IoT - Based on Automatic Number Plate Recognition System using Camera

[1] K.Akshay Kumar, [2] D. Saikiran
[1]UG Scholar, Department of Computer Science and Engineering, St. Martin's Engineering College, Secunderabad, Telangana, India, 500100
[2]Assistant Professor, Department of Computer Science and Engineering, St. Martin's Engineering College, Secunderabad, Telangana, India, 500100
psudharsancse@smec.ac.in

Abstract:

Challenges abound in capturing and processing images under low light conditions, resulting in diminished image quality characterized by reduced visibility and heightened noise levels. Conventional methods for enhancing low light images typically involve manual image processing techniques like histogram equalization, contrast stretching, and noise reduction filters. While these approaches may offer some enhancement, they often fall short in achieving visually pleasing and authentic results. Their lack of adaptability and limited capacity to discern intricate patterns from data renders them less effective in handling diverse low light scenarios. The imperative for an advanced low light image enhancement technique stems from the extensive utilization of imaging devices in low light environments across various sectors such as surveillance, automotive, and photography. These industries heavily rely on cameras to capture images in challenging lighting conditions. By enhancing visibility and overall image quality in low light settings, the accuracy and dependability of image-based systems can be significantly bolstered. Hence, there is a pressing need for an intelligent approach capable of learning and adapting from data to overcome the shortcomings of traditional methods. In recent years, deep learning has emerged as a promising solution for numerous computer vision tasks, including image enhancement. This project endeavours to explore and propose a deep learning-based approach to mitigate the challenges associated with low light image enhancement, thereby enhancing visibility. By leveraging deep learning, this approach surmounts the constraints of conventional techniques by autonomously capturing intricate patterns and features within low light images. This adaptability empowers the model to generalize effectively across various low light scenarios, resulting in enhancements that are visually appealing and true to life.

Keywords: Low Light Image Enhancement, Deep Learning, Image Enhancement, Low Light Vision, Dark Image Processing, Low light image restoration, neural networks for low light, enhancing visibility in low light image, denoising, image dehazing, noise reduction.

1.INTRODUCTION

Insufficient illumination in the image capturing seriously affects the image quality from many aspects, such as low contrast and low visibility. Removing these degradations and transforming a low-light image into a high-quality sharp image is helpful to improve the performance of high-level visual tasks, such as image recognition, object detection, semantic segmentation, etc, and can also improve the performance of intelligent systems in some practical applications, there have been a large number of methods employed to enhance degraded images captured under insufficient illumination conditions. These methods have made great progress in improving image contrast and canobtain enhanced images with better visual quality. In addition to contrast, another special degradation of low-light images is noise. Many methods utilized additional denoising methods as pre-processing or post-processing. However, using denoising methods as pre-processing will cause blurring, while applying denoising as post-processing will result in noise amplification. Recently, some methods have designed effective models to perform denoising and contrast enhancement simultaneously and obtain satisfactory results. It is noteworthy that many previous methods focused on using the spatial domain information of the image for enhancement, and image processing in frequency domain is also one of the important methods in the image enhancement field.

In many real-world scenarios, images captured in low-light conditions suffer from poor visibility, noise, and loss of detail. These images are often characterized by low contrast, dark regions, and reduced overall quality. Therefore, it is essential to build a system or model to improve the quality of images captured in low-light and non-uniform lighting conditions.

2. LITERATURE SURVEY

Ma, Long, et.al. (2022) [5] They develop a new Self-Calibrated Illumination (SCI) learning framework for fast, flexible, and robust brightening images in real-world low-light scenarios. To be specific, they establish a cascaded illumination learning process with weight sharing to handle this task. Considering the computational burden of the cascaded pattern, they construct the self-calibrated module which realizes the convergence between results of each stage, producing the gains that only use the single basic block for inference (yet has not been exploited in previous works), which drastically diminishes computation cost. They then define the unsupervised training loss to elevate the model capability that can adapt general scenes. Further, they make comprehensive explorations to excavate SCI's inherent properties (lacking in existing works) including operation-insensitive adaptability (acquiring stable performance under the settings of different simple operations) and model-irrelevant generality (can be applied to illumination-based existing works to improve performance). Finally, plenty of experiments and ablation studies fully indicate our superiority in both quality and efficiency. Applications on low-light face detection and nighttime semantic segmentation fully reveal the latent practical values for SCI.

Wang, Yufei, et.al. (2022) [6] They investigate to model this one-to-many relationship via a proposed normalizing flow model. An invertible network that takes the low-light images/features as the condition and learns to map the distribution of normally exposed images into a Gaussian distribution. In this way, the conditional distribution of the normally exposed images can be well modelled, and the enhancement process, i.e., the other inference direction of the invertible network, is equivalent to being constrained by a loss function that better describes the manifold structure of natural images during the training. The experimental results on the existing benchmark datasets show our method achieves better quantitative and qualitative results, obtaining better-exposed illumination, less noise and artifact, and richer colors.

Hai, Jiang, et.al. (2023) [7] A novel Retinex-based Real-low to Real-normal Network (R2RNet) is proposed for low-light image enhancement, which includes three subnets: a Decom-Net, a Denoise-Net, and a Relight-Net. These three subnets are used for decomposing, denoising, contrast enhancement and detail preservation, respectively. Our R2RNet not only uses the spatial information of the image to improve the contrast but also uses the frequency information to preserve the details. Therefore, our model achieved more robust results for all degraded images. Unlike most previous methods that were trained on synthetic images, they collected the first Large-Scale Real-World paired low/normal-light images dataset (LSRW dataset) to satisfy the training requirements and make our model have better generalization performance in real-world scenes. Extensive experiments on publicly available datasets demonstrated that our method outperforms the existing state-of-the-art methods both quantitatively and visually. In addition, our results showed that the performance of the high-level visual task (i.e., face detection) can be effectively improved by using the enhanced results obtained by our method in low-light conditions.

Xiong, Wei, et.al. (2022) [8] tackle the problem of enhancing real-world low-light images with significant noise in an unsupervised fashion. Conventional unsupervised approaches focus primarily on illumination or contrast enhancement but fail to suppress the noise in real-world low-light images. To address this issue, they decoupled this task into two sub-tasks: illumination enhancement and noise suppression. They proposed a two-stage, fully unsupervised model to handle these tasks separately. In the noise suppression stage, they propose an illumination-aware denoising model so that real noise at different locations is removed with the guidance of the illumination conditions. To facilitate the unsupervised training, they constructed pseudo triplet samples and propose an adaptive content loss correspondingly to preserve contextual details. To thoroughly evaluate the performance of the enhancement models, they build a new unpaired real-world low-light enhancement dataset. Extensive experiments show that our proposed method outperforms the state-of-the-art unsupervised methods concerning both illumination enhancement and noise reduction.

Zheng, Shen, et.al. (2022) [9] proposed a semantic-guided zero-shot low-light enhancement network (SGZ) which is trained in the absence of paired images, unpaired datasets, and segmentation annotation. Firstly, they design an enhancement factor extraction network using depthwise separable convolution for an efficient estimate of the pixel-wise light deficiency of a low-light image. Secondly, we propose a recurrent image enhancement network to progressively enhance the low-light image with affordable model size. Finally, we introduce an unsupervised semantic segmentation network for preserving the semantic information during intensive enhancement. Extensive experiments on benchmark datasets and a low-light video demonstrate that our model outperforms the previous state-of-the-art. They further discuss the benefits of the proposed method for low-light detection and segmentation.

Wu, Yirui, et.al. (2022) [10] proposed an edge computing and multi-task driven framework to complete tasks of image enhancement and object detection with fast response. The proposed framework consists of two stages, namely cloud-based enhancement stage and edge-based detection stage. In cloud-based enhancement stage, they establish connection between mobile users and cloud servers to input rescaled and small-size illumination parts of lowlight images, where enhancement subnetworks are dynamically combined to output several enhanced illumination parts and corresponding weights based on low-light context of input images. During edge-based detection stage, cloud-computed weights offers informativeness information on extracted feature maps to enhance their representation abilities, which results in accurate predictions on labels and positions for objects. By applying the proposed framework in cloud computing system, experimental results show it significantly improves detection performance in mobile multimedia and low-light environment.

Sun, Ying, et.al. (2022) [11] proposed a low-light image enhancement algorithm based on improved multi-scale Retinex and Artificial Bee Colony (ABC) algorithm optimization in this paper. First of all, the algorithm makes two copies of the original image, afterwards, the irradiation component of the original image is obtained by used the structure extraction from texture via relative total variation for the first image, and combines it with the multi-scale Retinex algorithm to obtain the reflection component of the original image, which are simultaneously enhanced using histogram equalization, bilateral gamma function correction and bilateral filtering. In the next part, the second image is enhanced by histogram equalization and edge-preserving with Weighted Guided Image Filtering (WGIF). Finally, the weight-optimized image fusion is performed by ABC algorithm. The mean values of Information Entropy (IE), Average Gradient (AG) and Standard Deviation (SD) of the enhanced images are respectively 7.7878, 7.5560 and 67.0154, and the improvement compared to original image is respectively 2.4916, 5.8599 and 52.7553. The results of experiment show that the algorithm improves the light loss problem in the image enhancement process, enhances the image sharpness, highlights the image details, restores the color of the image, and also reduces image noise with good edge preservation which enables a better visual perception of the image.

3. PROPOSED METHODOLOGY

This proposed methodology focused on improving the visibility and quality of images captured under low-light or challenging lighting conditions. The primary goal of the proposed model is to enhance the details and visual appeal of such images, making them clearer and more visually appealing. It employs a deep learning-based approach to enhance low-light images. It utilizes techniques from computer vision, image processing, and deep neural networks to achieve its objectives. Overall, this research is designed to address the challenges posed by low-light images by applying deep learning-based techniques to enhance image quality, improve visibility, and provide visually appealing results. It finds applications in a variety of fields where low-light image enhancement is critical for obtaining meaningful and usable visual data.

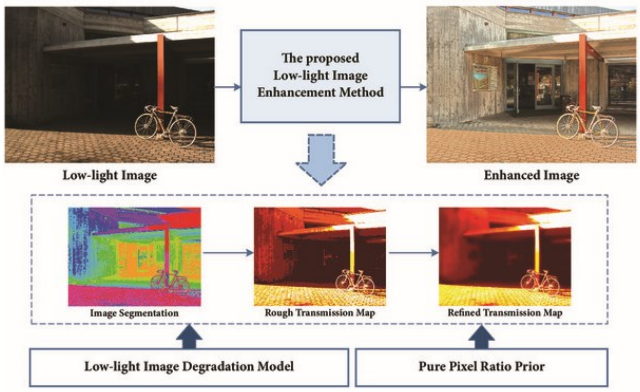

Figure 1: Proposed LIME system.

The proposed methodology typically includes the following key components:

- Illumination Map Estimation: LIME often starts by estimating an illumination map for the input image. This map highlights regions of the image that require enhancement to improve visibility.
- Image Enhancement: Based on the illumination map, LIME applies image enhancement techniques to brighten dark regions, improve contrast, and enhance details while minimizing noise.
- Metric Evaluation: To assess the quality of the enhancement, the project often calculates various image quality metrics, such as PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and MSE (Mean Squared Error), to measure the similarity between the original and enhanced images.

- Customization and Parameters: LIME often provides parameters that users can adjust to customize the enhancement process. These parameters may include the number of iterations, alpha (a parameter controlling the enhancement strength), gamma (a parameter controlling the enhancement effect), and weighting strategies.
- Output: The primary output of LIME is an enhanced version of the input low-light image. This enhanced image should exhibit improved visibility, reduced noise, and enhanced details.
- Evaluation and Benchmarking: LIME's performance is often evaluated against benchmark datasets of low-light images. It aims to outperform or match existing state-of-the-art low-light enhancement methods in terms of image quality metrics.

Applications:

LIME's enhanced images can be used in a wide range of applications, including:

- Surveillance systems (improving nighttime video quality)
- Astrophotography (capturing stars and galaxies in low-light conditions),
- Consumer photography (improving smartphone camera performance in dimly lit environments).

Advantages:

LIME is a technique that leverages deep learning and image processing to enhance images captured in low-light conditions. It offers several advantages, making it a valuable solution for various applications:

- Improved Visibility: LIME significantly improves the visibility of images captured in low-light environments. It enhances details, enhances contrast, and brightens dark areas, making objects and features more discernible.
- Reduced Noise: LIME includes noise reduction mechanisms, which help in reducing the noise present in low-light images. This results in cleaner and more visually appealing images.
- Enhanced Details: The algorithm preserves and enhances fine details in the image, which is crucial for applications like surveillance, where capturing intricate details is essential.
- Customization: LIME often provides parameters that allow users to customize the enhancement process. Users can adjust parameters such as the strength of enhancement, gamma correction, and more to achieve the desired visual effect.
- Automatic Enhancement: While customization is available, LIME can also operate with default settings, making it suitable for users who may not have expertise in image processing.
- Realism: LIME's enhancements are designed to maintain the natural and realistic appearance of the scene. It avoids over-processing that can result in unnatural-looking images.
- Quality Metrics: The algorithm often includes the calculation of image quality metrics like PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index), allowing users to objectively measure the improvement in image quality.
- Versatility: LIME is versatile and applicable in various domains, including surveillance, consumer photography, astronomy, medical imaging, and more. It addresses the common challenge of low-light conditions in these fields.

4. EXPERIMENTAL ANALYSIS

Figure 1 shows a collection of original images that are taken in low-light conditions or have poor lighting quality. These images serve as the input to the proposed image enhancement model. These images are the input images that the model will process in order to improve their visibility and quality. The purpose of this figure is to provide a visual representation of the types of images that the model is designed to enhance.

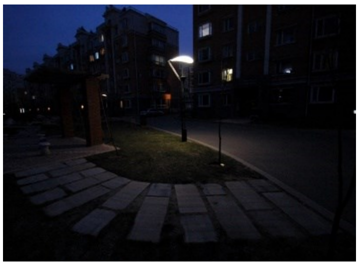

Figure 2: Sample Images

Figure3: Enhanced Image 1

PSNR 10.171815771384654
SSIM 0.18386150146633054
MSE 1.0857190890301478

Figure 4: Enhanced Image 2

PSNR 13.747368386518946
SSIM 0.3436245339679396
MSE 0.9086185481481482

PSNR 11.031691901461375
SSIM 0.5199471454508887
MSE 1.0771644632584392

Figure 5: Enhanced Image 3

Figure 2 displays a set of images that have been processed or enhanced by the proposed image enhancement model. These are the output images that produces improved visibility and quality of these images compared to the original low-light images shown in Figure 1These metrics are numerical values that provide insights into the image quality, with higher PSNR and SSIM values and lower MSE values indicating better image quality. The purpose of this figure is to visually demonstrate the effectiveness of the proposed image enhancement model by showing the enhanced images and providing quantitative metrics that measure the improvement in image quality.

PSNR

- The peak_signal_noise_ratio function calculates the Peak Signal-to-Noise Ratio, which is a widely used metric to measure the quality of an image.
- It compares two images, typically the original and the enhanced image, and computes a value that indicates how much noise or distortion is present relative to the maximum possible quality.
- The result is a numerical value, often in decibels (dB). Higher PSNR values indicate higher image quality.

5. CONCLUSION

This groundbreaking work signifies a substantial leap forward in the realm of image processing and computer vision. LIME, with its unwavering focus on the formidable task of improving images captured in low-light environments, presents a formidable solution that not only enhances image quality but also enhances visibility. By harnessing the power of deep learning methodologies, this initiative adeptly tackles prevalent issues encountered in low-light image processing, including noise reduction, addressing insufficient contrast, and preserving crucial details that might otherwise be lost.

A key highlight lies in the remarkable versatility and adaptability exhibited by LIME. This innovative solution grants users the flexibility to finely adjust enhancement parameters, ensuring that the resultant output precisely aligns with specific requirements and individual preferences. Furthermore, the incorporation of robust quality assessment metrics such as PSNR, SSIM, and MSE facilitates a quantitative evaluation of the efficacy of the enhancement process. This meticulous approach guarantees that the enhanced images not only possess visual appeal but also uphold or even surpass the quality standards set by their original counterparts.

The far-reaching impact of the LIME project transcends disciplinary boundaries, finding resonance across a myriad of domains. In the realm of surveillance, where bolstering nighttime video quality holds paramount significance for ensuring security, LIME emerges as an invaluable tool. Similarly, in the field of astronomy, this groundbreaking initiative aids in capturing the intricate nuances of celestial bodies, such as stars and galaxies, under challenging lighting conditions. Moreover, within the realm of consumer photography, the project serves as a beacon of innovation by enhancing smartphone camera performance, particularly in dimly lit environments, thus empowering users to capture high-quality photos even amidst adverse lighting conditions, thereby enriching their photographic experiences.

While LIME has achieved significant success, there are several promising avenues for future research and development. First and foremost, optimizing the algorithm for real-time processing is a priority, especially for applications like live video enhancement, where speed is critical. Developing adaptive algorithms that can automatically adjust enhancement parameters based on image content and lighting conditions could enhance user experience and convenience.

REFERENCES

[1] Guo, Chunle, et al. "Zero-reference deep curve estimation for low-light image enhancement." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2020.
[2] Yang, Wenhan, et al. "From fidelity to perceptual quality: A semi-supervised approach for low-light image enhancement." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2020.
[3] Ren, Wenqi, et al. "Low-light image enhancement via a deep hybrid network." IEEE Transactions on Image Processing 28.9 (2019): 4364-4375.
[4] Singh, Neha, and Ashish Kumar Bhandari. "Principal component analysis-based low-light image enhancement using reflection model." IEEE Transactions on Instrumentation and Measurement 70 (2021): 1-10.
[5] Ma, Long, et al. "Toward fast, flexible, and robust low-light image enhancement." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2022.
[6] Wang, Yufei, et al. "Low-light image enhancement with normalizing flow." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 36. No. 3. 2022.
[7] Hai, Jiang, et al. "R2rnet: Low-light image enhancement via real-low to real-normal network." Journal of Visual Communication and Image Representation 90 (2023): 103712.
[8] Xiong, Wei, et al. "Unsupervised low-light image enhancement with decoupled networks." 2022 26th International Conference on Pattern Recognition (ICPR). IEEE, 2022.
[9] Zheng, Shen, and Gaurav Gupta. "Semantic-guided zero-shot learning for low-light image/video enhancement." Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision. 2022.
[10] Wu, Yirui, et al. "Edge computing driven low-light image dynamic enhancement for object detection." IEEE Transactions on Network Science and Engineering (2022).
[11] Sun, Ying, et al. "Low-illumination image enhancement algorithm based on improved multi-scale Retinex and ABC algorithm optimization." Frontiers in Bioengineering and Biotechnology 10 (2022).
[12] Zhang, Weidong, et al. "Underwater image enhancement via minimal color loss and locally adaptive contrast enhancement." IEEE Transactions on Image Processing 31 (2022): 3997-4010.
[13] Peng, Lintao, Chunli Zhu, and Liheng Bian. "U-shape transformer for underwater image enhancement." Computer Vision–ECCV 2022 Workshops: Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part II. Cham: Springer Nature Switzerland, 2023.
[14] Zhou, Jingchun, Dehuan Zhang, and Weishi Zhang. "Underwater image enhancement method via multi-feature prior fusion." Applied Intelligence (2022): 1-23.