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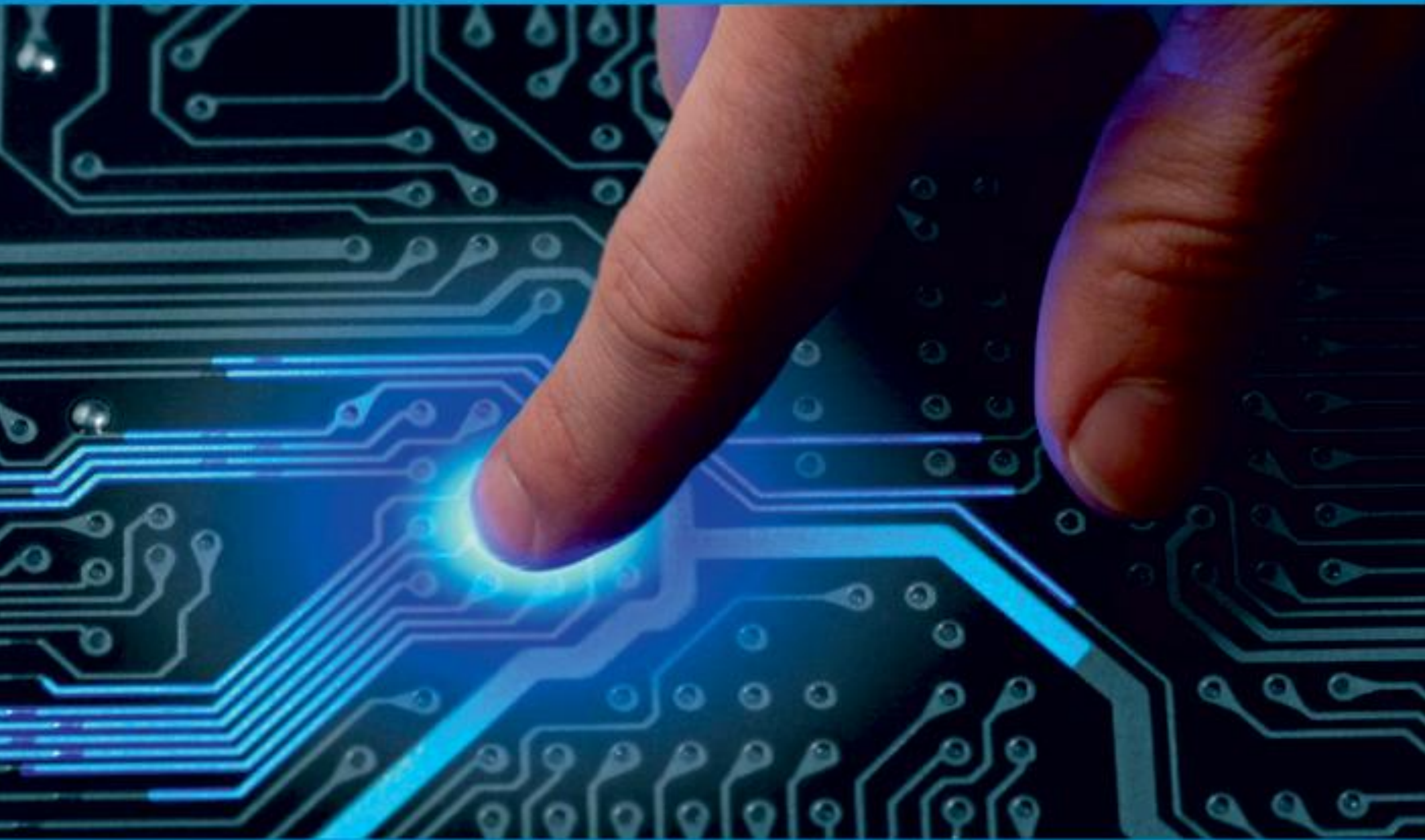

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An CNN Deep Learning Technique for Underwater Image Enhancement

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ABSTRACT: Underwater image enhancement is a critical component in various applications such as marine research, underwater exploration, and surveillance. This paper presents a Convolutional Neural Network (CNN) based approach for underwater image enhancement. Leveraging the power of deep learning, proposed technique aims to mitigate the adverse effects of underwater conditions, providing clearer and visually improved representations of submerged environments. The CNN architecture is tailored to address the specific intricacies of underwater image enhancement, and extensive experiments are conducted to validate its effectiveness. The results demonstrate significant improvements in image quality metrics, highlighting the potential of CNNs as a powerful tool for enhancing underwater imagery.

KEYWORDS: Underwater, CNN, Image, Color, Restoration, AI.

I. INTRODUCTION

Computer vision is an essential tool for a variety of underwater applications, including scientific research, the discovery of resources, and others. However, it has considerable color distortion, which is brought on by the scattering and absorption of light in the water. This is a problem since it makes the color less accurate.

Underwater imaging poses a unique set of challenges, stemming from factors such as light attenuation, backscatter, and water turbidity. These challenges often result in degraded image quality, hindering the interpretation and analysis of underwater scenes. Traditional image enhancement methods struggle to address these issues effectively. In recent years, Convolutional Neural Networks (CNNs) have emerged as potent tools in computer vision, demonstrating remarkable success in various image processing tasks. This paper focuses on harnessing the capabilities of CNNs to enhance the quality of underwater images.

The proposed CNN-based technique leverages the ability of deep learning models to learn complex hierarchical features from data, making it well-suited for the intricate task of underwater image enhancement. By training the network on a diverse dataset of underwater images with corresponding high-quality ground truth images, the model learns to map the distortions induced by underwater conditions to their corrected counterparts. The architecture is designed to capture and amplify important features while suppressing undesired artifacts inherent in underwater imagery.

Underwater imaging encounters formidable challenges due to the inherent properties of water, such as light absorption, scattering, and attenuation. These factors contribute to the degradation of image quality, particularly in terms of color fidelity. The need for accurate and vibrant color representation in underwater images is critical for various applications, including marine biology, environmental monitoring, and underwater archaeology. Traditional image processing techniques often fall short in addressing the complexities of underwater color restoration, prompting the exploration of advanced Artificial Intelligence (AI) methods.

In recent years, the integration of AI has emerged as a promising avenue for mitigating the effects of color distortion in underwater images. This review aims to provide a comprehensive overview of the current state of research on underwater image color restoration using AI techniques. We delve into the fundamental challenges posed by the underwater environment, emphasizing the impact on color perception. Subsequently, we explore the diverse range of AI methodologies applied in this context, such as deep learning models and convolutional neural networks (CNNs). The review also assesses the strengths and limitations of these approaches and discusses notable advancements in the field.

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Through a systematic analysis of the literature, this review seeks to offer valuable insights into the efficacy of AI-based techniques for underwater image color restoration. By understanding the current landscape of research in this domain, researchers and practitioners can make informed decisions in selecting or developing methodologies that align with the specific requirements of underwater imaging scenarios. The synthesis of AI and underwater imaging not only addresses the challenges posed by color distortion but also opens avenues for further advancements in the broader field of underwater computer vision.

II. PROPOSED METHODOLOGY

The proposed methodology is explained using following flow chart-

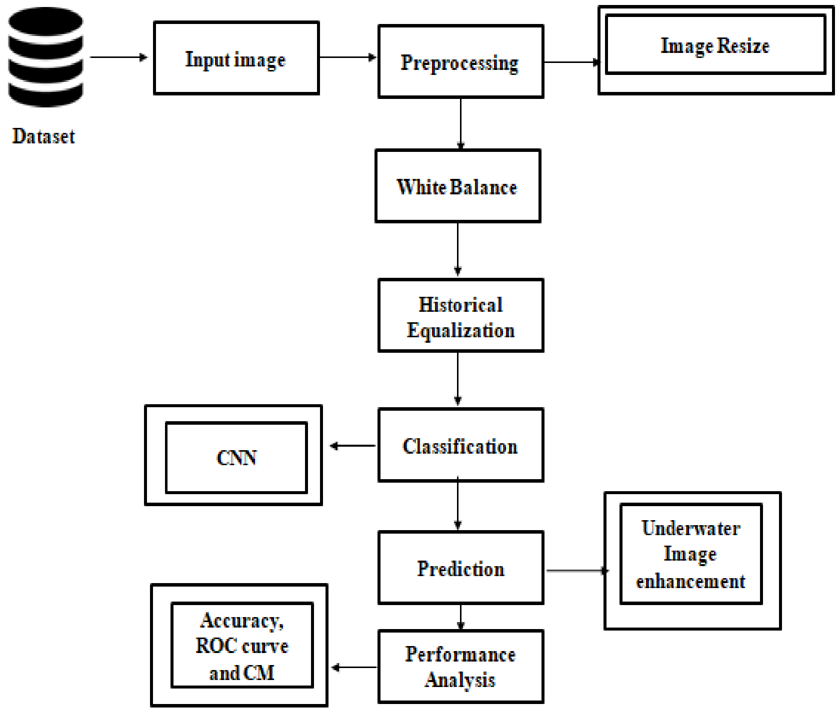

Figure 1: Flow chart

Dataset Preparation:
- Gather a diverse dataset of underwater images with varying conditions, such as different water types, depths, and lighting conditions.
- Annotate the dataset with ground truth images, which are high-quality, manually enhanced versions of the original underwater images.

Data Preprocessing:
- Adjust color balance, correct for distortion, and perform other preprocessing steps to make the dataset suitable for training.

Model Architecture:
- Design a CNN architecture suitable for image enhancement. You might consider architectures like U-Net, ResNet, or custom-designed architectures depending on the complexity of the task.
- The network should take an underwater image as input and output an enhanced version.

Loss Function:
- Define a loss function that measures the difference between the predicted enhanced image and the ground truth.
- Common loss functions for image enhancement tasks include Mean Squared Error (MSE), perceptual loss, or a combination of these.

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Data Augmentation:

- Augment the training dataset with transformations like rotations, flips, and changes in lighting conditions to improve the model's robustness.

Training:

- Train the CNN using the prepared dataset. Adjust the learning rate, batch size, and other hyperparameters to optimize the training process.
- Monitor the model's performance on a validation set to avoid overfitting.

Evaluation:

- Evaluate the model on a separate test set to assess its generalization to new, unseen data.
- Use quantitative metrics such as PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), or others depending on the specific requirements of your task.

III. SIMULATION RESULTS

The simulation is performed using the python spyder software.

Figure 2: Original Image

Figure 2 is presenting another sample of the original image of underwater from the dataset.

Figure 3: White balance

Figure 3 is presenting the white balance of the pixel. In this step the image removing unrealistic color casts sothat the object can be more cleared.

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Figure 4: Balanced images

Figure 4 is presenting the balanced image, this is the clear image or reconstructed image after the processing step.

Figure 5: Enhanced image

Figure 5 is presenting the white balance of the pixel. In this step the image removing unrealistic color casts sothat the object can be more cleared.

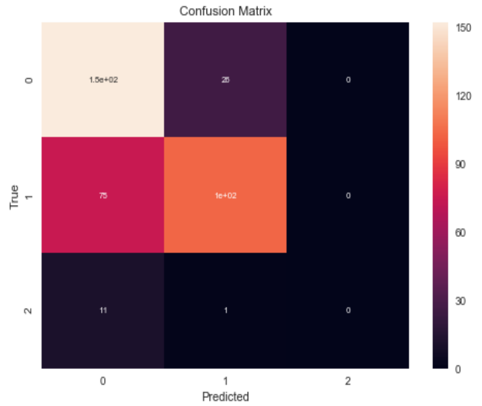

Figure 6: Confusion matrix

Figure 6 is showing the confusion matrix or the predictive matrix of the proposed research work. This matrix includes the values of true and false prediction.

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Table 1: Result Comparison

Sr. No	Parameters	Previous Work	Proposed Work
1	Method	Deep Neural Network	CNN
2	Accuracy (%)	96	99.72
3	Classification Error (%)	4	0.28

Table 1 is showing the result comparison of the previous and proposed work. The overall accuracy achieved by the proposed work is 99.72% while previous it is achieved 96%. The error rate of proposed work is 0.28% while 4% in existing work. Therefore it is clear from the simulation results; the proposed work is achieved significant better results than existing work.

IV. CONCLUSION

This paper presents a convolution neural network based deep learning technique for underwater image enhancement. The simulation is performed using the python spyder IDE 3.7 software. The dataset is trained and tested successfully. Generated the confusion matrix and optimized better accuracy. The overall accuracy achieved by the proposed work is 99.72% while previous it is achieved 96%. The error rate of proposed work is 0.28% while 4% in existing work. Therefore it is clear from the simulation results; the proposed work is achieved significant better results than existing work.

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