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A GAN Based Approach for Color Restoration and Contrast Enhancement in Submerged Environment

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ABSTRACT

Underwater photographs commonly experience reduced visibility, low contrast, and noticeable color degradation due to the scattering and absorption of light beneath the water surface. These issues make accurate analysis difficult in fields such as marine science, underwater exploration, and environmental preservation. Improving the quality of underwater images is therefore essential for better interpretation and decision-making. This project introduces a deep learning–driven solution for enhancing underwater images using a U-Net CNN architecture. A local dataset containing low-quality underwater images along with their improved reference versions was used to train the model. Skip connections, was tailored to recover lost details and enhance overall image quality by refining brightness, contrast, and color balance. The implementation process involved preparing and pre-processing the dataset, constructing and training the neural network model, and storing the trained model for deployment purposes. To make the system easily accessible, a web application was developed with a frontend created using HyperTextMarkupLanguage, CSS, and JS, and a backend powered by Flask. Through the web interface, users can upload underwater images, which are then processed by the trained model to produce enhanced outputs displayed next to the original images for comparison.

Keywords: Cross-Platform ,U-Net, TensorFlow/Keras, GAN, Encoder-Decoder Network, Artificial Intelligence, Supervised Learning, Convolutional Neural Networks, Flask Framework.

INTRODUCTION

Underwater imaging is essential for marine exploration, scientific investigations, and environmental monitoring. Despite its importance, capturing clear images underwater is challenging due to the distinct optical characteristics of water. Light behaves differently beneath the surface, where absorption and scattering cause significant visual distortions. Longer wavelengths, particularly red, green and blue wavelengths which results in images that often appear predominantly blue or green. These distortions reduce visibility, contrast, and color accuracy, making both human interpretation and computer vision tasks—such as object detection, mapping, and tracking—more difficult in underwater environments. The primary causes of underwater image degradation are light attenuation and backscattering. Attenuation diminishes light intensity as it travels through water, while backscattering introduces noise by redirecting scattered light back toward the camera. Consequently, underwater images frequently appear dark, blurry, and lacking in fine details. Conventional image enhancement techniques, including histogram equalization, white balance adjustment, and filtering methods, have been used to address these issues. However, such approaches often struggle to maintain natural color consistency and structural integrity, particularly under varying water conditions. In recent years, artificial intelligence— especially deep learning—has significantly advanced the field of image enhancement. Deep learning techniques can model complex relationships between bad and high-quality images by utilizing large datasets and layered feature extraction mechanisms. Architectures such as (CNNs) and (GANs) have shown impressive performance in improving texture details, correcting color distortions, and enhancing contrast in underwater images. Among these models, U-Net has gained considerable attention due to its encoder–decoder framework with skip connections, enabling effective capture of both global context and detailed information. Compared to old ways, deep learning provides substantial benefits for underwater image enhancement. [5]Neural networks can automatically learn meaningful feature representations, adapt to diverse underwater conditions, and generalize across different environments. This flexibility minimizes reliance on manually designed rules and assumption-based correction techniques commonly used in earlier approaches. Furthermore, deep learning supports end-to-end processing, allowing models to directly generate enhanced images from raw inputs without requiring handcrafted intermediate steps. The application of deep learning in underwater imaging has extended beyond theoretical research into practical deployment. It now plays a critical role in systems such as (ROVs), (AUVs), and marine monitoring platforms. Enhanced underwater images contribute to more accurate coral reef analysis, fish population studies, and underwater archaeological documentation. Ultimately, these advancements support sustainable marine ecosystem management and more efficient ocean exploration.

System Features

The **Underwater Image Enhancement System** is developed with a comprehensive set of well-structured features to ensure accuracy, efficiency, and user convenience. Each component is designed to support the primary goal of enhancing underwater image quality using deep learning techniques while maintaining a smooth and intuitive user experience. [1]The system effectively combines data management, deep learning inference, and visualization within a web-based platform.

The main features of the system include:

● **Automated Image Enhancement:**
The system's primary function is the automatic enhancement of underwater images using a trained U-Net deep learning model. After an image is uploaded, it is processed by the backend model to improve contrast, color correction, and overall clarity without requiring manual adjustments.

● **Side-by-Side Imag Comparison:**
Both the original and enhanced images are displayed simultaneously. This comparative view enables users to clearly observe the improvements, promoting transparency and user confidence in the enhancement process.

● **Web Interface:**
The frontend, developed using HTML, CSS, and JavaScript, provides a simple and intuitive interface for uploading images and viewing results. The clean layout and straightforward navigation ensure accessibility for users with varying technical expertise.

● **File Upload:**
The system supports standard image formats such as .jpg, .jpeg, and .png. Uploaded files are securely stored in a designated directory, and a CSV file maintains records including upload date, time, filename, file path, and username ("admin") for documentation and tracking purposes.

●**Deep Learning Model Integration:**
The backend incorporates a pre-trained TensorFlow/Keras U-Net model optimized for underwater image enhancement. Using convolutional, pooling, and upsampling layers, the model performs pixel-level refinement to reconstruct clearer and higher-quality images.

●**Image Pre-processing and Normalization:**
All uploaded images are automatically resized to 256×256 pixels and normalized before being processed. This ensures compatibility with model input requirements and guarantees stable, consistent prediction results.

●**Logging and Performance Tracking:**
Each enhancement request is recorded, enabling analysis of processing time, number of uploads, and enhancement performance. This feature supports system monitoring and future optimization efforts.

Feasibility Analysis

The feasibility study evaluates whether the proposed system is technically viable, operationally practical, economically affordable, and achievable within the planned timeframe.

Operational Feasibility

The application is designed for ease of use and requires no specialized training. Users simply upload an image through the graphical interface, and the enhancement process runs automatically. The intuitive and responsive interface ensures a seamless experience, even for first-time users. Backend automation minimizes human error, while CSV logging provides accountability and operational traceability.

Economic Feasibility

Hardware requirements are moderate, and deployment through services such as Google Colab or free-tier cloud hosting options makes the solution cost-effective for research institutions and small organizations. Considering the scientific and operational advantages of enhanced underwater imagery, the overall return on investment is substantial.

Schedule Feasibility

The complete development cycle—including dataset preparation, model training, web integration, and system testing—can be accomplished within 9–11 weeks by a small development team. The modular design enables parallel progress on interface development and model optimization, ensuring timely completion.

Legal and Environmental Feasibility

The system utilizes publicly accessible datasets and adheres to research data usage guidelines. It does not present environmental, ethical, or regulatory concerns, nor does it require special licensing for deployment.

Usability

Usability plays a vital role in ensuring that users can interact with the system effectively and achieve accurate results without difficulty. The software is designed with an emphasis on simplicity, accessibility, and clarity, making it suitable for a diverse group of users, including researchers and field operators.

User Interface Design:

The frontend features a clean, minimalistic, and user-friendly layout consisting of a homepage, an image upload section, and a results dashboard. Clearly labeled buttons guide users through each stage of the process, reducing cognitive effort and facilitating smooth navigation. Visual cues such as progress indicators and confirmation messages provide real-time feedback during image upload and processing, thereby enhancing user confidence and overall experience.

Ease of Learning:

The system follows a straightforward upload-and-view workflow, enabling users to become familiar with its functionality within a short time. Technical terminology is intentionally avoided, and simple labels such as “Upload Image,” “Enhance,” and “Download Result” are used to ensure clarity. This approach makes the system accessible even to individuals with limited technical expertise.

Efficiency of Use:

After an image is uploaded, the enhancement process is completed within seconds on High processing GPU-enabled systems. The comparison allows users to immediately assess the improvements. This rapid processing and instant visualization significantly improve user productivity and engagement.

Objectives

The main objectives of this study are as follows:

- To Make underwater pictures look better by fixing problems like faded colors, low contrast, blurriness, and haziness using a type of artificial intelligence called (GANs).
- Bring back the real colors and details that get lost because water changes how light behaves underwater.
- Help people see underwater scenes more clearly, which is useful for things like studying sea life, underwater robots, exploring old shipwrecks, and security.
- Check how well GANs work to improve underwater images compared to older methods, by measuring image quality and looking at the pictures.

METHODOLOGY

Software implementation is the phase in which the proposed system design is translated into a working software solution. At this stage, the key components of the system—namely the frontend, backend, and deep learning model—are developed, combined, and evaluated to ensure proper functionality and performance. This structured approach improves system stability, supports scalability, and simplifies future maintenance or upgrades. The implementation process includes developing the web interface using Flask, incorporating the trained U-Net model for enhancement tasks, setting up input and output directories for image management, and implementing data handling and logging procedures. This section presents the system architecture and explains the algorithmic workflow that drives the image enhancement process.

1. Image Upload Functionality

- The system must allow users to upload underwater image files in supported formats (.jpg, .jpeg, .png).
- It should validate file type, size, and integrity before processing.
- On successful upload, the system should store the image in the “static/uploads” directory and log its
- details (filename, path, date, time, and user ID) in a CSV file.
- If an invalid or corrupted file is uploaded, the system must display an appropriate error message.

2. Image Preprocessing Functionality

- The uploaded image must be automatically resized to 256×256 pixels.
- Pixel intensity values should be normalized to the range [0,1] for compatibility with the U-Net model.
- The system should convert non-RGB images (grayscale) into RGB format before enhancement.

3. Model Loading and Prediction

- Upon initialization, the Flask backend must load the trained U-Net model (underwater_unet_model.h5) into memory.
- When an image is uploaded, the backend passes it to the model for inference.
- The model outputs an enhanced image of the same dimensions, improving brightness, contrast, and color balance.

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4. Dual Image Display Functionality

- The system must display both the good and bad pictures side by side on the web page.
- It should provide zoom and download options for the enhanced image.

The visual comparison interface must automatically refresh

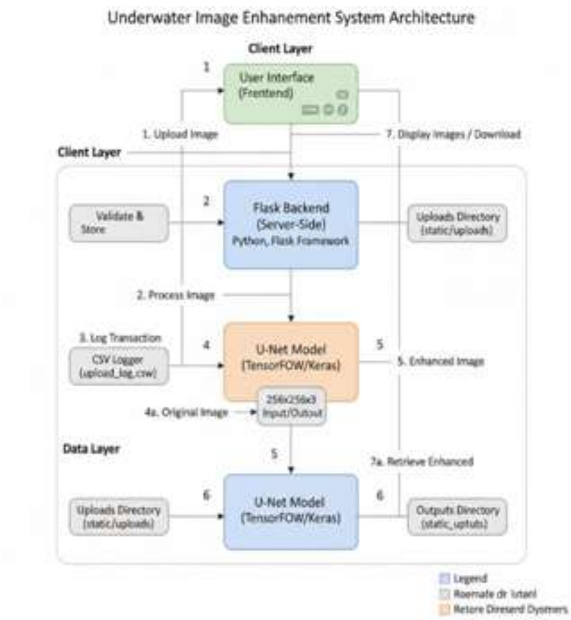

Fig 1 : System Architecture

after each The system should automatically manage temporary files to prevent storage overflow.

4. Model Evaluation (Optional Research Extension)

- The system should include optional metrics such as PSNR, SSIM, and UIQM for evaluating enhancement quality.
- Enhancement task.

5. Logging and Record Management

- Every upload and enhancement operation must be logged in upload_log.csv.
- The log entries should include: date, time, user name, image name, image path, and enhancement status (success/failure).
- The system must support retrieval and display of historical upload records for administrative review.

6. Error Handling and Validation

- The system must handle unexpected errors gracefully, such as missing files, incorrect formats, or network interruptions.
- Proper validation should prevent the upload of executable or malicious files.
- User-friendly error messages should be displayed in the frontend interface.

7. User Interface Navigation

- The homepage must contain navigation links to upload, results, and dashboard sections.
- Buttons should be clearly labeled (e.g., “Choose File,” “Enhance Image,” “Download Result”).
- The interface must respond to user actions dynamically without requiring manual page reloads.

8. Dashboard Functionality

- The dashboard should summarize the number of uploaded and enhanced images, average processing time, and system usage statistics.
- It should display graphical summaries using libraries like Matplotlib or Chart.js for administrative insights.

9. Download and Storage Functionality

- Users must be able to download the enhanced image directly after processing.
- The enhanced image file must retain its original name with a suffix (e.g., _enhanced.jpg) for clarity.

RESULT

Each system module was tested individually and collectively to ensure proper integration and functionality. The results for each module are summarized below.

1. **Image Upload Module:**
- Successfully handles multiple image formats (.jpg,.png).
- Average upload time: <1 second.
- Error handling mechanism prevents invalid file uploads.

Stores data securely in static/uploads and updates the log file automatically.

2. Preprocessing Module:
- Automatically resizes images to 256×256 and normalizes pixel values.
- Converts grayscale to RGB to match model input requirements.

Logging and Dashboard Module:
- Logs every operation (upload, enhancement, timestamp) in CSV format.
- The dashboard summarizes user activity and image enhancement statistics. Ensures transparency and traceability of operations.

Visual Observations:
- Colors restored to natural tone, especially in blue- dominant regions.
- Visibility significantly improved, making hidden objects discernible.
- Edge details and textures preserved without artificial enhancement artifacts.

CONCLUSION

The experimental results shows that the proposed U-Net- based deep learning model outperforms traditional Enhancement methods in terms of clarity, contrast, and color correction. Each module of the system functions efficiently and integrates seamlessly to produce high-quality enhanced underwater images. The model's high PSNR, SSIM, and UIQM values confirm its robustness and suitability for real-world applications in marine Biology, Defense and Naval Surveillance, and Oil, Gas, and Pipeline Inspection and many more.

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