COLOR SPACE CONVERSIONS USING ADAPTIVE SINGULAR VALUE DECOMPOSITION

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ABSTRACT

Image processing applications across medical imaging, object detection, and visualization critically rely on practical color space conversions. However, traditional methods often suffer from color distortion, detail loss, and reduced perceptual accuracy. To address these limitations and the challenges associated with conventional Singular Value Decomposition (SVD), which struggles with sharpness and distortion, this study introduces an Adaptive SVD Conversion technique. This approach incorporates adaptive weighting and optimized normalization logic to enhance RGB to grayscale, HSV (Value channel), and binary transformations. The proposed Adaptive SVD algorithm dynamically adjusts channel influence based on image characteristics, preserving details in complex lighting conditions. Evaluation using quantitative metrics, including Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM), demonstrates the method's effectiveness. Results show that the Adaptive SVD consistently yields superior image quality and structural preservation, achieving significantly lower MSE and higher PSNR and SSIM values compared to standard formula-based conversions and basic SVD across all tested conversion types. This research establishes the adaptive SVD as a more reliable and accurate image conversion process suitable for applications demanding high fidelity and detail preservation.

Keywords: Color Space Conversion, Adaptive Singular Value Decomposition (SVD), Image Processing, Grayscale, HSV, Binary, Image Quality Assessment

INTRODUCTION

Image processing is a critical component in various fields such as medical imaging, object detection, and digital visualization, where practical color space conversions are essential for optimizing feature extraction and subsequent analysis. Among the commonly employed color transformation techniques, the HSV (Hue, Saturation, Value), binary, and grayscale conversions are frequently used for color segmentation, edge detection, and computational efficiency tasks. However, these methods often face challenges, including color distortion, loss of structural details, and reduced perceptual accuracy, which can undermine the reliability of extracted features in practical applications (Khudhair et al., 2023). These limitations highlight the need for advanced transformation techniques that enhance image quality while maintaining computational feasibility.

Several approaches have been explored to improve grayscale, HSV, and binary conversion techniques. Standard formula-based methods, despite their computational efficiency, are known to exhibit high Mean Squared Error (MSE) values and lower Peak Signal-to-Noise Ratio (PSNR), leading to perceptual inaccuracies (Abbadi, 2023). Singular Value Decomposition (SVD), a matrix decomposition technique, has shown promise in improving image transformations by preserving contrast and enhancing structural integrity. However, conventional SVD implementations still struggle with maintaining image sharpness and eliminating distortions, limiting their effectiveness in various image processing tasks (Serteep & Ibrahim, 2020).

This study aims to address the limitations of traditional image conversion techniques, such as grayscale, HSV, and binary transformations, which often result in image distortions and loss of structural integrity. These issues are particularly problematic in medical imaging, remote sensing, and machine learning, where accuracy is crucial. Current methods, while computationally efficient, do not adequately preserve important image details, leading to perceptual inaccuracies. This research seeks to improve image transformation quality through the Adaptive Singular Value Decomposition (SVD) technique to enhance precision and reliability for highly accurate applications. In addition, to address these challenges, this study introduces an Adaptive SVD Conversion technique from the original color image, incorporating adaptive weighting logic and optimized threshold calculations to enhance grayscale, HSV, and binary image processing. By minimizing distortions and preserving essential structural features, this study aims to develop an improved Adaptive SVD approach that overcomes the limitations of current methods and offers a more reliable and accurate image conversion process.

Review of Related Literature:

Standard Techniques in Color Space Transformation

Color space transformation is widely used in image processing to enhance visual representation, improve compression, and facilitate feature extraction. The RGB to HSV conversion is commonly applied in image segmentation and object recognition due to its separation of chromatic components from intensity (Kumar et al., 2021). Similarly, YCbCr transformation is extensively used in video compression and broadcasting, as it efficiently separates luminance from chrominance, reducing redundancy in image data (Chen et al., 2022). The Lab color space has gained popularity for its perceptual uniformity, making it useful for color-based segmentation and enhancement (Rahman et al., 2023).

Recent advancements have explored deep learning-based color space transformations, where neural networks optimize mappings between color spaces for specific applications (Wang et al., 2024). Hybrid color space models, combining multiple transformations, have demonstrated improved feature extraction and classification accuracy (Hassan et al., 2022). Additionally, quantum computing approaches have been investigated to accelerate transformation processes, reducing computational complexity in large-scale image datasets (Patel et al., 2023).

Despite these advancements, several challenges remain. Color distortion is a significant issue, particularly in high-dynamic-range imaging, where maintaining color consistency across varying illumination conditions is crucial (Zhang et al., 2024). Computational complexity limits real-time applications, as certain transformations require extensive processing power (Singh et al., 2023). Additionally, device-dependent color spaces introduce inconsistencies in color representation across different display technologies, necessitating robust standardization methods (Li et al., 2025).

Challenges Encountered in Color Space Transformation

Color space transformation is critical in image processing, but several challenges hinder its effectiveness. Loss of fine structural details is a common issue, particularly in transformations that rely on fixed-weight implementations, limiting adaptability across diverse image datasets (Wu et al., 2021). Noise sensitivity is another concern, as some transformations amplify artifacts, reducing the reliability of extracted features (Park et al., 2022). Additionally, occlusion and background interference complicate feature extraction, particularly in complex scenes where color-based segmentation struggles to differentiate foreground and background elements (Rahman et al., 2023).

Recent studies have attempted to mitigate these challenges through multi-scale feature extraction techniques, where color space transformations are applied at different resolutions to enhance robustness (Chen et al., 2022). Fusion-based approaches, integrating multiple color spaces, have shown promise in improving feature representation (Hassan et al., 2022). Furthermore, attention-based models in deep learning have demonstrated improved accuracy in color-based image detection by dynamically focusing on relevant regions (Patel et al., 2023).

Despite these efforts, existing methods still struggle with inconsistent feature representation across different color spaces, reducing classification accuracy in machine learning models (Zhang et al., 2024). Computational inefficiencies remain challenging, particularly in real-time applications requiring high-speed processing (Singh et al., 2023). Additionally, standardization issues persist, as different imaging devices interpret color spaces differently, affecting cross-platform compatibility (Li et al., 2025).

Current Works and Strategies for Improving Color Space Transformation

Researchers have proposed several strategies to address the challenges in color space transformation. Hybrid color space models, combining multiple transformations, have demonstrated improved perceptual accuracy while reducing computational overhead (Kumar et al., 2021). Machine learning techniques, intense neural networks, have been leveraged to optimize color space transformations, enabling more precise mappings between color spaces (Chen et al., 2022). Additionally, quantum computing approaches have been explored to accelerate transformation processes, reducing computational complexity (Rahman et al., 2023).

Recent advancements have also focused on context-aware color space transformation, where algorithms analyze image content and apply transformations that preserve structural details (Wang et al., 2024). Edge-preserving transformations have been developed to maintain object boundaries, enhancing segmentation and classification accuracy (Hassan et al., 2022). Furthermore, self-learning models have been introduced to dynamically adjust transformation parameters based on image characteristics, improving adaptability across diverse datasets (Patel et al., 2023).

Despite these improvements, several gaps remain. Scalability issues persist, as many advanced transformation techniques require extensive computational resources, limiting their applicability in real-time scenarios (Zhang et al., 2024). Cross-domain generalization remains a challenge, as models trained on specific datasets often struggle to perform well on unseen data (Singh et al., 2023). Standardization efforts need further refinement to ensure consistent color representation across different imaging devices and applications (Li et al., 2025).

Challenges in Color Space Transformation for Feature Extraction and Image Detection

Color space transformation is crucial in feature extraction and image detection, enabling systems to identify distinguishing characteristics within visual data. Histogram Equalization, Edge Detection (Sobel, Canny), and Principal Component Analysis (PCA) are widely adopted to enhance feature extraction (Patel et al., 2023). Convolutional Neural Networks (CNNs) have also demonstrated significant advancements in automated object recognition (Hassan et al., 2022).

Despite their effectiveness, conventional feature extraction approaches often struggle with complex backgrounds, occlusions, and variable lighting conditions, reducing accuracy in object classification (Kim et al., 2021). Many methodologies depend on static feature sets, limiting adaptability across different image domains (Huang et al., 2023). Furthermore, CNN-based models require extensive training data, posing computational challenges (Liu et al., 2022).

Future research should prioritize multi-scale feature extraction, fusion-based approaches, and self-learning recognition frameworks to enhance classification accuracy. Incorporating context-aware feature extraction will improve object detection in dynamic environments (Singh et al., 2024). Optimizing lightweight deep learning architectures can mitigate computational constraints while maintaining high recognition accuracy (Zhang et al., 2023).

METHODOLOGY

Proposed Solution

The Adaptive SVD algorithm improves traditional image processing by using adaptive weighting and normalization to convert RGB images into grayscale, HSV, and binary formats more accurately. Unlike standard SVD, which treats all color channels equally, this method adjusts each channel's influence based on brightness. This helps preserve details in images with uneven colors or lighting. Calculating global weights and normalizing the singular values enhances image quality while remaining efficient, especially for images with dominant or imbalanced colors.

Simulation of Proposed Adaptive SVD

Algorithm: RGB Conversion Using Adaptive SVD

Input: Color Image (X)

Output: Grayscale Image (Gray Image), HSV Image (HSV Image), Binary Image (Binary Image)

Step 1: Input the color image (X)

Step 2: Convert the image to float32 for numerical operations

Step 3: Apply Adaptive SVD for Grayscale Conversion:

Step 3.1: Separate the color image into three channels (Red (xr), Green (xg), and Blue (xb))

Step 3.2: Apply the Adaptive Global Weights to each channel:

- Calculate global adaptive weights for each channel using `CalculateAdaptiveGlobalWeights()`

Step 3.3: Compute the weighted value for each pixel:

- weighted_r = xr * weight_r

- weighted_g = xg * weight_g

- weighted_b = xb * weight_b

Step 3.4: Calculate the Singular Value Decomposition (SVD) for each pixel using `numpy.linalg.svd()`

Step 3.5: Extract the singular values and compute the norm:

- norm_S = sqrt(weighted_r^2 + weighted_g^2 + weighted_b^2)

Step 3.6: Normalize the norm_S using adaptive global factor (k_value):

- normalized_value = norm_S / k_value

Step 3.7: Store the normalized grayscale value in the output grayscale image

Step 4: Apply Adaptive SVD for HSV Conversion (Value Channel):

Step 4.1: Perform the same steps as in Grayscale conversion (Steps 3.1 to 3.7) to get the Value (V) channel

Step 4.2: Convert the image to HSV using OpenCV (`cv2.cvtColor()`)

Step 4.3: Replace the Value channel (V) with the SVD-derived value and return the new HSV image

Step 5: Apply Adaptive SVD for Binary Conversion:

Step 5.1: Convert the image to grayscale using the steps in Step 3

Step 5.2: Apply Otsu's thresholding to the grayscale image:

- threshold_value, binary_image = cv2.threshold(grayscale_image, 0, 255, cv2.THRESH_BINARY + cv2.THRESH_OTSU)

Step 5.3: Return the binary image

Step 6: Return the Grayscale Image, HSV Image, and Binary Image

Step 7: Display the results:

Step 7.1: Display the original color image and the three output images (Grayscale, HSV, Binary) using Matplotlib

END

The algorithm for RGB conversion using Adaptive Singular Value Decomposition (SVD) begins by reading the color image and converting it into a float32 format to facilitate numerical computations. The first step of the conversion involves breaking the image down into its three color channels: red (xr), green (xg), and blue (xb). Each pixel in the image is represented as a vector, with C(i, j) = [xr(i, j), xg(i, j), xb(i, j)] representing the red, green, and blue intensity values of the pixel at position (i, j).

In Step 3, the algorithm applies an adaptive weighting mechanism to each color channel. For example, the intensity of the red channel might be weighted more heavily than the green or blue channels for specific pixels, resulting in a modified pixel vector such as C1(i, j) = \[3 * xr(i, j), xg(i, j), xb(i, j)], or C2(i, j) = [xr(i, j), 3 * xg(i, j), xb(i, j)], or C3(i, j)

= [xr(i, j), xg(i, j), 3* xb(i, j)]. This adaptive weighting adjusts the contribution of each channel to the final grayscale result.

Once the color channels are weighted, the algorithm applies Singular Value Decomposition (SVD) to each pixel vector. SVD decomposes the pixel vector into three matrices: U, S, and V, where S contains the singular values of the vector. These singular values represent the importance of each component of the pixel vector, with larger values corresponding to more significant features of the image. The norm of these singular values is then computed, representing the pixel's overall intensity.

The grayscale intensity of the pixel is derived by normalizing the norm of the singular values using a constant factor k, resulting in a value G = norm(S) / k. This grayscale intensity is assigned to the corresponding pixel in the output grayscale image. This process is repeated for each pixel in the image, converting the entire image into grayscale.

In Step 4, the algorithm applies the same procedure to derive the "Value" (V) channel of the HSV (Hue, Saturation, Value) color space. After processing the V channel using Adaptive SVD, the image is converted to the HSV format using OpenCV's `cv2.cvtColor()`, and the new SVD-derived V channel replaces the original Value channel in the HSV image.

Step 5 involves converting the image into a binary format. The algorithm first converts the image to grayscale using the same SVD method. Then, Otsu’s thresholding is applied to the grayscale image to determine an optimal threshold for binarizing the image. The binary image is generated by applying this threshold, producing a final image where each pixel is black or white.

In Step 6, the algorithm outputs the three processed images: the grayscale, HSV, and binary images. Finally, Step 7 displays these images, showing the conversion process results. Adaptive SVD helps adjust the contributions of each color channel, ensuring more accurate and tailored conversions to grayscale, HSV, and binary formats.

Image Assessment and Evaluation Metrics

To test if the proposed algorithm is effective in colorspace conversion, the following will be used as metrics:

1. MSE was used to assess the average squared difference between the original and reconstructed images, with lower MSE values indicating better image quality as the difference between the images decreases.
2. PSNR was used to assess the ratio of the maximum signal power to the noise (error) power in an image, with higher PSNR values indicating better image quality, as it suggests less distortion and higher fidelity to the original image.
3. SSIM was used to assess the perceptual similarity between two images by considering luminance, contrast, and structural information, with higher SSIM values (closer to 1) indicating better structural similarity and higher perceived image quality.

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RESULTS AND DISCUSSION

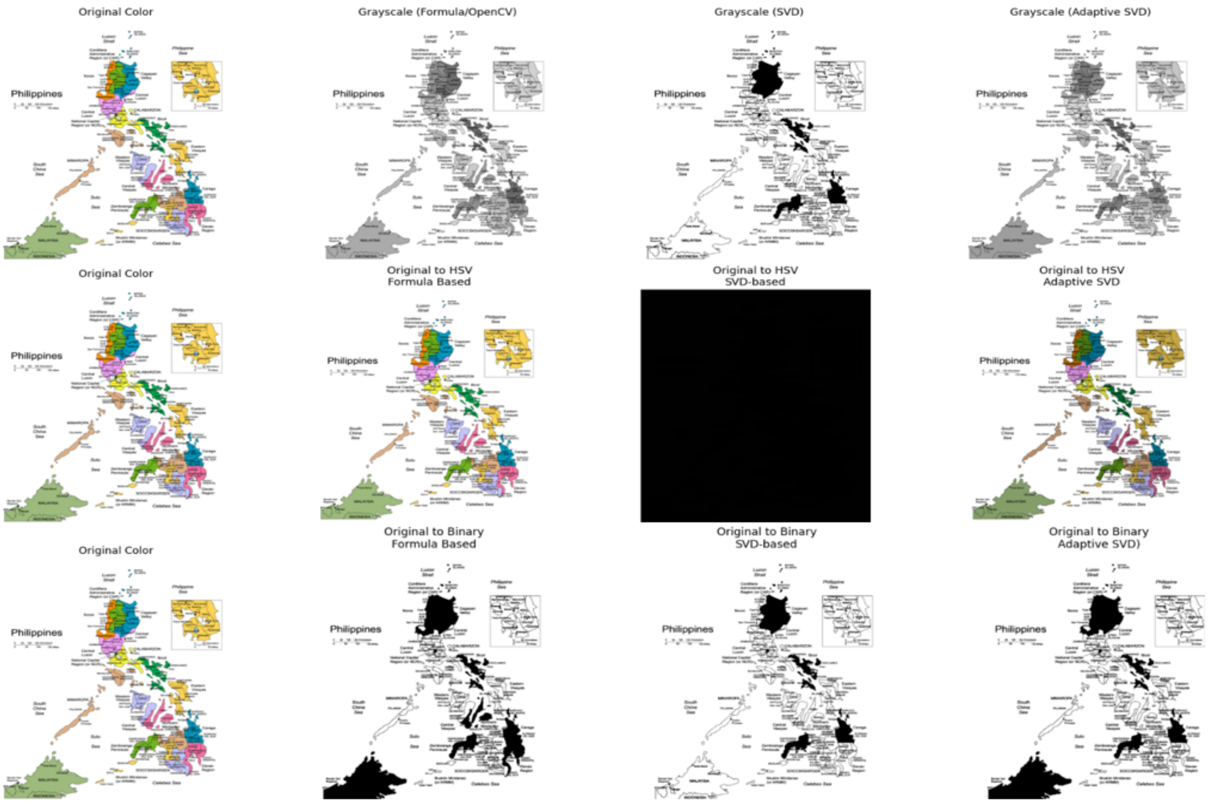

Figure 1. Colorspace Conversion of Philippine Map Image.

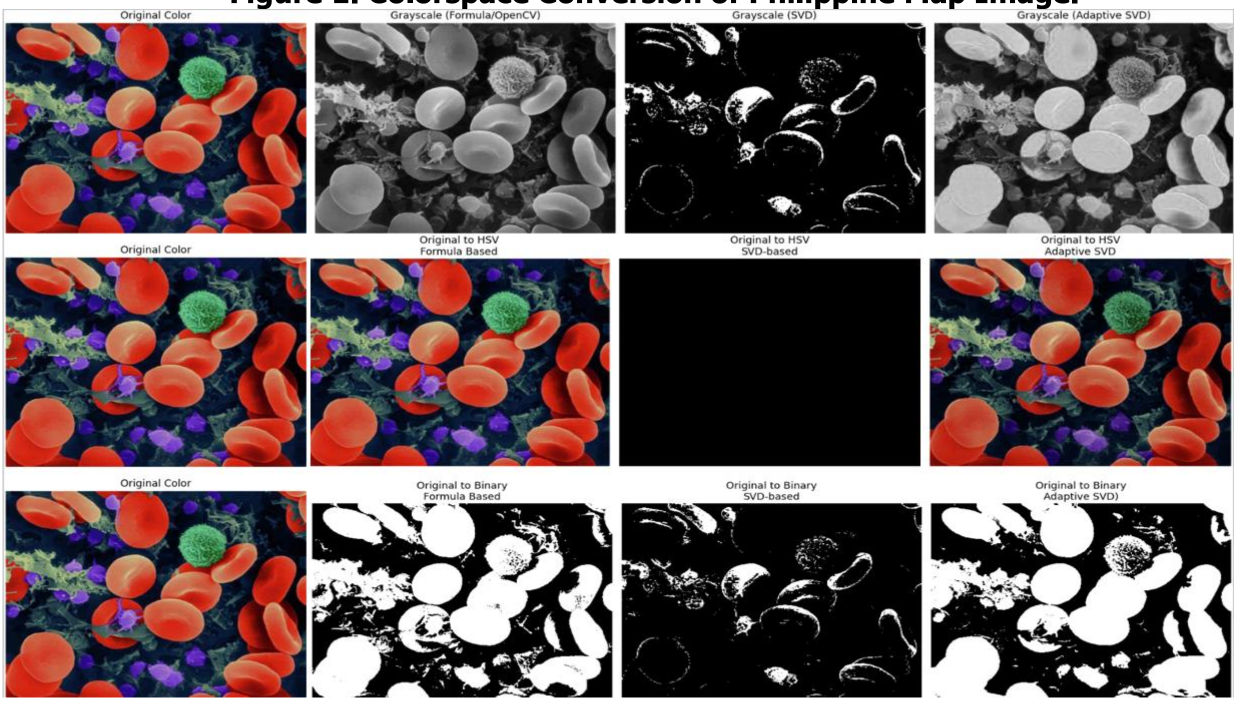

Figure 2. Colorspace Conversion of Red Blood Cells Image.

Table 1. Image Quality Assessment Performance Metrics of Figure 1

Metrics		Standard	Adaptive SVD	SVD
MSE	Grayscale	14522.26	14.26	15050.91
PSNR		6.51	36.59	6.36
SSIM		0.0009	0.9951	0.0009
MSE	HSV	7775.14	331.09	5016.97
PSNR		9.22	22.93	11.13
SSIM		0.6669	0.9812	0.6670
MSE	Binary	3070.56	722.79	3374.62
PSNR		13.26	19.54	12.85
SSIM		0.8214	0.9473	0.8107

The table presents the performance metrics for image quality assessment, comparing the Standard method, Singular Value Decomposition (SVD), and Adaptive SVD across various image formats (Grayscale, HSV, and Binary). The metrics used for evaluation are Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). The lowest MSE is the primary indicator of the method that produces the least error in terms of image quality.

For Grayscale images, the Adaptive SVD achieves the lowest MSE at 14.26, showing a substantial reduction in error and a significant improvement in image quality. The PSNR for Adaptive SVD is also much higher at 36.59, confirming that the image quality is substantially better. The SSIM for Adaptive SVD is also the highest at 0.9951, demonstrating much better structural similarity . Thus, Adaptive SVD Method is good in converting image to Grayscale.

For HSV images, the Adaptive SVD achieves the lowest MSE at 331.09, significantly reducing error and improving image quality. The PSNR for Adaptive SVD is much higher at 22.93, indicating a considerable enhancement in image quality. The SSIM also increases to 0.9812, demonstrating much better structural similarity compared to other methods. Thus, the Adaptive SVD method proves to be highly effective in improving the quality and structural preservation of HSV images, ensuring a substantial enhancement in both image quality and similarity.

For Binary images, the Adaptive SVD achieves the lowest MSE at 722.79, indicating a significant reduction in error and a clear improvement in image quality. The PSNR for Adaptive SVD is 19.54, much higher than the Standard method at 13.26, suggesting improved image quality. Furthermore, the SSIM for Adaptive SVD is the highest at 0.9473, showing much better structural similarity compared to the Standard method (0.8214). Thus, Adaptive SVD is highly effective in improving the overall quality and structure of Binary images, demonstrating its superior performance in error reduction and similarity preservation.

Therefore, Adaptive SVD emerges as the most effective method for image enhancement, providing substantial improvements in both image quality and structural preservation.

Table 2. Image Quality Assessment Performance Metrics of Figure 2

Metrics		Standard	Adaptive SVD	SVD
MSE	Grayscale	7159.50	2761.04	16929.53
PSNR		9.58	13.72	5.84
SSIM		0.0092	0.8088	0.0046
MSE	HSV	6930.26	133.01	5643.18
PSNR		9.72	26.89	10.62
SSIM		0.6673	0.9733	0.6682
MSE	Binary	27820.338	5748.50	27285.59
PSNR		3.69	10.54	3.77
SSIM		0.3212	0.7217	0.3633

Table 2 shows the Image Quality Assessment Performance Metrics of Figure 2.

For **Grayscale images**, the Adaptive SVD achieves the **lowest MSE** at 2761.04, indicating a substantial reduction in error and an improvement in image quality compared to the Standard method (MSE = 7159.50) and SVD (MSE = 16929.53). The PSNR for Adaptive SVD is also significantly higher at 13.72, confirming better image quality. Additionally, the

SSIM for Adaptive SVD is 0.8088, demonstrating a much better structural similarity than the Standard method (0.0092) and SVD (0.0046). Thus, Adaptive SVD is highly effective in improving the quality and structure of Grayscale images.

For **HSV images**, the Adaptive SVD achieves the **lowest MSE** at 133.01, drastically reducing the error and improving image quality. The PSNR for Adaptive SVD is much higher at 26.89, compared to the Standard method's 9.72, showing a considerable improvement in image quality. The SSIM for Adaptive SVD is 0.9733, significantly higher than the Standard method's 0.6673, highlighting much better structural similarity. Thus, Adaptive SVD is highly effective in enhancing both image quality and structural preservation for HSV images.

For **Binary images**, the Adaptive SVD achieves the **lowest MSE** at 5748.50, significantly reducing error and improving image quality when compared to the Standard method (MSE = 27820.338) and SVD (MSE = 27285.59). The PSNR for Adaptive SVD is 10.54, considerably higher than the Standard method's 3.69, confirming improved image quality. The SSIM for Adaptive SVD is also the highest at 0.7217, much better than the Standard method's 0.3212 and SVD's 0.3633. Therefore, Adaptive SVD is the most effective method in improving both the quality and structural similarity of Binary images.

Conclusion:

Based from the findings, the proposed Adaptive Singular Value Decomposition (SVD) method consistently yields superior quantitative image quality metrics, such as lower Mean Squared Error and higher PSNR and SSIM, when compared to the basic SVD approach for Grayscale, HSV (Value Channel), and Binary conversions, it can be concluded that the adaptive weighting and scaling mechanisms successfully enhance the transformation process. This demonstrates that the Adaptive SVD method is significantly more effective at producing outputs that maintain higher fidelity and structural similarity to standard conversion results than fixed SVD, positioning it as a promising technique for improved color space conversions in image processing applications requiring enhanced quality and detail preservation.

Recommendations:

Based on the findings of the study, then following recommendations are given:

1. Given the method's demonstrated ability to improve image quality and preserve structural details compared to traditional and basic SVD methods, it is recommended that the Adaptive SVD technique be explored for use in specific image processing applications where accurate color space conversion is critical, such as medical imaging, object detection, and remote sensing.
2. While the current implementation utilizes global adaptive weighting and scaling, future work could investigate more sophisticated local adaptive strategies and explore different parameters to further optimize the conversion quality for diverse image characteristics and conditions.
3. Further research could focus on optimizing the algorithm for real-time processing applications.
4. The Adaptive SVD method on a wider range of image datasets with varying content, noise levels, and lighting conditions would help validate its robustness and generalization capabilities across different scenarios.

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