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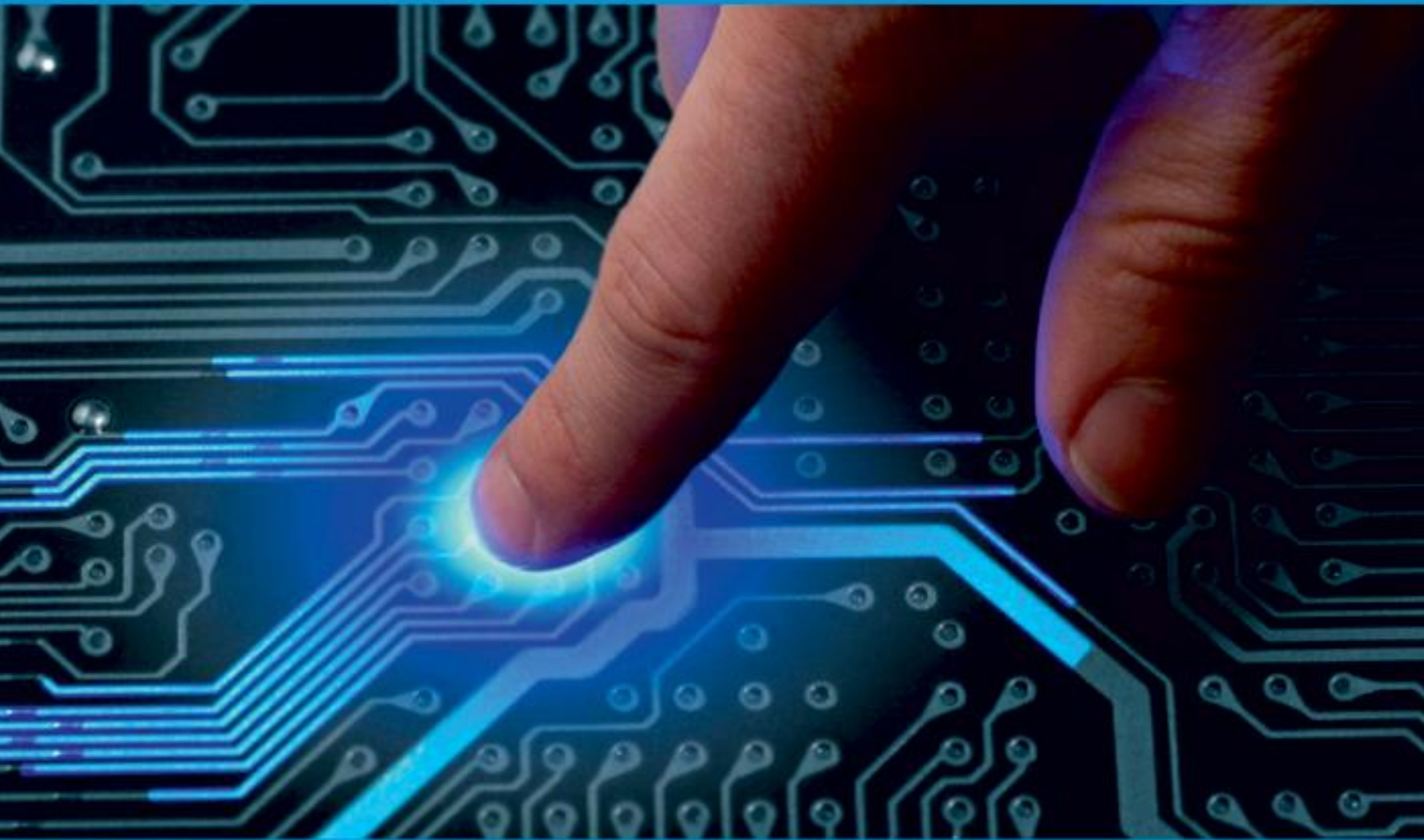

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SHARPSIGHT: Advancing Image Clarity with Deep Neural Network

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ABSTRACT: Image enhancement plays a crucial role in various applications such as medical imaging, surveillance, and entertainment. Images taken in low light frequently have poor visibility, which results in low contrast, lost details, and colour distortion. To increase the quality of the image, image enhancing techniques can be applied. Consequently, image enhancement is crucial to the image analysis process when dealing with noisy images. Although other works have focused on underexposed photographs or provided generic image enhancing methods, our suggested approach seeks to correct both overexposure and underexposure faults. The exposure correction problem can be divided into two main subproblems: (i) Improvement of colour and (ii) Improvement of detail. To address these challenges, we introduce a coarse-to-fine deep neural network (DNN) model, trainable end-to-end, which targets each sub-problem separately. Our method not only achieves comparable results to existing state-of-the-art methods for underexposed images but also delivers significant enhancements for images afflicted with over exposure errors.

KEYWORDS: Deep learning, colour enhancement, detail enhancement

I. INTRODUCTION

Closed-circuit television (CCTV) systems serve as critical tools for surveillance and monitoring in various settings, including public spaces, commercial establishments, and residential areas. However, despite their widespread deployment, the effectiveness of CCTV systems can be hindered by various factors, including poor lighting conditions, suboptimal camera settings, and image degradation over time. These factors often result in low-quality footage with reduced clarity, making it challenging for operators to discern crucial details and identify potential threats or incidents accurately. The study underscores the widespread adoption of CCTV systems for surveillance, yet it unveils a persistent challenge: the generation of low-quality images. Various factors contribute to this degradation, including noise, environmental conditions like fog or rain, and compression-induced artifacts at low resolutions. While image enhancement software has made strides, current solutions tend to focus on rectifying underexposure errors, leaving overexposure unaddressed. To bridge this gap, we introduce a novel deep learning approach that tackles both over and underexposed images. Our method employs a coarse-to-fine strategy, dividing the exposure correction task into two primary facets: colour enhancement and detail refinement. Through an end-to-end trainable deep neural network (DNN) model, we first correct global colour inconsistencies before fine-tuning image details. Notably, our method not only matches the performance of existing techniques for underexposed images but also significantly enhances the quality of overexposed ones. Extensive evaluations and comparisons with state-of-the-art methods confirm the effectiveness and robustness of our approach, which also exhibits remarkable generalization capabilities, extending its utility beyond the confines of the training dataset.

II. RELATED WORK

A Non-Reference Evaluation of Underwater Image Enhancement Methods Using a New Underwater Image Dataset

The proposed work introduced the Challenging Dataset for Underwater Image Enhancement (CDUIE), consisting of 85 underwater images captured at various depths in the Great Lake Superior, USA. Through the use of non-reference image quality evaluation metrics such as BRISQUE, NIQE, PIQE, Entropy, and CCF, the performance of these models was meticulously assessed. Conversely, GLN-HE exhibited improved contrast but introduced unbalanced color content, while JOE-ACDC displayed overexposure in lighter regions. Metrics like BRISQUE and PIQE provided insights into

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perceptual quality and color balance, with GLN-HE excelling in image distortion and UColor scoring lowest in PIQE, indicating a pleasing color balance. However, UWCNN and Image Inverse showed limited improvements.

Enhanced network optimized generative adversarial network for image

This proposed work addresses the common issue of poor visibility and loss of detail in low-light images through the development of an Enhanced Network Optimized Generative Adversarial Network (GAN). Traditional enhancement techniques often fail to adequately improve such images, necessitating a novel approach. This architecture, comprising components like the disposition-net, Restoration-Net, and adjust-net, is meticulously designed to target specific aspects of low-light image quality enhancement, offering a comprehensive solution to the problem. The enhanced network structure, with its emphasis on residual blocks and convolutional layers, facilitates the preservation of critical image details. However, despite its merits, the proposed method exhibits certain limitations. The computational demands, particularly during training with deep neural networks like GANs, can be substantial, posing challenges for resource-constrained environments. Furthermore, the effectiveness of the algorithm may vary depending on the complexity and characteristics of input low-light images, and its reliance on synthesized datasets for training could restrict its applicability to real-world scenarios.

Generative Adversarial Network based on Resnet for Conditional Image Restoration

This proposed work addresses the generation of high-quality images from extremely coarse or degraded inputs, focusing on image restoration using a Residual Generative Adversarial Network (ResGAN). The proposed ResGAN model extends traditional GAN schemes by directly utilizing coarse image features and attribute labels for image restoration. The goal is to efficiently restore input images by leveraging discriminative features learned through adversarial training, ultimately outperforming existing GAN models in terms of accuracy and loss metrics. The integration of a classifier into the discriminator enhances the generative accuracy of the network, leading to superior performance compared to state-of-the-art GANs. Despite its strengths, the ResGAN model may have certain limitations or demerits that warrant consideration. While the paper highlights the superior performance of ResGAN compared to existing GAN models, it is essential to assess the computational complexity and resource requirements of implementing the proposed network.

III. PROPOSED ARCHITECTURE

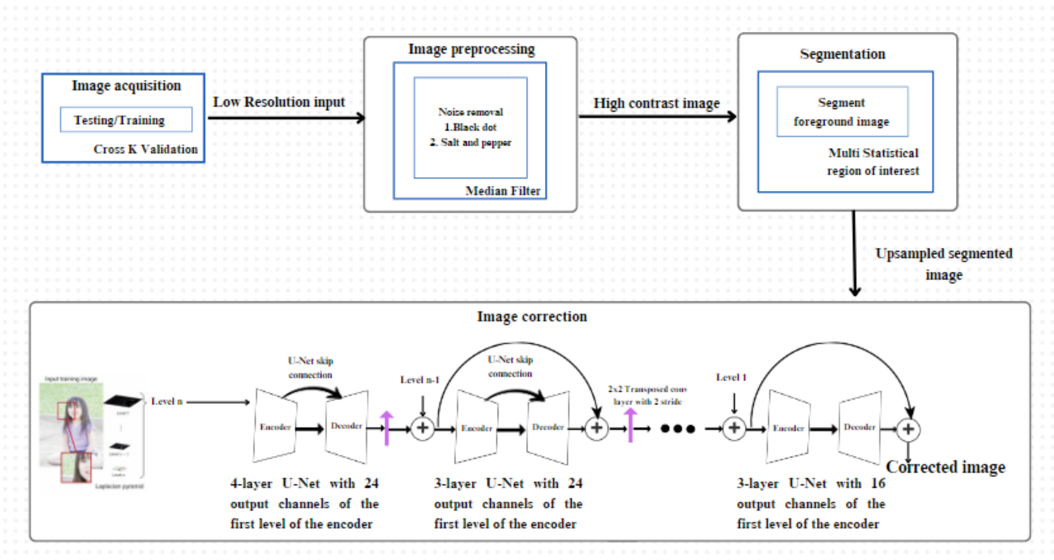

Figure 1: Proposed architecture of Advancing Image Clarity with Deep Neural Network

3.1 Image Acquisition

Image acquisition, the foundational step in image processing and computer vision tasks, involves gathering images from various. This module focuses on acquiring CCTV (Closed-Circuit Television) images from Kaggle. The module emphasizes the importance of obtaining high-quality images for accurate surveillance and monitoring purposes.

Cross-validation techniques are employed to assess image clarity. By employing cross-validation, the dataset is divided into multiple subsets or folds, ensuring that each fold contains a representative sample of the data. The process involves

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training a clarity assessment model on a portion of the dataset while evaluating its performance on the remaining portions. Images identified as completely unclear or of poor quality by the clarity assessment model are subsequently removed from the dataset. This iterative approach allows for a comprehensive evaluation of image clarity across different subsets of the dataset.

3.2 Image Preprocessing

Image pre-processing plays a critical role in enhancing the quality of images before they are fed into machine learning. One common pre-processing step involves the removal of noise, including types like salt and pepper noise and black dots. Similarly, black dots can also appear due to imperfections in image acquisition or transmission processes. These forms of noise can significantly degrade image quality and impede the performance of classifiers. Several methods can be employed for noise removal in image pre-processing. One popular approach is median filtering, which replaces each pixel's value with the median value within its local neighbourhood. This technique effectively eliminates outliers caused by noise while preserving the image's overall structure and edges. For salt and pepper noise specifically, median filtering is particularly advantageous as it does not blur the image excessively. By incorporating robust noise removal into the pre-processing pipeline, the quality of images can be significantly improved.

3.3 Image Segmentation

Image segmentation, particularly foreground-background segmentation, using the Multi-Statistical Region of Interest (ROI) algorithm is a comprehensive process that involves several intricate steps to effectively separate objects or regions of interest from the background in an image. The algorithm initially preprocesses the input image to enhance its features and reduce noise, employing techniques like smoothing filters or edge detection methods. Subsequently, it partitions the image into multiple regions based on statistical measures such as colour, texture, or intensity. These regions serve as initial candidates for foreground and background segments. It incorporates spatial constraints to ensure coherence and smoothness within segmented regions, minimizing over segmentation or under segmentation artifacts. The Multi-Statistical ROI algorithm incorporates probabilistic models to assess the likelihood of pixels belonging to the foreground or background, leveraging statistical distributions to estimate pixel classifications. The algorithm's versatility allows it to handle various types of images, including complex scenes with intricate foreground-background relationships or challenging lighting conditions. Its efficacy lies in its ability to exploit multiple statistical cues and spatial information to achieve precise and reliable segmentation results, making it indispensable in applications ranging from medical imaging and object detection to scene understanding and augmented reality.

3.4 Image Enhancement

Four sub-networks with 7M parameters trained end-to-end make up our main network. The initial sub-network, whose capacity decreases as we go from coarse to fine sizes, is allocated the maximum network capacity. Different representations of the input image obtained from the Laplacian pyramid decomposition are accepted by each sub-network. A four-layer encoder-decoder network with skip links, or a U-Net-like architecture, makes up the first sub-network. There are 24 channels in the first convolutional (conv) layer's output. Our first subnetwork accepts the Laplacian pyramid's low-frequency band level, or X(4), and has 4.4M learnable parameters. Next, the output of the first sub-network is upscaled using a stride and a 2x2xx3 transposed convolution layer with three output channels. The second sub-network receives this processed layer after it has been added to the Laplacian pyramid's initial mid-frequency band level, or X(3).

A three-layer encoder-decoder network with skip links makes up the second sub-network. The first convolution layer of the encoder contains 24 channels, totalling 1.1 million learnable parameters. Following the processing of the upscaled input from the first sub-network by the second sub-network, a residual layer with three output channels and a stride of two is added back to the input of the second sub-network.

The outcome is given to the third sub-network, which creates a new residual that is added back to the input of this sub-network, after being added to the second mid-frequency band level of the Laplacian pyramid (i.e., X(2)). The second network's design is carried over into the third sub-network. Ultimately, the outcome is integrated into the Laplacian pyramid's high-frequency band level (X(1)), and subsequently supplied to the fourth sub-network, yielding the ultimate processed image. With 482.2K learnable parameters, the final subnetwork is a three-layer encoder-decoder network with skip connections. The output of the encoder's first convolution layer contains 16 channels.

IV. RESULT

We evaluate our approach against a wide variety of currently used exposure correction and image enhancing techniques. To assess the pixel-by-pixel precision and perceptual quality of our findings, we utilize the subsequent three

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conventional metrics: the perceptual index (PI), the structural similarity index measure (SSIM), and the peak signal-to-noise ratio (PSNR). The formula for the PI is PI = 05(10 Ma+NIQE) (1), where Ma and NIQE are measurements. We compare the outcomes for the pixel-wise error metrics, PSNR and SSIM.

Figure 2: Result of input image

One thing that all expert photographers' rendered images have in common is that they all have fairly proper exposure settings, even though they may render the same image differently due to variations in camera-based rendering settings (such as tone mapping and white balance). Because the five expertly generated images all provide adequate exposure reference photos, we compare our approach to them in order to assess its performance.
On our test set, we also assess a range of prior learning-based and non-learning techniques for comparison: the weighted variational model (WVM), the low-light image enhancement method (LIME), HDR CNN, DPED models, deep photo enhancer (DPE) models, the high-quality exposure correction method (HQEC), RetinexNet, deep underexposed photo enhancer (UPE), and the zero-reference deep curve estimation method (Zero-DCE). Furthermore, we evaluate a variety of prior non-learning and learning-based techniques. We evaluated the deep reciprocating HDR transformation method (RHT) and Adobe Photoshop's (PS) HDRtool to turn the reconstructed HDR images produced by the HDR CNN method back into LDR.

V. CONCLUSION

We suggested a single coarse-to-fine deep learning model to fix images that are overexposed or underexposed. The Laplacian pyramid decomposition technique was utilized to handle input images across many frequency ranges. Our approach is structured to multi-scalely sequentially correct each Laplacian pyramid level, starting from the image's global hue and working our way down to the image details.

REFERENCES

1. Ashraf Saleem, Ali Awad, Navjot kaur (2023), “A Non-Reference Evaluation of Underwater Image Enhancement Methods Using a New Underwater Image Dataset” in Proc. IEEE 12th Int. Conf. Comput. Vis., May. 2023, pp. 349–356.
2. Lingyu Yan, JiarunFu, ChunzhiWang, ZhiweiYe(2019), “Enhanced network optimized generative adversarial network for image,” in Proc. IEEE 12th Int. Conf. Comput. Vis., Sep. 2019, pp. 349–356.
3. Meng Wang,Huafeng Li, Fang Li (2021),“ Generative Adversarial Network based on Resnet for Conditional Image Restoration,” arXiv preprint arXiv:1511.06434, pp. 1–15, 2021.
4. Xin Zhang And Xiawang(2021), “MARN: Multi-Scale Attention Retinex Network for Low-Light Image Enhancement,” in Proc. IEEE 12th Int. Conf. Comput. Vis., Sep. 2021, pp. 349–356.

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5. C. Guo, C. Li, J. Guo, C. C. Loy, J. Hou, (2020), “Zero reference deep curve estimation for low-light image enhancement”, in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2020, pp. 17801789.
6. Fengji Ma, Junyi chai(2019), “Two-Dimensional Compact Variational Mode Decomposition-Based Low-Light Image Enhancement” in Proc. IEEE 12th Int. Conf. Comput. Vis., Sep. 2019, pp. 349–356
7. W. Wang, C. Wei, W. Yang, and J. Liu(2018), “GLADNet: Low-light enhancement network with global awareness”, in Proc. 13th IEEE Int. Conf. Autom. Face Gesture Recognit. (FG), May 2018, pp. 751755.
8. L. Tao, C. Zhu, G. Xiang, Y. Li, H. Jia, and X. Xie(2017), “LLCNN: A convolutional neural network for low-light image enhancement”, in Proc. IEEE Vis. Commun. Image Process. (VCIP), Dec. 2017, pp. 14.
9. C. Wei, W. Wang, W. Yang, and J. Liu, “Deep retinex decomposition for low-light enhancement”, in Proc. Brit. Mach. Vis. Conf. (BMVC), 2019, Art. no. 61772043.
10. Y. Zhang, J. Zhang, and X. Guo(2019), “Kindling the darkness: A practical low-light image enhancer”, in Proc. 27th ACM Int. Conf. Multimedia, Oct. 2019, pp. 16321640.
11. D. Glasner, S. Bagon, and M. Irani, ‘‘Super-resolution from a sin gle image,’’ in Proc. IEEE 12th Int. Conf. Comput. Vis., Sep. 2009, pp. 349–356.
12. T. Michaeliand, M. Irani, ‘‘Non parametric blind super-resolution,’’ in Proc. IEEE Int. Conf. Comput. Vis., Dec. 2013, pp. 945–952.

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