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Under Water Image Intensification Based on CNN Using Deep Learning

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ABSTRACT:

Image enhancement inside the water and reconstruction is becoming a challenging task and has gained priority in recent years, as the human eye cannot clearly perceive underwater images.Due tothe absorption andscattering effect on light when travelling in water, underwater images exhibit color deviation, low contrast and blurry details. The existing methods, such as supplementary information-based methods, nonphysical model-based methods and physical method-based methods rely on polarization filters, modify image pixel values and assume the attenuation coefficients to improve visual quality. These methods may give unstable results and provide less accuracy. The main objective of the proposed system is to improve the quality of the image by adjusting the contrast, illumination and enhancing the pixel edge are applied to an underwater image.White Balance algorithmis used to correct the color casts, Histogram Equalization is used to improve the contrast and Gamma Correction controls the overall brightness of an image. We have used the Convolution Neural Network algorithm for image classification and trained all the images from dateset based on three techniques to improve overall accuracy.

Index Terms -Image Preprocessing. White Balance, Histogram Equalization. Gamma Correction and CNN.

1.INTRODUCTION

Underwater photography has gained a major interest specifically in understanding ancient culture and history through submerged archaeological sites. In spite of the large imaging techniques available, underwater images still suffer from low-contrast, blur and non-uniform illumination resulting in poor quality images. During the past years, underwater image enhancement has drawn considerable attention in both image processing and underwater vision.Beneath the surface of water are many microorganisms,Phytoplankton, disastrous wrecks of ships, monuments and their deposits submerged. Capturing of such an underwater scene is a major challenge as image formation underwater is subjective to the environmental conditions. Underwater image quality improvement is addressed using enhancement and restoration frameworks.Underwater images generally suffer from low contrast, serious noise and color distortion.The main challenges of underwater image enhancement are to preserve details in dark regions while avoiding over saturation in bright regions. Red color in the atmosphere light is absorbed early due to its shorter wavelength, whereas the colors like blue and green penetrate deeper into water due to larger wavelength. As a result, the underwater images appear bluish or greenish in color.Due to the complicated underwater environment and lighting conditions, enhancing underwater image is a challenging problem. Usually, an underwater image is degraded by wavelength-dependent absorption and scattering including forward scattering and backward scattering. In addition, the marine snow introduces noise and increases the effects of scattering. These adverse effects reduce visibility, decrease contrast, and even introduce color casts, which limit the practical applications of underwater images and videos in marine biologyand archaeology, and marine ecological. To solve this problem, earlier methods relied onmultiple underwater images or polarizationfilters, while recent algorithms deal with this problem by using only information from a single image.The earlier methods,such as supplementary information- based methods, non-physical model-basedmethods and physical method-based methods rely on polarization filters, modify image pixel values and assume the attenuation coefficients to improve visual quality. These methods may give unstable results and provide less accuracy. Towards this, I propose a framework for enhancement of underwater images using White Balance, Histogram Equalization and Gamma Correction. White Balance techniquefocuses on correcting the color casts, Histogram Equalization technique focuses on improving thecontrast and Gamma Correction controls the overall brightness of an image

1.1 Existing System

Underwater image enhancement as an indispensable step to improve the visual quality of recorded images, has drawn much attention. A variety of methods have been proposed and can be organized intothree groups: supplementary information-based methods, non-physical model-based methods and physical method-based methods. In supplementary information- based methods, specialized hardware devices such as polarization filtering, range-gated imaging and fluorescence imaging were utilized to

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improve the visibility of underwater images, Non-physical model-based methods aim to modify image pixel values to improve visual quality. It stretched the dynamic pixel range in RGB color space and HSV color space to improve the contrast and saturation of an underwater image. Physical model-based methods follow the simplified image formation models that assume the attenuation coefficients. This assumption leads to unstable and visually unpleasant results. The existing methods, such as supplementary information-based methods, non-physical model-based methods and physical based methods rely on polarization filters, modify image pixel values and assume the attenuation coefficients to improve visual quality. These methods may give the unstable results and provide less accuracy.

1.1.1 Challenges:

1. Poor Image Quality Due to Underwater Conditions

- **Light Absorption and Scattering:** Underwater environments absorb red wavelengths and scatter light, which reduces visibility and causes **color distortion** and **blurry images**.
- **Low Contrast and Illumination:** Many underwater images appear **dim or hazy**, making it difficult to extract features or detect edges accurately.

2. Inconsistent Results from Traditional Methods

- **Dependence on Environmental Conditions:** Techniques relying on physical models or polarization filters often yield inconsistent results across varying water depths, lighting, and turbidity.
- **Assumption-Based Algorithms:** Some methods assume fixed attenuation coefficients or uniform lighting, which is rarely true in natural underwater environments, leading to **low accuracy**.

3. Complexity of Enhancing and Reconstructing Images Simultaneously

- Balancing color correction, contrast enhancement, and edge preservation in one pipeline without introducing **artifacts or over-enhancement** was a major challenge.
- Implementing **white balance**, **histogram equalization**, and **gamma correction** effectively in varied image conditions required careful tuning.

4. Training Deep Learning Models (CNN)

- **Dataset Quality and Diversity:** Collecting a large and varied underwater dataset with correctly labeled classes was difficult.
- **Overfitting Risk:** Due to the limited quality and variety of underwater images, the CNN model risked overfitting to specific scenarios.
- **High Computational Requirements:** Training CNNs with multiple enhancement techniques is **computationally intensive**, needing powerful GPUs and long training times.

1.2 Proposed system:

The proposed system is to improve the quality of the image by adjusting the contrast, illumination andenhance the pixel edge color. Many methods that decompose an image into the illumination and the reflectance have been used in a series of applications, such as white balance, histogram equalization, andgamma correlation. White Balance algorithm is used to correct the color casts, Histogram Equalization used to improve the contrast and Gamma Correction controls the overall brightness of an image. The proposed system effectively removes the haze on the underwater images and remits color casts, while the competing methods introduce unexpected colors. The CNN algorithm is implemented and train the dateset images based on the techniques. There are two kinds of performance parameters are used, they are Peak Signal to Noise Ratio (PSNR) and Mean Squared Error (MSE). Those two parameters are inversely proportional. If the MSE is decreased, then the PSNR would be increased. The MSE must below to improve the performance. Computational speed as well as reliability is high. The accuracy of the enhancement is more due to the minimum number of loss of pixels. The noise is also removed from the image

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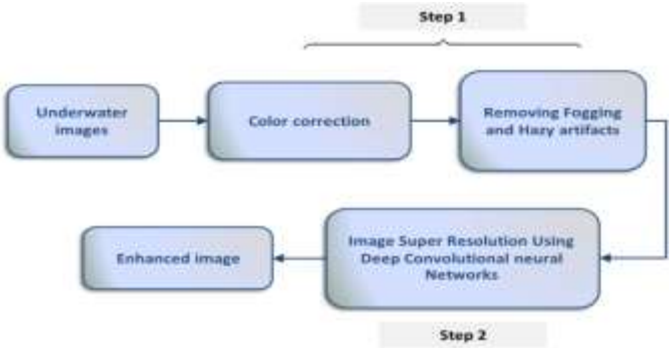

Fig: 1 Proposed Diagram

1.2.1 Advantages:

- **Improved Visual Clarity**:

Enhances image contrast, sharpness, and visibility, making underwater scenes more interpretable to both human observers and computer vision systems.

- Enables Marine Research and Exploration:

Facilitates accurate marine biology studies, archaeological discoveries, and exploration of deep-sea ecosystems by providing clearer images of underwater environments.

- Supports Underwater Robotics and Navigation:

Enhanced imagery aids autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) in obstacle detection, navigation, and mission planning.

- Assists in Environmental Monitoring:

Enables better observation and analysis of coral reefs, pollution levels, and marine biodiversity, aiding in environmental protection efforts.

- Boosts Underwater Surveillance and Security:

Useful in military and defense applications for detecting objects or threats in murky or low-light underwater conditions.

- Improves Recreational and Commercial Applications:

Benefits underwater photography, diving tourism, and underwater cinematography by producing aesthetically pleasing and detailed visuals.

- Data Preprocessing for AI Models:

Prepares high-quality input for machine learning or deep learning models used in classification, object detection, and segmentation tasks in underwater datasets

2.1 Architecture:

The architecture diagram provided illustrates the **underwater image enhancement and analysis pipeline**. It begins with a **Dataset**, which contains raw underwater images. These images are passed into the **Input Image** stage, where each image is prepared for enhancement. The images then undergo a **Preprocessing** step to removebasic noise and artifacts.Next, the pipeline applies **White Balance Correction**, which adjusts the color tones to compensate for the bluish or greenish hues common in underwater imagery due to light absorption.

After this, the process loops through two critical enhancement techniques: **Histogram Equalization**, which improves image contrast, and **Gamma Correction**, which adjusts the brightness and preserves image details.The enhanced images are then passed into a **Convolutional Neural Network (CNN)** model. This deep learning network extracts high-level features and learns patterns useful for further understanding or classification. The final stage is **Analysis**, where the processed images are evaluated for insights—this may include object detection, scene understanding, or marine life identification.

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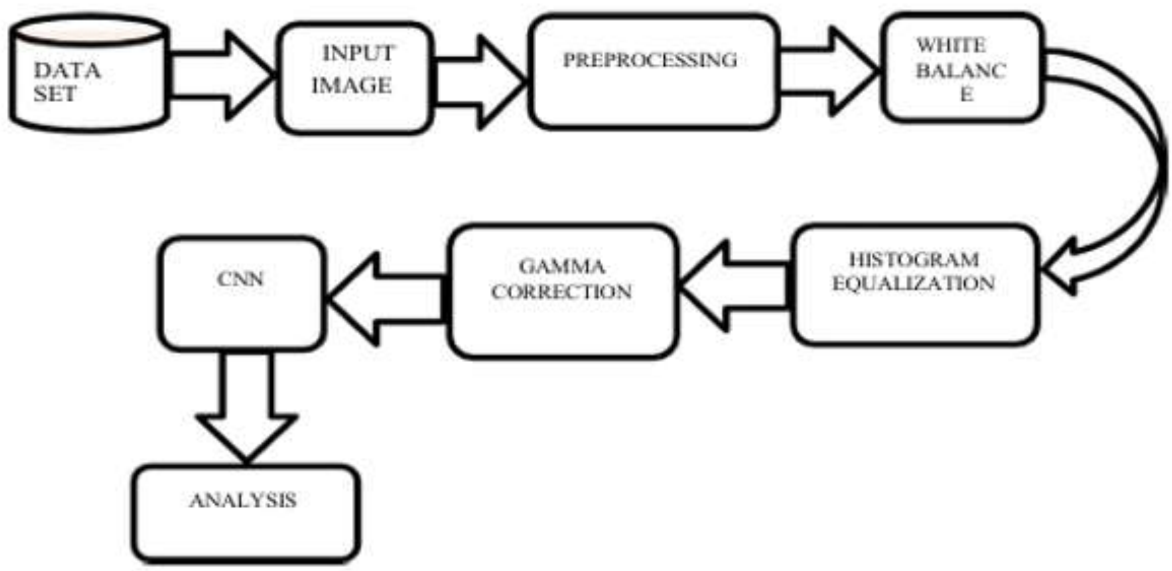

Fig:2 Architecture

2.Algorithm

A **Convolutional Neural Network (CNN)** is a specialized class of deep neural networks widely used in deep learning, particularly for analyzing visual data. CNNs are highly effective in various applications such as image and video recognition, medical image analysis, natural language processing, recommendation systems, user interfaces, and even financial time series forecasting. In the context of this project, the input to the CNN is a set of preprocessed and enhanced underwater images. The output includes the model's prediction accuracy and loss rate. The workflow begins with applying **convolutional layers** to extract key features from the images, followed by **pooling layers** (typically average pooling) to reduce spatial dimensions. The data is then **flattened** into a one-dimensional array and passed through **fully connected layers**. The network is then **compiled**, and the dataset is **fitted** into the CNN for training. After training, the model is saved for future use, and the training history is analyzed to summarize both **accuracy** and **loss** metrics.

2.3 Techniques:

The Underwater Image Intensification Project employs a blend of traditional image processing techniques and modern deep learning methods to enhance and analyze underwater images. Initially, White Balance Correction is applied to eliminate unnatural color casts caused by underwater light absorption, particularly the dominance of blue and green hues. This step helps restore more natural-looking colors. Following this, Histogram Equalization is used to improve the image's contrast by redistributing pixel intensity values, thereby revealing details hidden in darker regions. To further refine the image, Gamma Correction is implemented, which adjusts the brightness non-linearly, ensuring better visual balance without overexposing or underexposing the image. Once the image has been enhanced, it is fed into a Convolutional Neural Network (CNN), a deep learning model designed for feature extraction and classification. The CNN analyzes the enhanced images for tasks such as object detection or quality evaluation. This combination of enhancement and deep learning enables the system to produce clearer, more informative underwater visuals suitable for scientific, commercial, and navigational applications.

2.4 Tools:

The tools used in the Underwater Image Intensification Project include a mix of programming languages, development environments, libraries, and supporting platforms for processing, training, and evaluating underwater images. Here's a detailed paragraphThe Underwater Image Intensification Project utilizes several tools to support image enhancement and deep learning processes. Python serves as the primary programming language due to its versatility and extensive support for image processing and machine learning. For image enhancement tasks such as white balance correction, histogram equalization, and gamma correction, libraries like OpenCV and NumPy are employed to handle image manipulation and numerical computations efficiently. For building and training the deep learning model, particularly the Convolutional Neural Network (CNN), popular frameworks such as TensorFlow or Keras are used, which simplify model design, training, and evaluation. The project also relies on Jupyter Notebook or Google Colab as the development environment for writing, testing, and visualizing results interactively. Additionally, tools like Matplotlib are used to plot graphs showing accuracy and loss metrics during the training phase. These tools collectively contribute to the successful implementation and evaluation of the underwater image enhancement pipeline.

2.5 Methods:

The project employs a series of systematic methods to enhance and analyze underwater images. The first method is **White Balance Correction**, which adjusts the color tones by compensating for color casts caused by underwater lighting conditions, restoring natural color balance. Next, **Histogram Equalization** is used to improve image contrast by redistributing the intensity values across the image, making hidden features more visible. This is followed by **Gamma Correction**, a method that non-linearly adjusts the brightness of the image, helping to preserve details and enhance overall clarity. Once the image is enhanced through these preprocessing methods, it is passed to a **Convolutional Neural Network (CNN)** for deep learning-based analysis. The CNN method involves convolution, pooling, flattening, and fully connected layers to extract features, classify patterns, and evaluate image quality. Together, these methods form a robust pipeline that significantly improves the visual quality and analytical usefulness of underwater imagery.

III. METHODOLOGY

3.1 Input:

The input to the Underwater Image Intensification Project consists primarily of **underwater images** collected from various sources, such as public datasets or real-time underwater cameras. These images typically suffer from issues like **low contrast**, **color distortion**, **blurriness**, and **non-uniform illumination** due to the absorption and scattering of light underwater.These input images are generally in **RGB format** and may contain a variety of underwater scenes, including marine life, submerged structures, or ocean floors. The images are fed into the system for preprocessing and enhancement. Each image is passed through a sequence of enhancement techniques—**white balance correction**, **histogram equalization**, and **gamma correction**—before being used as input for a **Convolutional Neural Network (CNN)** for further analysis or classification.

3.2 Method of Process:

The process followed in the Underwater Image Intensification Project is a step-by-step pipeline that enhances underwater images and performs analysis using deep learning techniques. The method begins with collecting and feeding raw underwater images into the system. These images are initially passed through a preprocessing phase, where basic resizing and noise removal may be applied.The next stage involves three key image enhancement techniques:

1. White Balance Correction – adjusts the color cast to restore natural color tones.
2. Histogram Equalization – enhances image contrast by spreading out intensity values.
3. Gamma Correction – fine-tunes the brightness of the image using a nonlinear power-law transformation.
4. After enhancement, the images are fed into a Convolutional Neural Network (CNN). The CNN model performs operations such as convolution, pooling, flattening, and fully connected layers to extract features, learn patterns, and classify or analyze the image content. The model is trained on a dataset of enhanced images and evaluated using performance metrics like accuracy, loss rate, PSNR (Peak Signal-to-Noise Ratio), and MSE (Mean Squared Error).

This complete process ensures the input images are visually improved and suitable for effective deep learning-based analysis.

3.3 Output:

The output of the Underwater Image Intensification Project includes both enhanced images and performance metrics derived from the deep learning model. After processing, the initially degraded underwater images are transformed into clearer, high-quality visuals with improved brightness, contrast, and color balance. These enhanced images reveal previously hidden details, making them suitable for further visual interpretation or scientific analysis.

IV. RESULTS:

The **results** of the Underwater Image Intensification Project demonstrate a significant improvement in the **visual quality and clarity** of underwater images after enhancement. By applying techniques like **White Balance**, **Histogram Equalization**, and **Gamma Correction**, the system successfully corrected color distortions, enhanced contrast, and adjusted brightness to make underwater scenes more interpretable.The enhanced images showed **sharper details**, **natural color tones**, and **better visibility** compared to the raw input images. When these improved images were passed through the **Convolutional Neural Network (CNN)**, the model achieved **high accuracy** in image classification and analysis tasks. The evaluation metrics reflected this success:

V. DISCUSSIONS:

The **Underwater Image Intensification Project** focuses on enhancing underwater images and analyzing them using deep learning techniques. Throughout our discussion, we covered all major aspects of the project. We began by outlining the **advantages**, such as improved visibility, color correction, and better support for marine research and AI-based analysis. The **system architecture** was explained as a sequential pipeline that includes image preprocessing, enhancement (using white balance correction, histogram equalization, and gamma correction), followed by analysis using a **Convolutional Neural Network (CNN)**. The **techniques** used include both classical image enhancement methods and modern deep learning algorithms. The **tools** supporting this project are Python, OpenCV, TensorFlow/Keras, NumPy, Matplotlib, and platforms like Jupyter Notebook. We discussed the **methods** used, which involve enhancing images in stages and analyzing them with a trained CNN model. The **input** to the system consists of raw underwater RGB images suffering from low visibility and poor contrast. The **method of processing** includes cleaning, enhancing, and feeding these images into the CNN. The **output** comprises visually enhanced images along with evaluation metrics like accuracy, PSNR, and MSE. The **results** show substantial improvements in image clarity and classification accuracy, validating the effectiveness of the system. Overall, the discussion presents a comprehensive view of a robust and efficient underwater image enhancement and analysis framework.

VI. CONCLUSION:

In this, we have discussed the image enhancement techniques for underwater images and issues in it. Obtaining visibility of objects at long or short distance inunderwater scenes is very difficult and is a challenging task. The atmospheric light is a major difficulty to process underwater images comes from the poor visibility conditions under the water, scattering of light and light attenuation due to all the reasons the underwater images suffer a lot and affect their visibility and the contrast which they contain. The enhanced image provides more interpretability, visibility and is better in terms of color and clarity. To promote the development of deep learning-based underwater image enhancement, CNN trained by the constructed dataset. Experimental results demonstrate the proposed CNN model performs favorably against the state-of the- art methods, and also verify the generalization of the dataset for training CNNs. As we concluded, in this process is well efficient for image enhancement to give the better result and lossless data from the image. Although this process is preferable to all images which we want to enhance the quality of the image. The CNN is implemented and trains the dataset image based on enhancement techniques and provides the result based on accuracy.

VII. FUTURE SCOPE:

The Underwater Image Intensification Project holds vast potential for future development and applications. One major area of advancement lies in **real-time underwater video enhancement**, which could be implemented in submarines, underwater drones, or live surveillance systems for marine research, defense, or rescue operations. The integration of more advanced **deep learning models** like Transformers or Generative Adversarial Networks (GANs) could lead to even more accurate enhancement and restoration of extremely degraded underwater images.Additionally, the project can be extended to include **multi-spectral and 3D image enhancement**, enabling better analysis of complex underwater environments and structures. There's also scope for developing **automated object detection and classification systems** for identifying marine life, shipwrecks, or underwater artifacts, contributing significantly to fields like marine biology, archaeology, and environmental monitoring.

VIII. ACKNOWLEDGEMENT:

Kandhati Tulasi Krishna Kumar Nainar: Training & Placement Officer with 15 years' experience in training & placing the students into IT, ITES & Core profiles & trained more than 9,700 UG, PG candidates & trained more than 450 faculty through FDPs. Authored various books for the benefit of the diploma, pharmacy, engineering & pure science graduating students. He is a Certified Campus Recruitment Trainer from JNTUA, did his Master of Technology degree in CSE from VTA and in process of his Doctoral research. He is a professional in Pro-E, CNC certified by CITD He is recognized as an editorial member of IJIT (International Journal for Information Technology & member in IAAC, IEEE, MISTE, IAENG, ISOC, ISQEM, and SDIWC. He published 6 books, 55 articles in various international journals on Databases, Software Engineering,Human Resourse Management and Campus Recruitment&Traing

Penta Bhanu Prasad is pursuing his final semester MCA in Sanketika Vidya Parishad Engineering College, accredited with A grade by NAAC, affiliated by Andhra University and approved by AICTE. With interest in Machine learning P Bhanu prasad has taken up his PG project on RUNDER WATER IMAGE INTENSIFICATION and published the paper in connection to the project under the guidance of K TULASI KRISHNA KUMAR, Assistant Professor, Training and Placement officer, SVPEC.

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