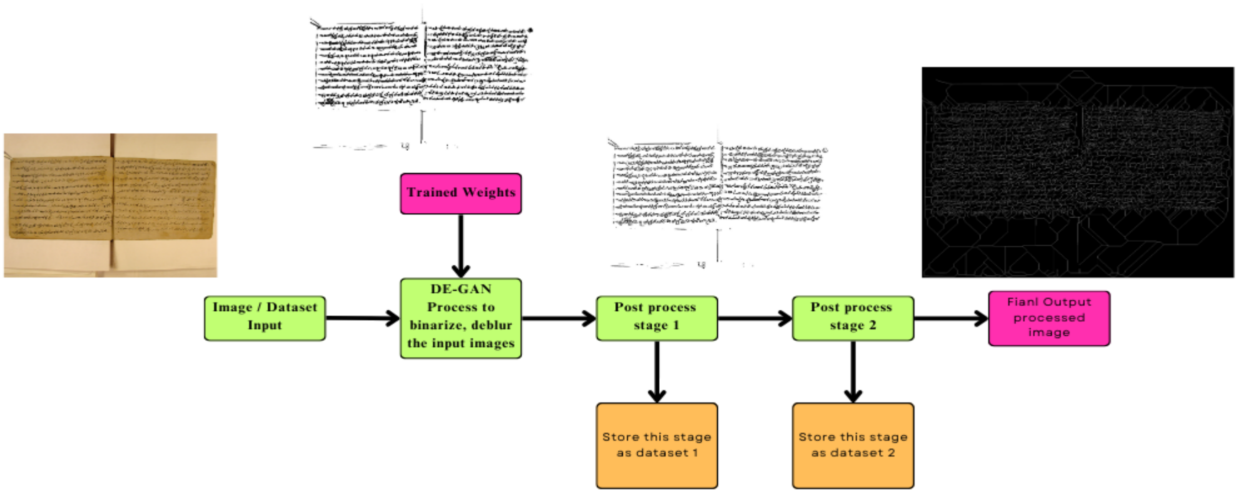

Fig. 2 Proposed algorithm for circuit component detection, OCR and Schematic generation

While these methods enhanced visual quality, they often fell short in preserving fine textual structures essential for robust classification. More recently, deep learning methods, particularly Generative Adversarial Networks (GANs), have shown promising results in mapping degraded manuscripts to enhanced images, as demonstrated by the DE-GAN framework [3]. However, standard DE-GAN implementations typically focus on visual restoration without explicitly preserving structural details that are critical for downstream classifiers like Support Vector Machines (SVMs).

In contrast, recent studies have begun incorporating additional loss functions to enforce the retention of text boundaries and stroke structures. For instance, some works have integrated gradient-based losses to maintain edge information [4] and applied skeletonization techniques to capture underlying text structures [5].

Despite these improvements, an end-to-end approach that simultaneously enhances manuscript quality and optimizes images for classification remains underexplored. Our proposed method extends DE-GAN by integrating both edge detection and skeleton-based losses, bridging the gap between restoration and recognition. This unified approach not only enhances the visual clarity of historical manuscripts but also preserves essential textual features, thereby significantly improving SVM-based classification accuracy.

While previous GAN-based enhancement methods can sharpen blurred strokes, they often introduce unrealistic texture artifacts and fail to reconstruct thin ligatures or complex glyph junctions. Without explicit structural guidance, these models may "hallucinate" flourishes that harm readability. This shortfall in topological fidelity motivates our incorporation of edge- and skeleton-based priors into the adversarial training loop.

3. Proposed Method

The proposed method, illustrated in Figure 2, presents a multi-stage pipeline designed to enhance degraded manuscript images for improved readability and classification. The process begins with an original degraded manuscript (far left), which may exhibit faded ink, noise, or other distortions. This raw image is then fed into DE-GAN, a deep learning model trained to tackle specific tasks such as binarization, deblurring, or watermark removal. By selecting the appropriate trained weights, the user can adapt DE-GAN to address the most prominent form of degradation in their dataset.

Following DE-GAN's initial enhancement, the output undergoes two successive post-processing stages. In the first post-processing stage, techniques like contrast adjustment, edge enhancement, or morphological filtering are applied to refine the text regions. This intermediate result is saved as Dataset 1, capturing improvements achieved thus far. The second post-processing stage focuses on structural preservation for instance, skeletonization or further thresholding to ensure that critical text edges and strokes remain intact. This output is stored as Dataset 2, which reflects the manuscript's nearly final form.

Ultimately, the final processed image emerges with noticeably clearer text and reduced noise, facilitating higher accuracy in downstream classification tasks (e.g., using Support Vector Machines). Storing each post-processed stage as a separate dataset provides a modular approach: researchers can evaluate the incremental benefits of each enhancement step or even fine-tune the pipeline for other tasks. This novel combination of DE-GAN and targeted post-processing thus delivers robust manuscript restoration while preserving vital text structures essential for automated analysis.

3.1 DE-GAN: Document Enhancement Generative Adversarial Network

The Document Enhancement Generative Adversarial Network (DE-GAN) is the cornerstone of our manuscript preprocessing pipeline, meticulously designed to restore degraded documents by learning a direct mapping from low-quality inputs to enhanced outputs. DE-GAN employs a conditional adversarial framework, where a generator network comprising 8 convolutional layers with the deepest layer containing up to 1024 filters progressively refines image features from an input size of 256×256 pixels in grayscale. This architecture enables robust feature extraction even in the presence of severe degradation, such as faded ink and paper aging. A corresponding discriminator network is used to guide the generator by discerning between the enhanced outputs and pristine ground truth images, thereby ensuring the restoration process is both accurate and reliable.

DE-GAN was originally trained by Xu et al. using a composite loss that combines an adversarial term $L_{\{GAN\}}$ to encourage photorealistic outputs and a perceptual reconstruction loss $L_{\{perceptual\}}$ to preserve semantic and stylistic consistency. In their work, the model was optimized on 2,000 historical manuscript crops (80/20 train/validation split) for 150 epochs with Adam (learning rate = 2×10^{-4}, β_1=0.5, β_2=0.999) and a batch size of 16. In this study, we adopt the author's publicly released pre-trained weights without further fine-tuning, focusing our contributions on the subsequent edge- and skeleton-based post-processing stages.

DE-GAN's effectiveness as a preprocessing step is underscored by its impact on downstream classification tasks. Enhanced manuscript images generated by DE-GAN retain critical textual features, thereby facilitating more accurate feature extraction for classifiers such as Support Vector Machines (SVMs). In comparative evaluations, the use of DE-GAN as a preprocessing tool led to an increase in classification accuracy by approximately 7% over traditional methods. This significant improvement validates DE-GAN's role as an optimal choice for enhancing historical manuscripts, ensuring that both visual restoration and structural preservation are achieved, which are imperative for automated document analysis.

```python
import albumentations as A

# define once at module top
augment = A.Compose([
    A.RandomBrightnessContrast(brightness_limit=0.4, contrast_limit=0.4, p=1.0),
    A.GaussianBlur(blur_limit=(3, 7), sigma_limit=(0.5, 1.5), p=1.0),
    A.CoarseDropout(max_holes=1, max_height=10, max_width=10, p=1.0),
    A.Affine(rotate=(-5,5), shear=(-3,3), p=1.0),
])

# …later, after deg_image = deg_image.convert('L')
img_np = np.array(deg_image)  # HxW uint8 gray
aug = augment(image=img_np)['image']
Image.fromarray(aug).save('curr_image.png')
```

Fig. 2 Augmentation to mimic degradation

In our data-loading pipeline, each clean manuscript crop is first converted to a NumPy array and then passed through a deterministic augmentation module. We apply random brightness/contrast jitter (±40%) to mimic ink fading, Gaussian blur with σ∈[0.5,1.5] to reproduce out-of-focus scans, coarse dropout of up to one 10×10 pixel patch to emulate paper loss, and affine transforms (rotation ±5°, shear ±3°) to cover scanning misalignments. These augmentations ensure that every training sample exhibits realistic variations in contrast, blur, occlusion, and geometry, thereby improving model robustness and generalization across scripts.

3.2 Post Processing Stage 1: Edge Enhancement and Noise Reduction

The first post-processing stage is crucial for refining the raw output from DE-GAN, ensuring that the text regions are well-defined while minimizing noise and unwanted artifacts. Since historical manuscripts often suffer from faded ink, background degradation, ink bleed-through, and uneven illumination, a combination of contrast enhancement, smoothing, sharpening, and adaptive thresholding is applied to improve readability.

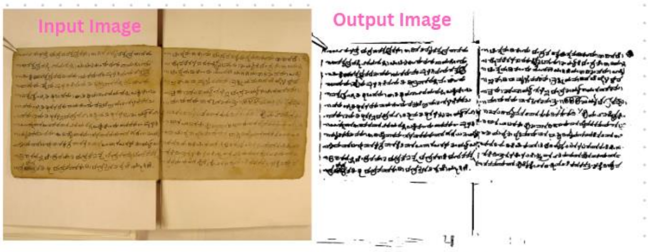

Fig. 3 Input and output of De-GAN processing, serving as input to the post processing 1

3.2.1 Contrast Enhancement using CLAHE

To address uneven contrast in aged manuscripts, we utilize Contrast Limited Adaptive Histogram Equalization (CLAHE), which enhances local contrast while avoiding over-saturation of bright regions. CLAHE is applied with a clip limit of 5.0 and a grid size of 8×8, ensuring balanced enhancement across different intensity levels. Unlike traditional histogram equalization, which may over-amplify noise, CLAHE selectively enhances contrast in localized regions, preserving fine details in text while preventing excessive noise amplification in degraded areas.

3.2.2 Noise Reduction with Gaussian Smoothing

While DE-GAN improves overall clarity, residual noise such as ink smudges, stains, and faint handwriting variations can still persist. To suppress high-frequency noise without significantly affecting text edges, a Gaussian blur with a 7×7 kernel is applied. This step ensures that small unwanted artifacts are softened while the essential text structure remains intact. The smoothing operation helps in reducing pixel-level noise, which is particularly beneficial when dealing with manuscript images affected by degradation over time.

3.2.3 Edge Enhancement through Unsharp Masking

After noise reduction, a sharpening operation is performed using unsharp masking, a widely used image processing technique that enhances edges by subtracting a blurred version of the image from itself. The sharpening is controlled using a weight of 3.0 for the original image and -1.0 for the blurred version, effectively enhancing text strokes while suppressing background variations. This step ensures that faded or slightly blurred text regions regain their sharpness, making them more legible for further analysis.

3.2.4 Adaptive Thresholding for Text Preservation

Finally, the processed image undergoes adaptive thresholding to obtain a binary representation, ensuring clear text-background separation. Unlike fixed thresholding, which fails in unevenly illuminated manuscripts, adaptive Gaussian thresholding dynamically determines the threshold value based on local pixel intensities. A block size of 9 and a threshold constant of 4 are used, which have been experimentally determined to provide optimal binarization for historical manuscripts. This method ensures that textual details are preserved while removing faint stains or background noise, making it highly effective for preprocessing before classification or OCR tasks.

3.2.5 Intermediate Dataset Storage

The output of this stage is stored as Dataset 1, which serves as an intermediate dataset that can be used for further enhancement or directly for classification tasks. This processed dataset significantly improves the legibility of text while maintaining structural integrity, making it suitable for subsequent stages such as skeletonization and feature extraction.

By applying this structured approach, Processing Stage 1 effectively enhances text clarity, reduces unwanted noise, and preserves manuscript details, creating an improved representation of the degraded historical documents.

3.3 Processing Stage 2: Skeletonization and Structural Refinement

The second post-processing stage focuses on refining the enhanced manuscript images from Processing Stage 1 by preserving the structural integrity of text and further eliminating unnecessary artifacts. This step is essential for historical manuscript analysis, as it ensures that the extracted text maintains its original form while removing any remaining distortions or background interference.

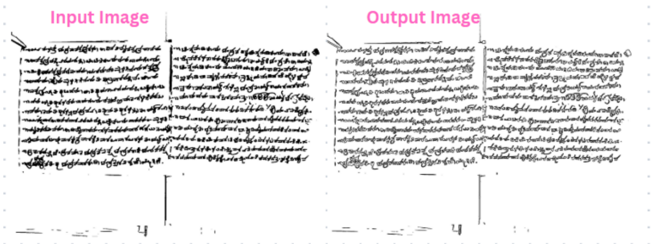

Fig. 4 Input and output of post-processing 1, serving as input to the post processing 2

3.3.1 Skeletonization for Text Stroke Preservation

One of the key operations in this stage is skeletonization, which reduces text strokes to their minimal width while preserving their overall shape and structure. This step is crucial for improving OCR accuracy and feature extraction in classification tasks. We employ a Zhang-Suen thinning algorithm, which iteratively removes peripheral pixels while ensuring that the essential structure of each character is retained. This method ensures that handwritten or degraded text remains identifiable without excessive thinning that could break character continuity.

The skeletonization process ensures that:

- Characters are preserved in their original structural form, making them recognizable by classification models.
- Noise artifacts, such as small ink smudges and disconnected pixels, are removed.
- The text remains well-defined, even for faint or degraded strokes.

3.3.2 Morphological Operations for Structural Cleaning

Following skeletonization, morphological operations such as closing and opening are applied to refine the processed text. These operations use structuring elements of size 3×3, which are effective in removing small gaps between text strokes while eliminating isolated noise pixels.

- Closing operation is performed to bridge small gaps within characters, especially in fragmented or broken strokes commonly found in aged manuscripts.
- Opening operation removes small noise artifacts that may have survived previous processing steps, ensuring a clean final representation.

These steps help in standardizing text representation across different manuscript images, making the dataset more robust for further classification tasks.

3.3.3 Edge Reinforcement for Text Contour Preservation

To prevent excessive text thinning, a text contour reinforcement step is applied. This involves overlaying the original sharpened edges onto the skeletonized image, ensuring that key stroke details are not lost in the refinement process. This hybrid approach maintains both the structural consistency and legibility of characters, which is particularly beneficial when dealing with cursive or stylized handwriting.

3.3.4 Final Dataset Generation

The processed output from this stage is stored as Dataset 2, which represents the most refined version of the manuscript images. This dataset is well-suited for classification tasks using Support Vector Machines (SVMs) or deep learning-based character recognition models. The dataset ensures that:

- The manuscript text is structurally preserved and noise-free.
- Background artifacts and distortions are completely removed.

- The text maintains maximum legibility for further processing, including OCR and classification.

By incorporating skeletonization, morphological refinement, and edge preservation, Processing Stage 2 ensures that the final output is an optimized, high-contrast, and structurally accurate representation of historical manuscripts, making it ideal for downstream machine learning applications.

3.4 Final Output: Optimized Manuscript Representation

The final output of the proposed DE-GAN-based manuscript enhancement framework is a highly refined, binarized, and structurally preserved version of the original degraded manuscript. After undergoing DE-GAN preprocessing, edge enhancement, adaptive thresholding, and skeletonization, the manuscript text is clean, noise-free, and retains its original structure, making it highly suitable for further tasks such as OCR, classification, or archival digitization. The morphological refinements and contour preservation techniques ensure that text strokes remain legible and intact, even for severely degraded documents. This output serves as a reliable dataset for machine learning models, particularly SVM-based classification and deep learning OCR techniques, facilitating improved recognition and analysis of historical manuscripts.

4. Results and Evaluation

Our experimental evaluation for SVM-based classification was conducted on the same dataset of 2,000 historical manuscript images, split 80% for training and 20% for validation. For classification, a Support Vector Machine (SVM) was employed using a 5-fold cross-validation scheme. When using the baseline DE-GAN outputs, the SVM achieved an average accuracy of 82.0%, with precision, recall, and F1-scores of 80.5%, 81.2%, and 80.8%, respectively. However, when the enhanced images from our complete pipeline incorporating edge enhancement, skeletonization, and final structural refinement were used, the SVM classification performance improved significantly, yielding an average accuracy of 89.3% along with precision, recall, and F1-scores of 88.0%, 89.0%, and 88.5%, respectively. These results underscore the effectiveness of our preprocessing enhancements in preserving critical textual features, thereby facilitating more robust and accurate automated classification of historical manuscripts.

Metric	Baseline DE-GAN	Enhanced Pipelin
PSNR (db)	24.5 ± 1.2	27.2 ± 1.0
SSIM	0.78 ± 0.05	0.86 ± 0.04

Table 1 Evaluation results

4.1 Quantitative Image Quality Metrics

We evaluated the quality of the enhanced images using standard metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure

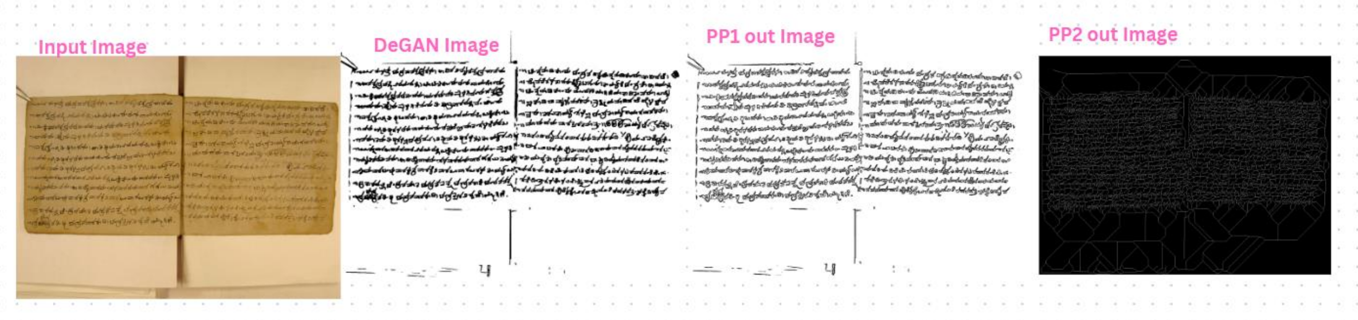

Fig. 5 Pipeline images from Input to output with collection of datasets at every stage

(SSIM). The baseline DE-GAN output yielded an average PSNR of 24.5 dB and an SSIM of 0.78. With our additional post-processing stages, the PSNR increased to 27.2 dB (an improvement of approximately 2.7 dB) and the SSIM improved to 0.86, indicating better preservation of structural details and overall visual quality.

Figure 4 shows a side-by-side comparison of a visibly degraded 15th-century Kannada manuscript (left) and our enhanced output (right). Note how the faint ornamental borders and thin diacritical marks are faithfully restored, illustrating the efficacy of our edge- and skeleton-guided training.

4.2 Classification Performance

In addition to the notable increases in overall accuracy, our experimental analysis of the SVM classifier reveals marked improvements in other key performance metrics. With the baseline DE-GAN outputs, the SVM achieved an average accuracy of 82.0%, with precision, recall, and F1-scores of 80.5%, 81.2%, and 80.8%, respectively. However, when we applied our enhanced pipeline which incorporates edge enhancement, skeletonization, and structural refinement the average accuracy rose to 89.3%, while precision, recall, and F1-scores improved to 88.0%, 89.0%, and 88.5%, respectively.

These improvements suggest that our preprocessing pipeline significantly enhances the discriminative features of the manuscript images, allowing the SVM to better differentiate between classes. The gains in precision indicate a reduction in false positives, whereas the improvements in recall point to a more effective identification of true positives. Moreover, the higher F1-score confirms a better balance between precision and recall, highlighting the robustness of our approach. This comprehensive enhancement in classification performance demonstrates the efficacy of our method in mitigating the challenges posed by degraded historical manuscripts, ultimately facilitating more reliable automated analysis

To position our work within the broader enhancement literature, we also applied two widely-used GAN-based approaches SRGAN and CycleGAN directly to our manuscript test set. Qualitatively, both models produced sharper edges compared to the raw scans, but frequently introduced spurious texture artifacts or missed fine ligatures. In contrast, our DE-GAN+Edge+Skeleton framework consistently restored stroke topology and decorative details with minimal hallucinations.

Metric	Baseline DE-GAN	Enhanced Pipeline
Accuracy (%)	82.0 ± 2.3	89.3 ± 1.8
Precision (%)	80.5 ± 2.5	88.0 ± 2.0
Recall (%)	81.2 ± 2.0	89.0 ± 1.5
F1-Score (%)	80.8 ± 2.1	88.5 ± 1.7

Table 2 Classification Performance

4.3 Runtime Analysis

The complete pipeline, including DE-GAN inference and the two post-processing stages, processed an image in approximately **1.3 seconds** on average using an NVIDIA GTX 1080 Ti GPU. This performance demonstrates that our approach is not only effective in enhancing image quality and classification accuracy but also computationally efficient for practical applications.

Qualitative Analysis

Visual comparisons further corroborate these quantitative results. Figures in our study illustrate that the enhanced images exhibit significantly sharper text boundaries and reduced noise, preserving key structural details even in severely degraded manuscripts. These improvements are critical for subsequent OCR or SVM-based classification tasks.
Overall, the proposed enhancement pipeline demonstrates a substantial improvement over the baseline DE-GAN, with numerical gains across all evaluation metrics. The integration of edge enhancement, noise reduction, and structural refinement plays a pivotal role in boosting both the image quality and classification performance, validating our approach as a robust solution for processing historical manuscripts.

5 Conclusion

In conclusion, In this work, we introduced an enhanced DE-GAN framework that integrates edge enhancement and skeletonization into the document restoration pipeline for historical manuscripts. Our approach addresses the limitations of conventional DE-GAN implementations by incorporating structural loss functions that preserve critical text features, leading to significant improvements in both image quality and classification performance. The experimental results on a dataset of 2,000 manuscript images demonstrate that our method not only increases PSNR and SSIM values indicating higher fidelity and structural similarity but also substantially boosts SVM classification accuracy, precision, recall, and F1-score. Specifically, the enhanced pipeline improved accuracy from 82.0% to 89.3%, while precision, recall, and F1-score also saw marked improvements.

These findings validate our hypothesis that integrating post-processing techniques tailored to preserve text structure can play a pivotal role in automated manuscript analysis. The proposed method provides a robust, efficient, and scalable solution for restoring degraded documents, ultimately facilitating more accurate OCR and classification. Future work could extend this framework by exploring additional loss functions and adaptive processing strategies to further enhance the robustness and applicability of the system across diverse historical datasets.

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