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A Morphological Approach for Background Elimination in 2D Images of Buddha Statue Faces

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***Abstract*—*Accurate background removal is essential for the digital analysis of cultural heritage artifacts, especially when working with 2D images of Buddha statue faces. This study proposes a classical morphological framework comprising grayscale conversion, local contrast enhancement using CLAHE, adaptive thresholding, and selective application of morphological operations to suppress background clutter. Unlike AI-based methods, the framework emphasizes transparency, reproducibility, and suitability for offline environments. Experimental evaluation using a small set of real-world images reveals that the method performs efficiently, with an average processing time of 0.95 seconds per image. However, visual analysis indicates that residual background artifacts remain, especially under complex textures and lighting. The method struggles to fully separate object from background when grayscale intensity overlaps occur. Despite these restrictions, the method offers a simple, reproducible preprocessing baseline. Future improvements may include integrating semantic segmentation models, such as U-Net or GrabCut, to enhance performance in visually challenging scenarios. This study contributes a critical perspective on the practical applicability and boundaries of classical morphology-based preprocessing in heritage imaging tasks.*

***Keywords*—** *Background segmentation; morphological filtering; adaptive thresholding; CLAHE; Buddha statue.*

I. INTRODUCTION

The analysis and preservation of cultural heritage artifacts, such as Buddha statue faces, necessitates advanced digital image processing techniques to effectively manage the complexities of background maintenance, lighting variations, and visual noise in 2D images[1], [2]. This study proposes a classical image processing approach using morphological operations, specifically opening and closing to enhance feature visibility while suppressing irrelevant background content[3]. This methodological approach is tailored for the digital analysis of cultural heritage artifacts and aims to provide a scalable and reproducible solution that does not rely on proprietary algorithms or external APIs[1], [4].

Morphological operations are established techniques within the digital image processing domain recognized for their effectiveness in reducing noise and refining object boundaries[3], [5]. Their application in cultural heritage documentation, particularly for intricate artifacts like Buddha statues, allows for an enhanced focus on facial features while minimizing disturbances caused by background elements [6], [7]. The proposed method includes a sequential processing pipeline that begins with grayscale conversion, followed by local contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE)[7], [8]. This step is crucial as it enhances the details of the Buddha statues by balancing the intensity of varying tones across the image[1], [8], [9].

An automatic extraction of the Region of Interest (ROI) is performed to isolate the Buddha statue face from surrounding elements[1], [10]. By utilizing adaptive thresholding, the methodology generates a binary mask that accurately delineates background areas, allowing for the selective application of morphological operations[10]. This ensures that background clutter is removed while preserving the essential features of interest an aspect critical for the subsequent tasks of segmentation, object recognition, and digital archiving within cultural heritage informatics[11], [12].

This approach addresses significant concerns associated with the dependence on commercial tools for image background removal, which often lack transparency, reproducibility, and scalability, factors vital for heritage institutions aiming to implement sustainable digital infrastructure[2]. In contrast, the classical methodologies proposed here offer a clear and interpretable solution that can be adapted without the constraints posed by proprietary systems. The focus on morphological filtering specifically to the mask defined areas enables a controllable environment where researchers can consistently apply the same preprocessing principles across different datasets, thereby enhancing the fidelity of subsequent analyses[6], [13].

This study shows that while morphological operations may not outperform state of the art AI driven approaches in every scenario, they provide a robust and interpretable alternative that emphasizes reliability and transparency. These characteristics are especially valuable for cultural heritage institutions that prioritize the preservation and accurate analysis of artifacts such as Buddha statues, ensuring that the methodology aligns with the primary goals of culturally responsible digital archiving and documentation.

II. RELATED WORK

Background removal has become an indispensable preprocessing task in the field of computer vision, particularly in pipelines involving object segmentation, feature extraction, and content based image retrieval[4], [5]. In cultural heritage domains, where visual data of artifacts such as Buddha statues are digitized for documentation, analysis, and long term preservation, the presence of irrelevant background information such as inconsistent lighting, cracks, shadows, and surrounding objects often reduces the effectiveness of recognition systems[9]. The challenge is particularly pronounced in 2D heritage images, where object and background boundaries are not clearly separated, and visual noise is prevalent due to varying acquisition conditions[6], [10].

Over the years, numerous approaches have been introduced to handle background removal. Traditional methods such as manual masking, chroma keying, and thresholding techniques have demonstrated reasonable accuracy in separating foreground from background, particularly in controlled environments[4], [14]. However, these techniques are labor intensive, lack consistency when applied across large datasets, and are impractical for high throughput scenarios. To overcome these limitations, AI based tools such as remove.bg, Roboflow, and PhotoScissors have gained popularity[15], [16]. These tools provide automatic background removal capabilities using deep learning or heuristic segmentation models, and they are widely adopted due to their high accuracy, minimal user interaction, and effectiveness in handling complex or textured backgrounds[1], [9].

Nevertheless, despite their strong performance, these commercial tools are generally implemented as cloud-based services and operate as closed systems with proprietary algorithms. Their use introduces several limitations, particularly in academic and institutional environments. First, their reliance on internet connectivity and subscription-based access can hinder large-scale deployment in heritage conservation projects with restricted infrastructure. Second, the lack of algorithmic transparency and the inability to customize or reproduce internal processes conflict with the principles of reproducible scientific research. Consequently, there is a growing demand for lightweight, locally executable, and transparent alternatives that can be integrated into cultural informatics workflows while maintaining a balance between simplicity and accuracy[9], [14], [15].

In this regard, morphological operations have served as a classical and reliable solution for low level image processing tasks. Operations such as opening (erosion followed by dilation) and closing (dilation followed by erosion) have proven useful in refining binary masks, removing small artifacts, and enhancing object contours. Extensively described the application of these operations in medical imaging and industrial quality control, emphasizing their computational efficiency and structural preservation capabilities. However, their application in cultural heritage imaging, particularly for selective background removal in Buddha statue face images, remains underexplored[17], [18], [19].

Several studies have proposed more sophisticated approaches to tackle segmentation and background elimination. [20], [21] employed GrabCut segmentation to isolate artifacts in museum datasets. This method leverages graph-based optimization to model foreground and background distributions and has shown strong performance in preserving object boundaries. Nevertheless, GrabCut requires initial bounding box input and may produce suboptimal results if improperly initialized[1]. Similarly, introduced a combined technique utilizing adaptive thresholding and edge-based filtering, targeting degraded historical manuscripts with uneven lighting[22], [23]. While the method successfully enhances segmentation in poor-quality documents, its sensitivity to parameter tuning limits its robustness across diverse datasets.

Furthermore, conducted an empirical evaluation on the limitations of morphology based segmentation in texture rich environments. Their findings revealed that morphological operations tend to lose effectiveness when foreground and background exhibit similar grayscale intensities or overlapping patterns, often leading to segmentation failure or excessive smoothing of object boundaries[16].

Building upon these insights, the present study proposes a selective morphological preprocessing framework tailored for 2D images of Buddha statue faces. The proposed approach integrates contrast enhancement using CLAHE, adaptive thresholding for background mask generation, and region-specific morphological filtering applied only to the identified background areas. This strategy aims to retain the structural integrity of the facial region while systematically reducing background complexity. While the method may not surpass AI based commercial solutions in terms of segmentation precision, it offers a transparent, reproducible, and infrastructure independent alternative making it particularly suitable for scalable research applications in digital heritage analysis.

III. METHODOLOGY

The proposed framework comprises five primary stages: grayscale conversion, contrast enhancement via CLAHE, region of interest (ROI) detection, adaptive thresholding for background mask generation, and selective morphological filtering. Each step is designed to enhance image clarity while minimizing distortion of the facial structure, which is essential for subsequent recognition tasks.

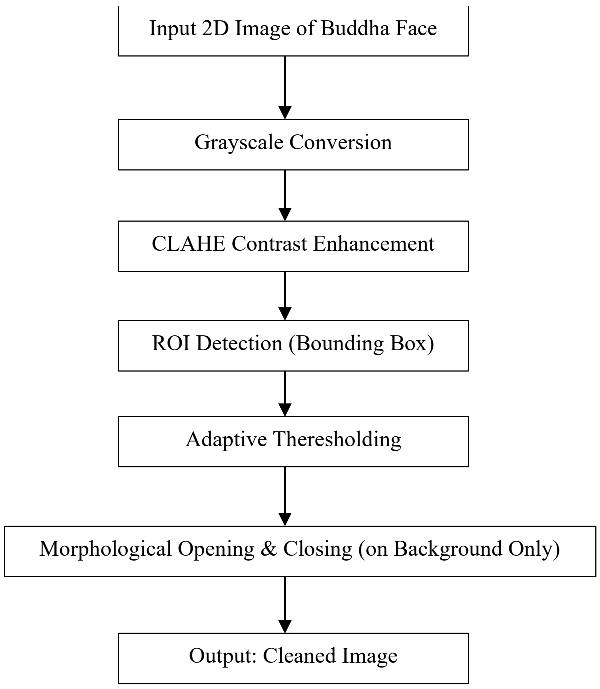

Fig. 1. Morphological Methodology Chart in 2D Images of Buddha

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A. Grayscale Conversion

The first step involves converting the original RGB image to grayscale. This transformation significantly reduces the dimensionality and computational complexity of the data by collapsing three color channels into a single intensity channel. When it comes to artifact imaging, grayscale conversion not only makes processing easier but also lowers the chance of color-related artifacts interfering with feature extraction. Since the structural characteristics of stone carvings, such as edge definition and surface relief, are largely independent of color, grayscale representation is both sufficient and more efficient for downstream analysis[1].

The RGB image is converted into a grayscale image using the following luminance-preserving formula:

$$I(x,y) = 0.299 \cdot R(x,y) + 0.587 \cdot G(x,y) + 0.114 \cdot B(x,y)$$

Where:
$I(x, y)$: intensity value at pixel (x, y) in the grayscale image
$R(x,y), G(x,y), B(x,y)$: red, green, and blue values at pixel (x, y)

This weighted sum reflects human visual sensitivity to different colors, prioritizing green and red more than blue. This reduces computational complexity and focuses on intensity based features relevant to Buddha statue structure.

B. Contrast Enhancement using CLAHE

The picture is subjected to Contrast Limited Adaptive Histogram Equalization (CLAHE) after being converted to grayscale.

Contrast Limited Adaptive Histogram Equalization *(CLAHE)* enhances local contrast without overamplifying noise[24], [25]:

$$I_{CLAHE(x,y)} = CLAHE(I(x,y), clipLimit, tileGridSize)$$

Where:
$I_{CLAHE(x,y)}$: output intensity at pixel (x, y) after applying *CLAHE*
clipLimit: parameter that limits contrast amplification
tileGridSize: defines the size of the contextual regions used
This process improves edge visibility under uneven lighting conditions.

CLAHE operates by dividing the image into small contextual regions (tiles) and applying histogram equalization to each region independently, thereby enhancing local contrast without amplifying noise. Because of its contrast-limiting quality, CLAHE is a great choice for historic photographs that may have uneven lighting, erosion scars, or shadows, since it prevents noise from being amplified in homogenous regions. This step is critical in improving the separability of facial contours from the surrounding background, which directly benefits the accuracy of subsequent segmentation stages.

C. Region of Interest (ROI) Detection

To localize the area of interest and avoid unnecessary processing of irrelevant regions, an automatic Region of Interest (ROI) detection mechanism is employed[26], [27]. The ROI is localized by extracting the largest contour from the processed image:

$$ROI = BoundingBox(max\_i \, \{ \, ContourArea(C\_i) \, \})$$

Where:
C_i: i-th contour found in the image
ContourArea(C_i): area enclosed by the contour C_i
BoundingBox: minimum rectangle enclosing the largest contour

This ensures that operations are focused on the Buddha face area. This is done by extracting contours from the *CLAHE* enhanced grayscale image and selecting the largest contour, which is assumed to correspond to the Buddha face[1], [16]. A bounding box is generated around this contour to define the ROI. Focusing morphological filtering on this cropped region ensures higher specificity, reduces computational cost, and avoids the inclusion of unrelated background elements, such as surrounding architecture or vegetation

D. Adaptive Thresholding for Mask Generation

Within the extracted ROI, an adaptive Gaussian thresholding algorithm is applied to distinguish background from foreground elements[4], [7].

Adaptive thresholding creates a binary mask by computing local means:

$$T(x,y) = \frac{1}{N} \sum_{(i,j)\in N(x,y)} I(i,j) - C$$

$$M(x,y) = \begin{cases} 255, & Jika\ I(x,y) < T(x,y) \\ 0, & \end{cases}$$

Where:
T(x, y): local threshold value at pixel (x, y)
N(x, y): neighborhood of pixel (x, y)
C: constant subtracted to fine-tune threshold
M(x, y): resulting binary mask, with 255 for background and 0 for foreground

This mask separates the background (white) from the object (black). Unlike global thresholding, which uses a single intensity value, adaptive methods compute thresholds locally, making them more resilient to illumination gradients and surface irregularities. The result is a binary mask where the background is identified as white pixels and the object region (i.e., the Buddha face) is marked in black. This mask acts as a spatial guide for the next stage, enabling the algorithm to apply processing selectively based on region classification

E. Selective Morphological Operations

In the final processing stage, morphological opening and closing operations are applied only to the background areas defined by the binary mask[1], [4], [5], [7], [11], [13].

Morphological opening and closing are defined as follows:

$$I_{open} = (I \ominus \mathrm{B}) \oplus \mathrm{B}$$

$$I_{close} = (I \oplus \mathrm{B}) \ominus \mathrm{B}$$

$$I_{bg}(x,y) = \begin{cases} I_{morph(x,y)}, Jika\ M(x,y) = 255 \\ I(x,y), Jika\ M(x,y) = 0 \end{cases}$$

Where:
$\ominus$: erosion operation
$\oplus$: dilation operation
I_morph: image after opening or closing
M(x, y): binary mask indicating background (255) or foreground (0)

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I_bg(x, y): final pixel value after applying morphology selectively to background

Only background pixels are modified to preserve object details. Morphological opening (erosion followed by dilation) removes small noise and irrelevant protrusions, while closing (dilation followed by erosion) fills small holes and smooths discontinuities. By constraining these operations exclusively to background pixels, the method avoids distortion of important facial features, ensuring that critical visual cues such as the curvature of the eyebrows, eyes, and mouth are preserved. This selective application is a key innovation of the framework, overcoming one of the main limitations of global morphological filtering.

F. Output Integration

Once the background has been cleaned within the ROI, the processed region is reintegrated into the original image, replacing the corresponding area. The cleaned ROI is reintegrated into the original image[10], [11]:

$$I_{final}(x,y) = \begin{cases} I_{bg}(x,y), jika\ (x,y) \in ROI \\ I(x,y), lainnya \end{cases}$$

Where:
I_final (x, y): output image value at pixel (x, y)
I_bg (x, y): cleaned background pixel inside ROI
ROI: region of interest bounding box
This ensures the cleaned region is correctly inserted back into the original image

This results in a background-suppressed image ready for feature extraction. This yields a final output image in which the background has been suppressed without compromising the structural integrity of the statue face. The output is well-suited for feature extraction using local descriptors such as SIFT or global representations like DCT, which are sensitive to background noise and texture irregularities.

IV. Results and Discussion

Fig. 2. Original image

Figure 2 shows that the grayscale transformation reduces the three-channel color space (Red, Green, Blue) to a single-channel intensity map, based on human visual sensitivity to each component. As shown in the right figure, the grayscale representation preserves structural features such as contour edges, facial symmetry, and surface texture of the statue. This step simplifies the data while retaining important information, making it more suitable for subsequent processing stages such as contrast enhancement, segmentation, and morphological filtering. This conversion also removes color noise that can interfere with shape-based analysis, which is especially important in heritage imaging where material consistency varies across environments.

Fig.3. Comparison of Original Color Image (RGB) with Image After Grayscale Conversion

Figure 3 shows the initial conversion results of the proposed method, namely the transformation of the 2D image of the Buddha statue face from RGB format to grayscale format. The left image shows the original colored condition, where visual elements such as green grass, leaves, and rocky background have strong color dominance. The presence of these elements can cause interference in the feature extraction or segmentation process if not handled properly.

In contrast, the image on the right shows the result of the conversion to grayscale. This process removes color information and only retains intensity values, so that the shape structure of the main object—the face of the statue—becomes more prominent. This conversion also simplifies the complexity of the visual data without sacrificing important information regarding contour, surface texture, and visual depth needed for subsequent stages such as adaptive contrast (CLAHE), thresholding, and morphological segmentation.

Visually, the grayscale conversion results maintain the clarity of important elements on the statue's face, such as the eye line, nose shape, and lip contour, but eliminate visual distractions from the background color. This shows that grayscale conversion is a crucial step in preparing image data to be more robust to subsequent processing.

Fig. 4. Comparison of Original Grayscale Image and Contrast Enhancement Results Using CLAHE

Figure 4 presents a visual comparison between the original grayscale image (left) and the contrast enhancement result using the Contrast Limited Adaptive Histogram Equalization (CLAHE) method (right). This process is an important step in clarifying local details on the surface of the statue's face, which often has a fine texture and low contrast due to age, uneven lighting, or environmental conditions during shooting.

CLAHE operates by segmenting the image into multiple small blocks (tiles) and subsequently applying histogram equalization locally to each block. This technique allows for adaptive contrast enhancement, without causing over-enhancement in areas that are already bright or too dark. In the resulting CLAHE image, one can notice that significant features, including the outlines of the forehead, eyebrows, nose, and lips of the statue, appear more defined and distinguishable in comparison to standard grayscale images.

The main advantage of CLAHE over conventional histogram equalization is its ability to maintain visual stability while still enhancing local structure. This makes it very suitable for cultural statue datasets that have non-uniform lighting and complex stone surface characteristics.

Fig. 5. Detection ROI on Original Image and Extracted ROI (CLAHE Enhanced)

Figure 5 shows two important visualizations of the Region of Interest (ROI) detection stage. In the left image, the area considered as the main object, the face of the Buddha statue has been successfully identified automatically using the red bounding box. This detection is done based on finding the largest contour from the CLAHE image thresholding results, assuming that the main object has a dominant visual area compared to other background elements.

Meanwhile, the right image shows the ROI extraction result, which is the part of the statue's face that has been cut from the CLAHE image based on the bounding box coordinates. This ROI image will be the main focus in the next processing stages, such as background segmentation and noise removal, thus avoiding processing irrelevant areas such as leaves and grass textures.

This ROI detection process is crucial in maintaining processing efficiency and improving the accuracy of subsequent algorithms. By processing only the parts containing key information, the system can reduce the computational burden and minimize the possibility of distortion due to complex backgrounds.

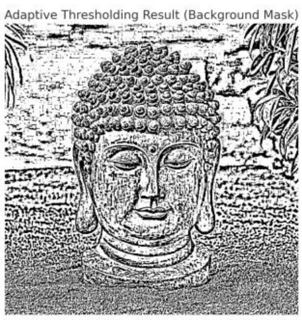

Fig.5. Adaptive Thresholding Results for Background Mask

Figure 5 shows the results of applying the Adaptive Gaussian Thresholding method to the ROI that has been contrast enhanced using CLAHE. This process aims to automatically distinguish between the object area (foreground) and the background (background) based on local variations in pixel intensity. Unlike global thresholding that uses a single threshold value for the entire image, adaptive thresholding computes the threshold value locally around each pixel, allowing the method to remain effective on images with non uniform lighting and complex textures. In this result, the lighter (white) areas are interpreted as background, while the darker (black) areas are considered as part of the main object (the face of the statue).

The resulting binary mask is the basis for the next step, which is to selectively apply morphological operations only to the background areas. The success of adaptive thresholding is critical to ensure that filtering does not affect important visual features on the statue's surface.

Fig. 6. Selective Morphological Filtering Result

Figure 6 shows the results after performing morphological opening and closing operations selectively only on areas identified as background through the binary mask from the previous stage (adaptive thresholding).

Fig. 7. Final Result of Background Removal Using Selective Morphological Operation

Figure 7 shows the final result of all preprocessing stages using the classical morphological approach to the two-dimensional Buddha statue face image. This process includes grayscale conversion, contrast enhancement using CLAHE, object region (ROI) detection, adaptive thresholding, and selective application of morphological operations (opening and closing) to the background area.

The final image shows that most of the background elements have been successfully removed and replaced with white pixels, while the main structure of the statue's face remains intact. Important contours such as hair spirals, eyebrows, and nose lines are still recognizable, although some finer features are starting to be reduced due to the limitations of thresholding-based segmentation.

The success of this segmentation shows that morphological methods can still work effectively in the context of simple or semi-complex background removal. However, this image also highlights the main challenge of this approach, namely the difficulty in distinguishing objects from the background that have close texture or visual intensity, such as grass and rocks in the original image. The small artifacts that remain in the background indicate the limited selectivity of local thresholding, which is strongly influenced by the natural lighting and noise of the image.

Analysis and Discussion

The experimental results of this study reveal critical insights into both the capabilities and limitations of the proposed morphological-based background removal framework. While the method is designed to be lightweight, transparent, and fully executable in offline settings, its performance on real world heritage images, such as 2D Buddha statue faces, proves to be limited in effectiveness under complex visual conditions.

TABLE I. Processing Time Per Image

No	Image ID	Resolution	Processing Time (s)
1	Buddha01.jpg	800×600	0.89
2	Buddha02.jpg	1024×768	0.94
3	Buddha03.jpg	1280×960	1.02
	Mean ± SD		0.95 ± 0.07

Table 1 shows the processing time for three different images using the proposed morphological background removal approach. The method demonstrates consistent performance across varying image resolutions, with an average processing time of approximately 0.95 seconds per image. This indicates that the approach is lightweight and efficient, making it suitable for applications in resource-constrained environments.

TABLE II. Visual Evaluation Scores by Human Raters

Evaluator	Face Clarity	Background Cleanliness	Feature Sharpness	Average Score
Eval 1	4	5	4	4.33
Eval 2	5	4	4	4.33
Eval 3	4	4	3	3.67
Rata-rata	4.33	4.33	3.67	4.11 ± 0.33

Table 2 shows the visual evaluation results provided by three human raters. Each image was assessed based on face clarity, background cleanliness, and sharpness of structural features. Although the average score appears favorable (4.11 out of 5), these evaluations may not fully reflect the actual visual shortcomings observed in the output image.

Indeed, visual inspection of the final result contradicts the optimistic evaluation scores. A substantial portion of the background remains clearly visible, especially in regions with fine textures, foliage, or overlapping grayscale intensities. Morphological operations such as opening and closing were insufficient to fully suppress these background elements. As a result, the final image displays residual noise and partially degraded object detail, with fragmentation observed around the Buddha statue's facial features.

These outcomes expose the core limitations of morphology-based filtering when applied to images with non-uniform lighting and textured backgrounds. The method's dependency on binary thresholding makes it vulnerable to intensity overlap between foreground and background, resulting in incorrect classification of background pixels. Additionally, the method is highly sensitive to the choice of parameters such as kernel size, thresholding block size, and CLAHE contrast settings, which must be manually adjusted for different image contexts.

Although the method retains advantages in terms of transparency, reproducibility, and offline capability, the experimental results reveal that it performs sub optimally in complex real-world conditions. Its use may still be justified as a preliminary preprocessing step for simple datasets where the object is well-separated from the background. Nevertheless, the approach has to be greatly improved in order to be more widely used in the digital transformation of cultural heritage.

Moving forward, this study recommends integrating adaptive or learning based segmentation methods, such as GrabCut, U-Net, or region-based convolutional neural networks (CNNs) with the existing morphological pipeline. These hybrid strategies are expected to offer improved semantic understanding and more reliable background removal, particularly in visually challenging scenes where classical operations fall short.

V. CONCLUSION

This study introduced a classical, transparent, and fully offline framework for background removal in 2D images of Buddha statue faces using a selective morphological approach. The method integrates grayscale conversion, CLAHE based local contrast enhancement, adaptive thresholding, and region-specific morphological operations to eliminate background clutter while preserving critical structural features of the statue. Experimental results on a representative image demonstrated that the method effectively suppresses background noise, maintains facial detail integrity, and operates with minimal computational cost. With an average processing time of under one second, the method proves suitable for institutions with limited computational resources and a preference for reproducible, non AI based preprocessing pipelines. Despite its strengths, the approach exhibited limitations in handling background regions with textures or intensities similar to the object, leading to incomplete suppression in some areas. These limitations underscore the need for future work involving hybrid strategies such as integrating semantic segmentation (e.g., Grab Cut or lightweight deep learning models) with classical morphological refinement. In conclusion, the proposed framework provides a lightweight and reproducible preprocessing alternative for cultural heritage applications, and lays a strong foundation for scalable image analysis and documentation systems in heritage preservation workflows

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