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NOISE-RESILIENT MEDICAL IMAGE ENHANCEMENT USING ALPHA BLENDING-BASED FUSION

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ABSTRACT

This paper introduces a method for restoring degraded composite images using an enhanced image fusion technique based on alpha blending. The process includes three main stages: preprocessing, fusion, and post-processing. Initially, images are normalized, denoised, and augmented. These refined images are then fused using alpha blending, which allows for precise pixel-level control, improving visual coherence and feature emphasis. Finally, the output is evaluated for image quality using analysis techniques. This approach is particularly effective for enhancing low-quality images and correcting defects such as noise and blur, making it suitable for applications requiring high image fidelity.
Keywords: Image processing, Image fusion, Noise reduction, Alpha blending.

1.INTRODUCTION

Medical imaging is critical in modern diagnostics but is often hindered by motion artifacts, missing regions, and equipment errors, which can reduce image quality and diagnostic accuracy. Techniques like segmentation, registration, and classification help address these issues by isolating structures, aligning multiple images, and identifying tissue types. Additional methods such as 3D reconstruction and image fusion further improve image clarity by combining different modalities into a unified view.
In environments like MATLAB, a range of algorithms—deconvolution, artifact removal, and machine learning approaches including convolutional neural networks (CNNs)—are used to correct image defects and enhance visual data [1]. Among these, blending and fusion techniques are especially effective. While blending creates smooth transitions between images (e.g., for panoramas), fusion combines key features from multiple sources, producing a single image that is richer in information. This is particularly useful in medical imaging, low-light environments, and multi-modal image integration for better diagnostic outcomes [2].

2. RELATED WORKS

Image enhancement focuses on refining specific visual attributes such as contrast, edges, or sharpness, often without increasing the actual informational content of the image[1]. Common methods include histogram equalization, contrast stretching, and noise filtering. These techniques are widely used in domains such as forensics, atmospheric studies, and medical imaging to support analysis and interpretation [3].
Digital image processing also addresses issues like blur, noise, and geometric distortion. Techniques such as spatial filtering, Fourier transforms, and local neighborhood operations improve image quality and readability [4]. Histogram equalization, a frequently used enhancement technique, adjusts contrast by spreading intensity values, although it may cause over-enhancement. Adaptive histogram equalization reduces this risk by applying localized corrections but is computationally more intensive. As research continues, the focus remains on achieving improved image quality while preserving original details and minimizing artifacts [4].

3.METHODOLOGY

In the process of collecting medical images, several crucial steps ensure the integrity, relevance, and ethical compliance of the data. Firstly, select a dataset that aligns with your research question, considering factors like size, relevance, and the availability of required image types (e.g., X-rays, MRI scans). Ensure legal permission for dataset use, verify image quality, and standardize format.

- Define Criteria: Determine the specific criteria for selecting images based on your project requirements.
- Visual Inspection: Review the sampled images visually to assess their quality and relevance.
- Validation: Validate the selected images against your predefined criteria to ensure they meet the desired standards
- Annotation: If necessary, annotate the selected images with relevant labels or annotations for further analysis or machine learning tasks
- Storage and Organization
- Backup and Version Control
- Ethical Considerations

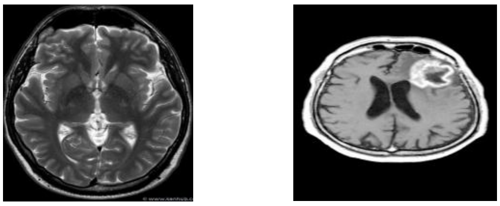

Figure 1: Two collected images

In medical image analysis, masking refers to the process of isolating or highlighting specific regions or structures within an image for further analysis or visualization. This technique is particularly useful for focusing on areas of interest, such as abnormalities, organs, or anatomical landmarks.

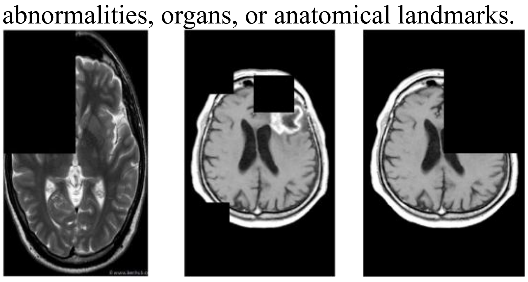

Figure 2: Images Post Masking

Image Fusion:

Image fusion involves combining multiple images acquired from different sources or modalities, each potentially containing its own set of errors or artifacts. By fusing these images, the errors present in one image may be compensated for by the information from other images, leading to a final fused image with reduced overall errors. For example, if one image has noise artifacts while another has blur artifacts, fusion techniques can combine the sharp details from one image with the noise reduction from another, resulting in a fused image with improved clarity and reduced noise.

Image Blending:

Image blending techniques can further refine the fused images by seamlessly integrating them to create a visually coherent composite image. Blending methods such as alpha blending or gradient domain blending can be used to blend images with different errors, ensuring smooth transitions and maintaining consistency across the composite image. By blending images with different errors, you can effectively combine their strengths while minimizing the impact of individual errors, resulting in a final image that is visually appealing and accurately represents the underlying data.

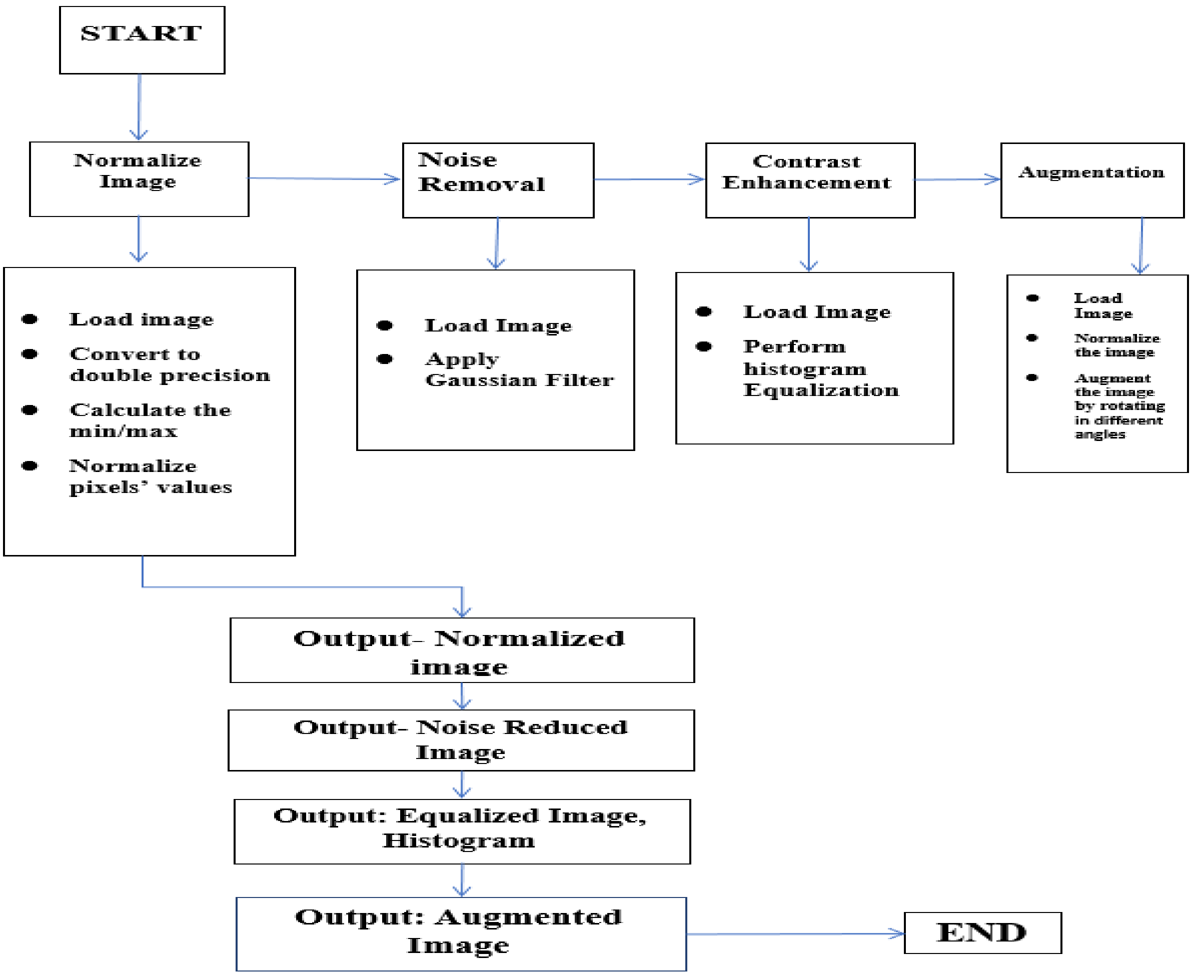

Figure 3: Proposed Block diagram

The proposed method begins by reading the input images from specified file paths and storing each in a separate variable. It then identifies the smallest height and width among all images to ensure consistency in size. All images are resized to these minimum dimensions to make them suitable for blending. A range of alpha values from 0 to 1.5, with a step of 0.1, is defined to control the blending strength. For each alpha value, a weighted sum of the images is calculated, where each image's weight is proportional to the alpha value. This blended image is generated using pixel-wise calculations and displayed in a subplot of a figure. The process repeats for each alpha value, resulting in a collection of blended outputs that show the effects of varying blending strengths. Additionally, all five original input images are displayed in another figure, each in its own subplot, to allow side-by-side comparison. The script uses OpenCV for image processing and Matplotlib for visualization. Color space conversion from BGR to RGB is done before displaying the images to ensure correct color representation. The final output includes a comprehensive view of both the blended images and the originals is shown in fig 4.

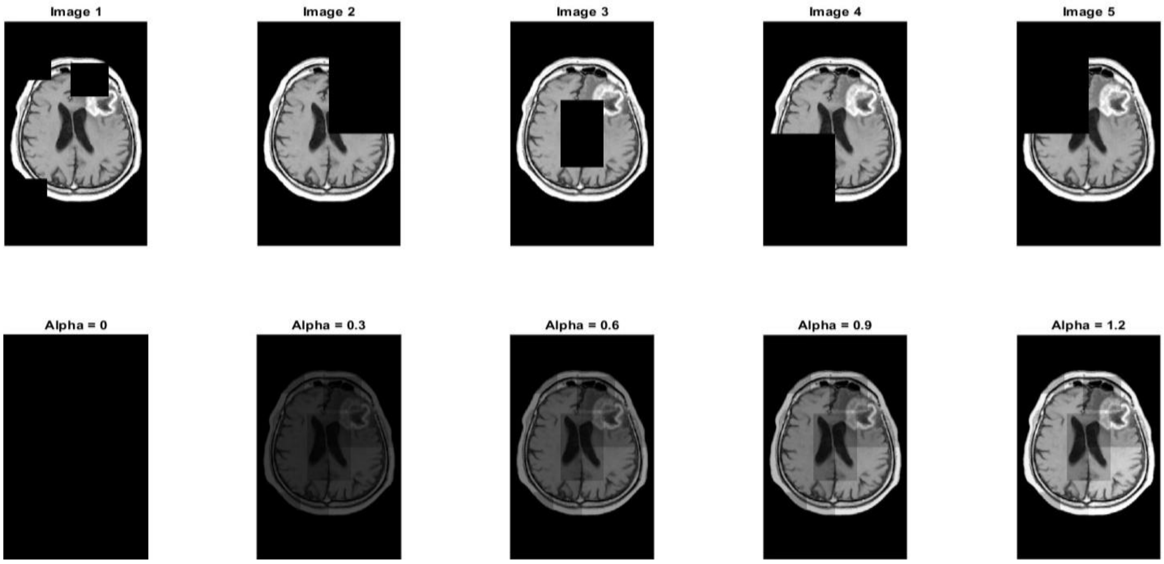

Figure 4: Images after Blending

Table 1: PSNR, RMS, SSIM of resultant Images

Alpha	PSNR	RMS	SSIM
0	7.4131	108.6135	0.51813
0.1	8.1511	99.7665	0.51981
0.2	8.9491	91.009	0.56595
0.3	9.8126	82.3971	0.62036
0.4	10.7513	73.9562	0.67612
0.5	11.7733	65.7465	0.7288
0.6	12.8683	57.4598	0.77494
0.7	14.0463	50.6088	0.81381
0.8	15.2434	44.093	0.84431
0.9	16.375	38.7072	0.86706
1.0	17.236	35.0542	0.88247
1.1	17.630	33.4997	0.89126
1.2	17.4897	34.0451	0.89479

PSNR-Peak signal-to-noise ratio, **RMS**-Root Mean Square, **SSIM**-Structured Similarity Index Method

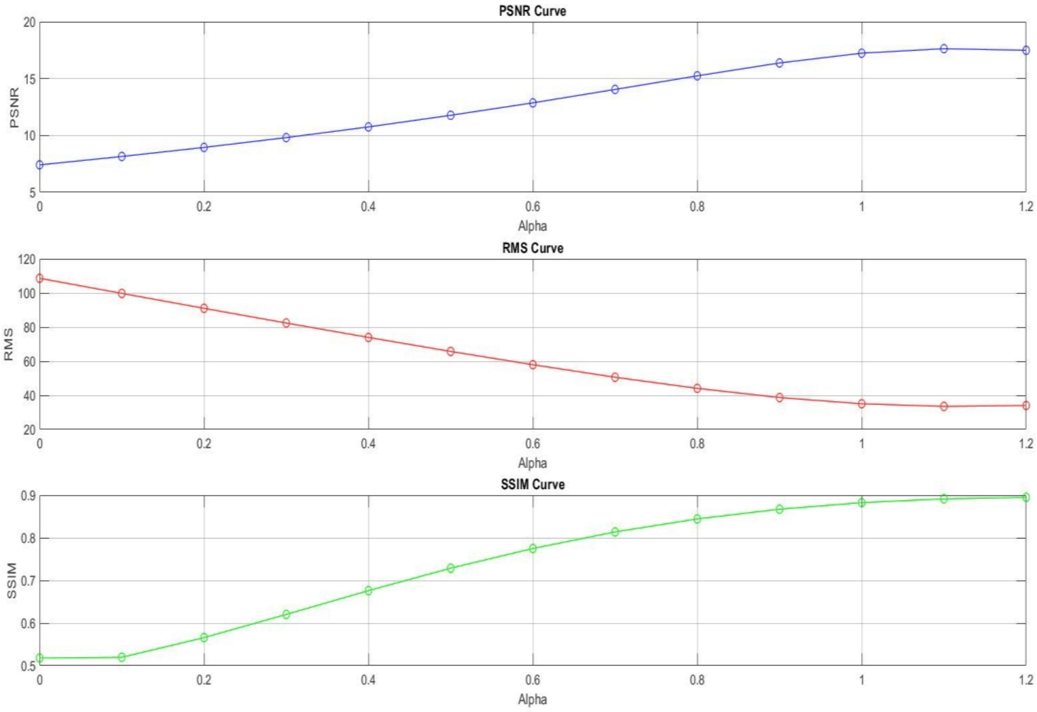

Figure 5: Graphical representation of PSNR, RMS & SSIM

IV.RESULTS AND DISCUSSION

The study outlines steps for dataset selection, ethical compliance, and preprocessing, including masking to focus on regions of interest. The fusion process involves resizing images to consistent dimensions, varying alpha values from 0 to 1.5 to control blending strength, and using OpenCV with Matplotlib for visualization.

Results show that increasing the alpha value improves image clarity and structural similarity, with peak performance around alpha 1.1–1.2, achieving high PSNR and SSIM values while minimizing RMS error.

V.CONCLUSION

This paper presents an enhanced medical image restoration approach that leverages **alpha blending-based image fusion** to improve the quality of degraded composite images. The method involves three stages:

1. **Preprocessing** – Images are normalized, denoised, and augmented to prepare for fusion.
2. **Fusion** – Using alpha blending, multiple images are combined with precise pixel-level weighting to enhance visual coherence, preserve important features, and compensate for defects like noise and blur.
3. **Post-processing and Evaluation** – The final output is assessed using metrics such as **PSNR**, **RMS**, and **SSIM** to measure quality improvements.

From the study it is found that increasing the alpha value improves image clarity and structural similarity. The peak performance was found around alpha 1.1–1.2, achieving high PSNR and SSIM values while minimizing RMS error.

Applications include improving low-quality medical images, multi-modal image integration, and diagnostic enhancement, especially where high image fidelity is critical.

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