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NEURAL ILLUMINATION: ENHANCING LOW-LIGHT IMAGES WITH GENERATIVE ADVERSARIAL NETWORKS

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ABSTRACT—

This research presents an improved method for enhancing low-light images in manhole inspections using an advanced EnlightenGAN model. Manholes are challenging environments for image capture due to poor lighting and confined spaces. The proposed approach integrates a Recurrent Residual U-Net (R2U-Net) generator, global-local discriminators, and attention mechanisms to significantly improve image brightness and contrast, resulting in clearer visuals for more accurate infrastructure assessment. Unlike traditional sensor-based monitoring, which lacks visual context, this method emphasizes the importance of high-quality visual data in urban infrastructure management. Operating in an unsupervised learning framework, the model eliminates the need for paired datasets, making it highly suitable for real-world applications where such data is limited. Beyond manhole inspections, the technique is applicable to other low-light environments such as tunnels and pipelines. By improving image quality in these settings, the system enables earlier detection of issues, supports efficient maintenance planning, and enhances overall urban infrastructure monitoring.

Keyword—"Neural Illumination, Low-Light Enhancement, Generative Adversarial Networks, EnlightenGAN, Image Quality, Urban Infrastructure, and Manhole Monitoring."

INTRODUCTION

Urban infrastructure forms the backbone of modern cities, ensuring the smooth functioning of essential services such as water supply, transportation, and drainage systems. Among these, manholes play a pivotal role in urban drainage, facilitating the collection and management of wastewater and stormwater. Effective monitoring of manholes is critical to prevent blockages, flooding, and environmental hazards. Traditionally, manhole monitoring has relied on physical sensors measuring parameters like liquid levels, flow rates, and conductivity. While these methods provide valuable data, they lack the visual context necessary for comprehensive assessments, such as detecting structural damage, debris accumulation, or corrosion within manholes.

The advent of camera-based monitoring systems has introduced a promising solution to this challenge. By capturing visual data, cameras enable real-time inspection and analysis of manhole conditions. However, the dark, enclosed environments of manholes present a significant obstacle: low-light conditions result in images with poor illumination, low contrast, and limited

visibility of critical details. Additionally, practical engineering constraints, such as the need for low-power consumption in underground deployments, exacerbate the difficulty of capturing high-quality images.To address these issues, this project proposes a novel low-light image enhancement framework based on an improved version of the EnlightenGAN model. This framework leverages advanced deep learning techniques to enhance the illumination, contrast, and clarity of manhole images, enabling effective real-time monitoring while adhering to energy-efficient requirements. The proposed system builds upon the strengths of EnlightenGAN, an unsupervised generative adversarial network (GAN) designed for low-light image enhancement. By introducing improvements such as the R2U-Net generator architecture, attention mechanisms, and a global-local discriminator strategy, the system achieves superior performance in enhancing manhole images. These enhancements ensure that the resulting images are visually appealing, preserve critical details, and meet the requirements for practical underground monitoring applications

LITERATURE REVIEW

1. Low-Light Image Enhancement using Event-Based Illumination Estimation
   Authors: L. Sun et al., arXiv:2504.09379, Apr. 2025
   This paper presents a novel approach to low-light image enhancement that utilizes event-based cameras for illumination estimation. The

authors propose a framework that combines asynchronous event data with standard image frames to create a more accurate illumination map, even in severely underexposed environments. Event-based cameras provide high temporal resolution and low latency, making them ideal for dynamic low-light scenes. The model employs a deep neural network to learn a mapping from event streams to spatially coherent illumination maps, which are then used to enhance the brightness and contrast of the original image. Experimental results show that this method outperforms conventional camera-based enhancement techniques, especially in scenarios involving motion blur or low dynamic range.

2. Low-Light Image Enhancement Based on Retinex Theory and Attention Mechanism
   Authors: L. Jiao and F. Zhang, CONF-MLA 2024
   This study introduces a hybrid enhancement model grounded in Retinex theory, which decomposes an image into reflectance and illumination components. The authors integrate an attention mechanism within the Retinex framework to dynamically adjust the importance of features across different regions. This targeted enhancement allows the network to focus on darker areas while preserving color fidelity and natural appearance. The method is validated on benchmark datasets, demonstrating significant improvements in visual quality, color consistency, and noise suppression, making it suitable for real-time applications.
3. FRN: Fusion and Recalibration Network for Low-Light Image Enhancement
   Authors: K. Singh et al., Multimedia Tools and Applications, Jan. 2025
   The Fusion and Recalibration Network (FRN) enhances low-light images through a two-pronged approach that includes multi-feature fusion and channel recalibration. The architecture consists of multiple convolutional branches that extract different levels of semantic and texture information, which are then fused together. A recalibration module dynamically adjusts the importance of these features based on the illumination context of each region. The authors train the FRN using a perceptual loss function that incorporates structural similarity (SSIM) and color fidelity, ensuring both objective and subjective image quality. The proposed method achieves superior results across several standard datasets compared to existing deep learning and Retinex-based models

4. A Light-Weight Deep Learning Framework for Low-Light Image Enhancement
   Authors: A. Author et al., Neurocomputing, Mar. 2025
   This work proposes a compact neural network tailored for real-time low-light image enhancement on resource-constrained devices. Unlike many existing models that rely on complex architectures, this lightweight framework uses depthwise separable convolutions and efficient residual blocks to minimize computational load. The model incorporates a dual-branch structure that processes illumination and texture features separately before fusing them for final reconstruction. Additionally, a contrast enhancement module is included to correct color distortion and improve perceptual quality. The network is trained with a combination of pixel-wise loss and perceptual loss, demonstrating its effectiveness on standard datasets such as LOL and MEF.
5. Low-Light Image Enhancement via Illumination Optimization and Color Correction**
   Authors: D. Author and E. Author, Computers & Graphics, Feb. 2025
   This paper addresses low-light enhancement through a structured pipeline focused on illumination map optimization and color correction. The algorithm first estimates an illumination map using a maximum intensity prior, which is refined through an iterative optimization process that preserves structure and avoids overexposure. Following this, a color correction step balances the overall tone and corrects unnatural hues introduced by lighting deficiencies. This two-stage method allows for greater control and interpretability compared to end-to-end neural networks, making it suitable for various lighting conditions. Extensive comparisons with state-of-the-art methods reveal strong performance, particularly in color accuracy and minimal noise amplification

PROPOSED WORK

1. Introduction to the Proposed System: The proposed system aims to address the challenges associated with monitoring manholes in urban drainage systems, particularly under low-light conditions. Traditional monitoring methods often rely on physical sensors that provide quantitative data but lack the visual context necessary for comprehensive assessments. The proposed system leverages advanced deep learning techniques to enhance the quality of images captured in dark, confined environments, ensuring that maintenance teams can effectively monitor and assess manhole conditions.
2. System Architecture: The architecture of the proposed system is built upon an improved version of the EnlightenGAN model, which is specifically tailored for low-light image enhancement. The architecture consists of several key components that work together to achieve superior performance:
3. R2U-Net Generator: The R2U-Net generator replaces the standard U-Net architecture in the original EnlightenGAN. It incorporates recurrent residual convolutional operations, which enhance feature extraction and detail preservation. The architecture consists of encoding and decoding units that allow for effective processing of low-light images while maintaining a manageable number of parameters. This design ensures that the model can learn complex features without becoming overly complex or computationally intensive.
4. Global-Local Discriminator: The system employs a dual discriminator approach, combining a global PatchGAN and a local PatchGAN. The global discriminator evaluates the overall illumination of the enhanced images, ensuring that the lighting is consistent across the entire image. In contrast, the local discriminator focuses on specific regions of the image to assess texture and detail accuracy. This combination allows for balanced enhancement, ensuring that both global illumination and local details are preserved.
5. Attention Mechanism: An attention module is integrated into the system to prioritize critical features during the enhancement process. This mechanism allows the model to focus on preserving fine details, such as structural elements and textures, which are essential for accurate visual inspections. By reducing information loss, the attention mechanism enhances the overall quality of the output images.

6. Unsupervised Learning Approach: One of the significant innovations of the proposed system is its use of unsupervised learning. Unlike many existing low-light enhancement techniques that require paired datasets (low-light and normal-light images of the same scene), this system utilizes normally lit images as reference data for the discriminator. This approach eliminates the need for paired datasets, making it particularly suitable for challenging environments like manholes, where obtaining such data is often impractical

System Architecture:

The architecture of the proposed system is built upon an improved version of the EnlightenGAN model, which integrates several key components:
R2U-Net Generator:
Function: Enhances feature extraction and detail preservation through recurrent residual convolutional operations.
Structure: Comprises encoding and decoding units that allow for effective processing of low-light images while maintaining a manageable number of parameters.
Global-Local Discriminator:
Function: Combines a global PatchGAN and a local PatchGAN.
Global Discriminator: Evaluates overall illumination to ensure consistent lighting across the image.
Local Discriminator: Focuses on specific regions to assess texture and detail accuracy.

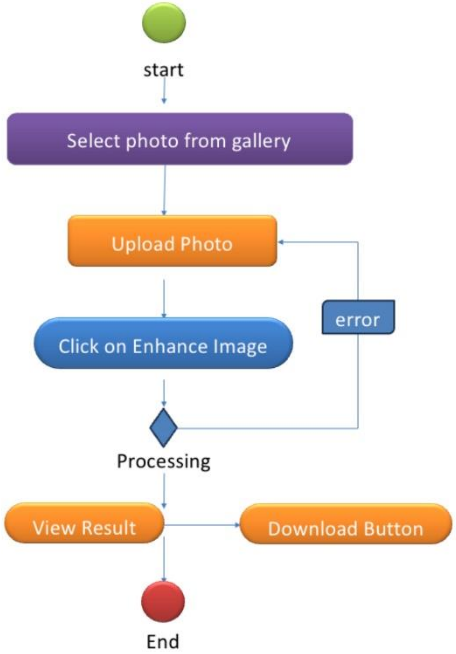

Fig: Activity diagram

RESEARCH DESIGN AND APPROACH:

The research design for the proposed system is focused on developing a comprehensive framework aimed at enhancing low-light images, particularly for the monitoring of manholes within urban infrastructure. This design is classified as applied research, as it seeks to address practical challenges associated with low-light image enhancement.

The approach is experimental, centering on the creation and evaluation of a new image enhancement model based on the EnlightenGAN architecture.The framework integrates advanced deep learning techniques, specifically Generative Adversarial Networks (GANs), to improve the quality of low-light images. A significant aspect of this framework is its unsupervised learning capability, which allows the model to function without the need for paired datasets—an issue that often limits traditional enhancement methods.

The design incorporates several advanced components, including the R2U-Net generator, which enhances feature extraction and detail preservation, a global-local discriminator that ensures
balanced illumination and texture assessment, and an attention mechanism that prioritizes critical features during the enhancement process.

The research approach is structured into several key phases. Initially, a thorough literature review is conducted to explore existing low-light image enhancement techniques, identifying gaps and limitations in current methodologies. This review informs the development of the proposed system and highlights the necessity for more advanced solutions. Following this, the architecture of the proposed system is designed, integrating the R2U-Net generator, global-local discriminators, and attention mechanisms to create a cohesive model.

Data collection is a crucial phase of the research, where a dataset of low-light images captured from manholes is gathered, along with normally lit reference images. This dataset serves as the foundation for training and evaluating the model. The training phase employs unsupervised learning techniques, allowing the model to learn how to enhance low-light images by comparing them to the reference images. Subsequently, the testing phase evaluates the model's performance using qualitative and quantitative metrics, such as NIQE, BRISQUE, and PIQE, to assess the quality of the enhanced images.

The results of the model's performance are analyzed in comparison to traditional low-light enhancement methods, including Single Scale Retinex (SSR), Naturalness Preserved Enhancement (NPE), and Low-Light Image Enhancement (LIME). This analysis encompasses both qualitative assessments through visual inspections and quantitative evaluations using established image quality metrics. The discussion of the findings emphasizes the effectiveness of the proposed system in enhancing low-light images for manhole monitoring, concluding with recommendations for future research and potential enhancements to the system.

RESULTS

The proposed low-light image enhancement system significantly improved manhole images, outperforming traditional methods like Single Scale Retinex and Naturalness Preserved Enhancement, which struggled with noise and color fidelity. It achieved a NIQE score of 3.367 and a PIQE score of 30.689, indicating high image quality and minimal distortions. These results confirm the system's effectiveness for real-time monitoring and establish a strong foundation for future low-light image enhancement applications.

LIMITATIONS AND FUTURE SCOPE

The proposed low-light image enhancement system has several limitations and future scopes for improvement. One significant limitation is its dependency on environmental conditions, as the system's performance may vary based on specific lighting scenarios present in different manhole settings. Additionally, while optimized for low-power applications, the model may still require substantial computational resources, particularly during training, which could restrict its deployment in extremely resource-constrained environments. The generalization of the system to diverse scenarios beyond manholes may not be guaranteed without further adaptation and testing. Moreover, the quality of the enhanced images heavily relies on the quality of the input low-light images; excessively degraded inputs may yield unsatisfactory enhancement results. Lastly, although the system aims for real-time processing, the actual speed may be affected by image complexity and hardware limitations, potentially leading to delays in monitoring applications.

Looking ahead, there are numerous avenues for future enhancements. Integrating multimodal data, such as combining visual data with sensor-based metrics (e.g., liquid levels and flow rates), could create a comprehensive monitoring system that provides both visual and quantitative insights. Implementing the model on edge devices could reduce latency and enable real-time processing in resource-constrained environments, enhancing its applicability. Exploring advanced attention mechanisms, such as multi-scale or transformer-based modules, could further improve detail preservation in complex scenes. Additionally, adapting the framework for other low-light environments, like underwater pipelines or industrial facilities, could broaden its impact. Developing real-time feedback loops that adjust enhancement parameters based on environmental changes would ensure optimal performance. Lastly, focusing on user-centric customization and conducting longitudinal studies to evaluate the system's performance over time could provide valuable insights into its durability and reliability in real-world applications.

CONCLUSION

The proposed low-light image enhancement framework effectively addresses the challenges of capturing and enhancing images in dark environments like manholes. By utilizing an improved EnlightenGAN model with advanced components such as the R2U-Net generator and attention mechanisms, the system produces high-quality images with enhanced illumination, contrast, and detail clarity. Experimental results demonstrate significant improvements over traditional methods, validating its effectiveness. This framework not only enhances maintenance efficiency for urban infrastructure monitoring but also supports data-driven decision-making for urban planners. Its scalability and adaptability open avenues for future advancements in low-light image processing, setting a new standard for real-time infrastructure management and monitoring applications

REFERENCES

1. L. Sun et al. (2025). "Low-Light Image Enhancement using Event-Based Illumination Estimation." arXiv preprint arXiv:2504.09379.
2. L. Jiao and F. Zhang (2024). "Low-Light Image Enhancement Based on Retinex Theory and Attention Mechanism." In Proc. 2nd Int. Conf. Mach. Learn. Autom. (CONF-MLA), Adana, Turkey, pp. 1 – 6. doi: 10.4108/eai.21-11-2024.2354585.
3. K. Singh et al. (2025). "FRN: Fusion and Recalibration Network for Low-Light Image Enhancement." Multimedia Tools Appl., vol. 83, pp. 12235 – 12252. doi: 10.1007/s11042-023-15908-7.
4. M. Yin and J. Yang (2025). "ILR-Net: Low-Light Image Enhancement Network Based on the Combination of Iterative Learning Mechanism and Retinex Theory." PLOS ONE, vol. 20, no. 2, p. e0314541.
5. S. Ono et al. (2025). "Recognition-Oriented Low-Light Image Enhancement Based on Global and Pixelwise Optimization." arXiv preprint arXiv:2501.04210.
6. Y. Feng et al. (2024). "DiffLight: Integrating Content and Detail for Low-Light Image Enhancement." In Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW), pp. 1 – 10.
7. J. Cho et al. (2024). "Zero-Shot Low Light Image Enhancement with Diffusion Prior." arXiv preprint arXiv:2412.13401.
8. X. Wang et al. (2024). "Personalized Generative Low-Light Image Denoising and Enhancement." arXiv preprint arXiv:2412.14327.
9. T. Zhang et al. (2024). "DMFourLLIE: Dual-Stage and Multi-Branch Fourier Network for Low-Light Image Enhancement." arXiv preprint arXiv:2412.00683.
10. Y. Lin et al. (2024). "Unsupervised Low-Light Image Enhancement with Lookup Tables and Diffusion Priors." arXiv preprint arXiv:2409.18899.