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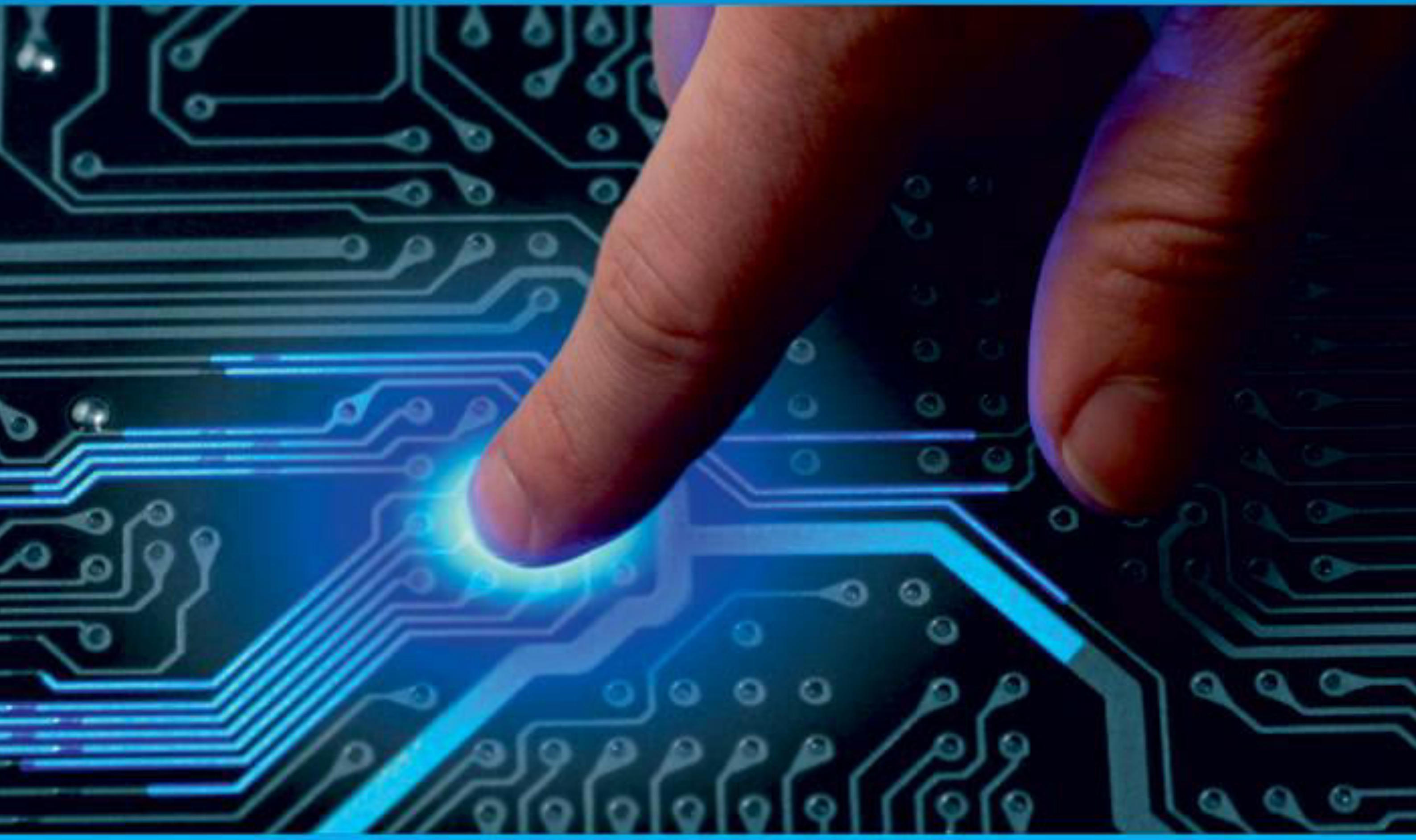

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Image Enhancement in Under Water Using Machine Learning

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ABSTRACT: This paper introduces an innovative underwater image enhancement method using Principal Component Analysis (PCA) fusion, which does not require prior knowledge of underwater scene parameters. The approach derives dual images from a single degraded underwater image, preprocesses them through homomorphic filtering and adaptive histogram equalization in individual color channels, and then smoothens them. These preprocessed images are fused and further refined using a color constancy technique to improve exposure, edge definition, contrast, and color preservation. The method's efficacy is validated against contemporary algorithms through visual and quantitative analysis, utilizing metrics like entropy and edge restoration.

I. INTRODUCTION

When photographs are taken in turbid media such as underwater, hazy or foggy conditions, the visibility of the scene is degraded significantly. This is due to the fact that the radiance of a point in the scene is directly influenced by the medium scattering. Practically, distant objects and parts of the scene suffer from poor visibility, loss of contrast and faded colors. Recently, it has been seen a growing interest in restoring visibility of images altered due to such atmospheric conditions. Recovering this kind of degraded images is important for various applications such as oceanic engineering and research in marine biology, archaeology, surveillance etc. Underwater visibility has been typically investigated by involving acoustic imaging and optical imaging systems. Acoustic sensors have the major advantage to penetrate water much easily despite of their lower spatial resolution in comparison with the optical systems. However, acoustic sensors become very large when aiming for high resolution outputs. On the other hand, optical systems despite of several shortcomings such as poor underwater visibility have been applied recently by analyzing the physical effects of visibility degradation. Mainly, the existing techniques employ several images of the same scene registered with different states of polarization for underwater images but as well for hazy inputs.

II. EXISTING SYSTEM

Mainly, the existing techniques employ several images of the same scene registered with different states of polarization for underwater images but as well for hazy inputs. As well, de-hazing techniques have been related with the underwater restoration problem made in several inputs of experiments and these techniques shown limitations to tackle with this problem. Different than most of the existing techniques, many algorithm does not use supplemental information (e.g. images, depth estimation of the scene, hardware, etc.) processing only the content of the input degraded image.

III. PROPOSED SYSTEM

The proposed system for enhancing underwater images through a multi-step process. Initially, an underwater input image undergoes homomorphic filtering to balance the illumination and enhance contrast, followed by contrast stretching to further improve visibility, producing Image. Simultaneously, the same input image is decomposed into its RGB color channels—Red (R), Green (G), and Blue (B). Each channel is then processed through adaptive histogram equalization to enhance details, followed by image smoothing to reduce noise, culminating in Image. Both images (Image 1 and Image 2) are then fused together to integrate the enhancements and produce a single improved output.

3.1 BASIC WORKING

Image enhancement in underwater environments using machine learning involves several fundamental tasks aimed at improving the quality and clarity of underwater imagery. One of the basic works in this field is preprocessing to mitigate the effects of attenuation, scattering, and color distortion caused by the absorption of light in water. Machine learning algorithms are employed to automatically correct these distortions and enhance the visibility of underwater objects and scenes. Another essential aspect is the enhancement of contrast and sharpness in underwater images.

Traditional methods often fall short in addressing the unique challenges of underwater photography, such as low light conditions and the presence of particles in the water. Machine learning techniques can adaptively enhance image features by learning from a large dataset of underwater images, thereby improving the visibility of fine details and textures. Moreover, object detection and recognition in underwater imagery are crucial for various applications like marine biology, underwater archaeology, and surveillance. Machine learning models can be trained to detect and classify objects of interest despite the inherent challenges of underwater imaging, such as uneven illumination and background clutter.

3.2 DESIGN METHODOLOGY

Designing a methodology for image enhancement in underwater environments using machine learning typically involves several key steps. Firstly, preprocessing techniques are applied to address underwater-specific challenges such as color distortion and light attenuation. These techniques may include color correction algorithms to compensate for the absorption of light at different wavelengths in water, as well as methods to reduce noise and mitigate the effects of backscatter caused by suspended particles. Next, feature extraction and selection are crucial steps in identifying relevant image features that contribute to enhancing visibility and clarity in underwater images. Machine learning algorithms, such as convolutional neural networks (CNNs), can be trained on annotated datasets of underwater images to automatically extract features that are important for image enhancement tasks. After feature extraction, the chosen machine learning model is trained using a supervised learning approach, where the model learns to map input underwater images to corresponding enhanced output images. The training process involves optimizing model parameters to minimize a defined loss function, thereby improving the model's ability to enhance underwater images effectively. Once trained, the model can be deployed to enhance new underwater images in real-time or batch processing scenarios. This deployment phase may involve optimizing the model for efficiency and performance, ensuring that it can handle the computational demands of processing large volumes of underwater imagery.

IV. SYSTEM FLOW DIAGRAM

The selection of suitable inputs to fusion forms the crucial component of the proposed algorithm. Improper selection of input methodologies results in the ineffective enhancement and unrealistic restoration. In the following sections, we have explained the reasons for selecting the choice of Homomorphic filtering and Adaptive histogram equalization as two inputs derived from the raw underwater hazy image. In this paper, we introduce enhancement algorithm based on principal component analysis fusion method. The simplified block representation of the proposed underwater image enhancement is as shown in Fig.

The basic architect diagram is given below:

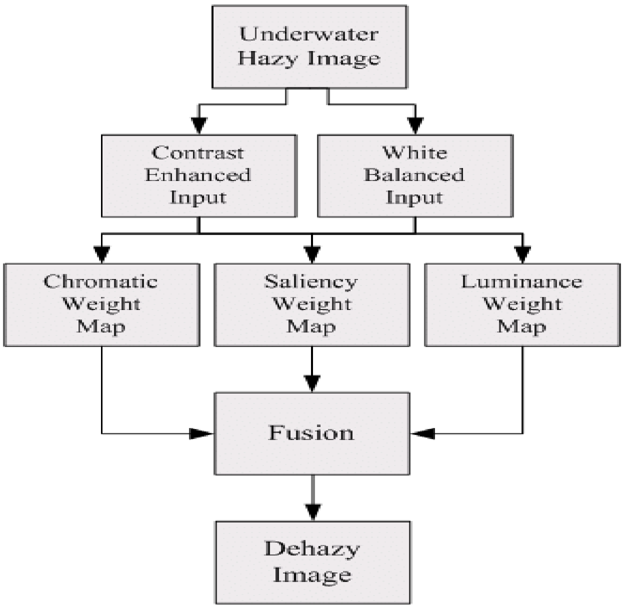

Fig-1: System Flow Diagram

V. IMPLEMENTATION

Implementing image enhancement in underwater environments using machine learning involves translating the designed methodology into practical applications. Firstly, it requires selecting appropriate machine learning algorithms and frameworks suitable for handling underwater image data. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), or generative adversarial networks (GANs) are often employed due to their effectiveness in learning complex patterns and features from underwater images. Data preprocessing plays a crucial role in preparing the input data by correcting color distortions, reducing noise, and enhancing contrast. Techniques such as histogram equalization, gamma correction, and adaptive filtering are commonly used to preprocess underwater images before feeding them into the machine learning models. The implementation phase also involves acquiring or generating a suitable dataset of underwater images for training and validation. This dataset should encompass a diverse range of underwater conditions, depths, and environments to ensure the robustness and generalization capability of the trained model.

VI. RESULTS

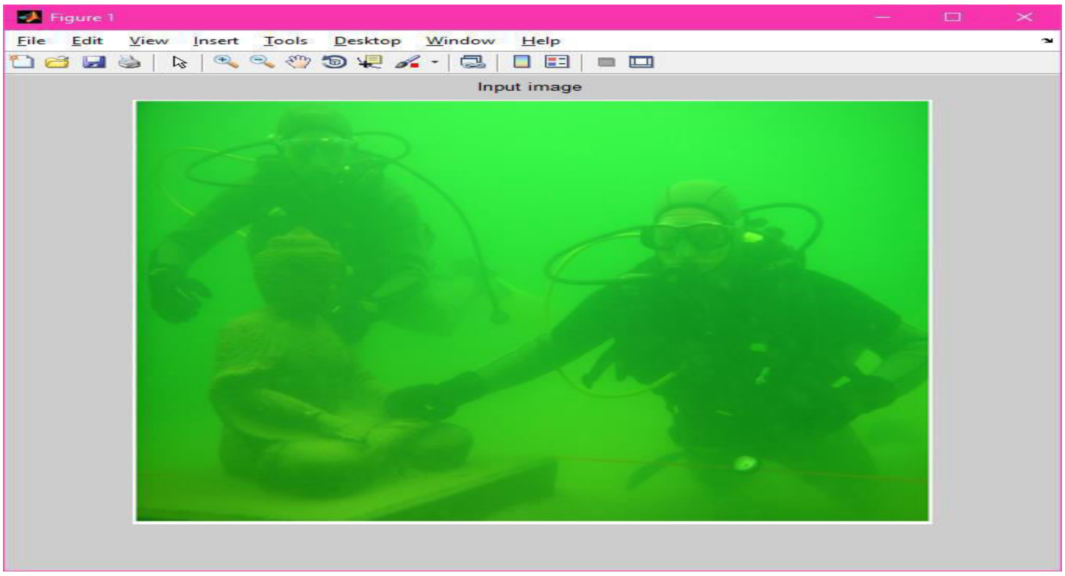

Fig-2: Input Image

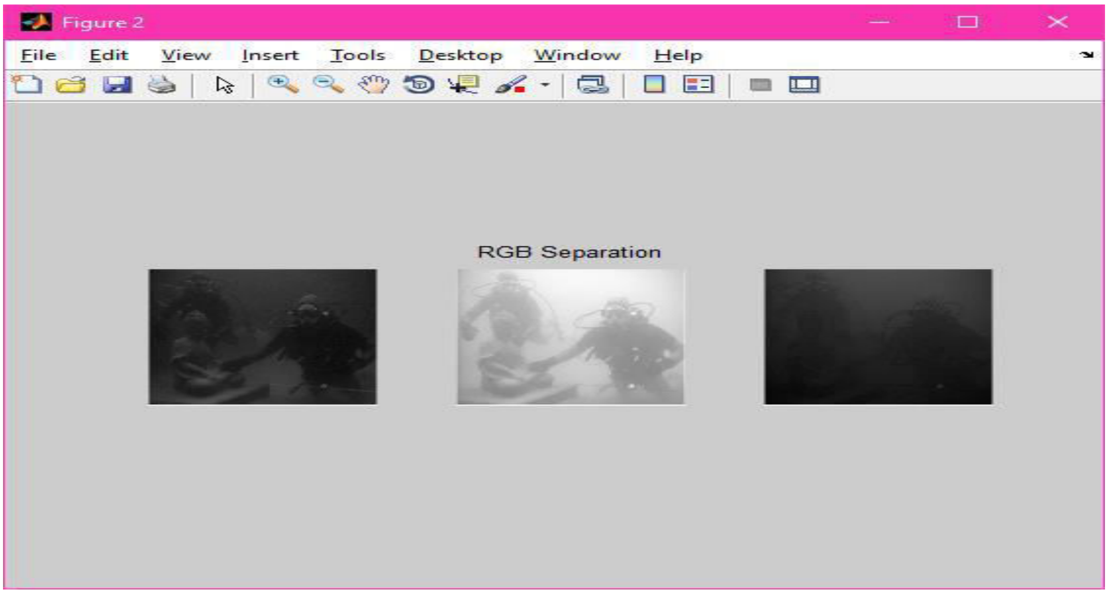

Fig-3: Three Separated Channel Images

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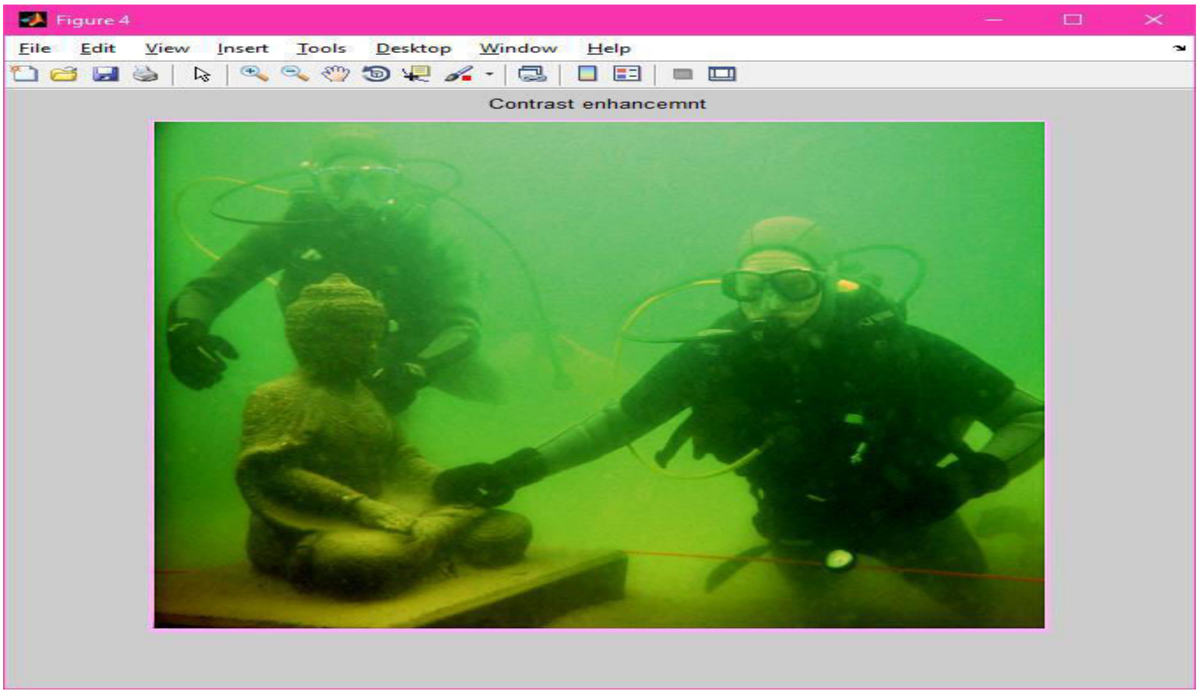

Fig-4: Enhancement Process After Filtering

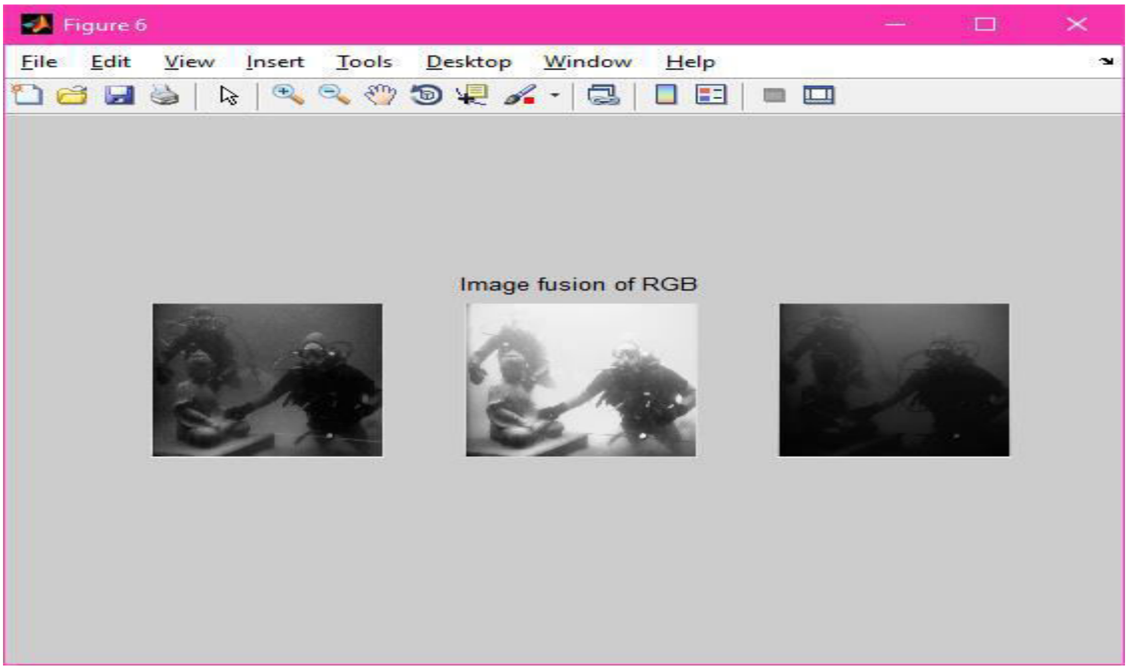

Fig-5: Image Fusion Of Rgb

VII. FUTURE SCOPE

The future of image enhancement in underwater environments using machine learning holds significant promise, driven by ongoing advancements in technology and research. One key area of future scope lies in the development of more sophisticated deep learning models specifically tailored for underwater image processing. These models will likely integrate novel architectures and learning techniques to further improve their ability to handle the unique challenges of underwater imaging, such as color distortion, low visibility, and complex light scattering phenomena. Moreover, there is growing interest in leveraging multimodal data sources for enhanced underwater image analysis. Integrating data from sensors such as sonar, LiDAR, and underwater cameras with machine learning algorithms could enable comprehensive environmental monitoring, underwater exploration, and marine life research with improved accuracy and efficiency. Another promising direction is the application of reinforcement learning (RL) techniques to optimize image enhancement algorithms dynamically in response to changing underwater conditions. RL can enable adaptive tuning of parameters based on real-time feedback, thereby enhancing the adaptability and performance of image enhancement systems in varying underwater environments.

VIII. CONCLUSION

In conclusion, enhancing underwater images is crucial for a variety of applications, ranging from scientific research in marine biology to practical uses in underwater engineering and surveillance. The challenges posed by turbid water conditions, such as reduced visibility, contrast, and color fidelity, necessitate advanced image processing techniques. Methods like homomorphic filtering and PCA-based image fusion have proven effective in mitigating these issues by improving the dynamic range and integrating valuable information from multiple images. The development and application of these techniques enhance the quality and usability of underwater imagery, allowing for better data interpretation and analysis. Continuing advancements in these image processing methods are essential to further improve the clarity and detail of underwater imaging, potentially unlocking new opportunities and insights in underwater environments.

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