DEEP LEARNING-BASED VIDEO LIGHT IMAGE ENHANCEMENT FOR IMPROVED VISIBILITY

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ABSTRACT

Low light conditions present significant challenges in video capture and processing, often resulting in reduced visibility and increased noise. Traditional video enhancement methods typically involve converting video frames to images and applying image processing techniques such as histogram equalization, contrast stretching, and noise reduction filters. While these approaches can provide some improvement, they often fail to produce visually pleasing or natural results. Their lack of adaptability and limited ability to learn complex patterns from data make them less effective in handling diverse low light scenarios. As imaging devices are increasingly used in low light conditions, industries like surveillance, automotive, and photography rely heavily on improving video quality in such settings. Enhancing visibility and quality in low light videos can significantly improve the accuracy and reliability of video-based systems. This underscores the need for advanced techniques that can handle complex low light challenges effectively. Deep learning has shown considerable promise in solving various computer vision tasks, including video and image enhancement. Unlike traditional methods, deep learning-based approaches can learn from data, automatically capturing intricate patterns and features in low light videos. This adaptability enables the model to perform well across a wide range of low light scenarios, producing visually appealing and realistic results. This project explores a deep learning-based solution to enhance low light video, overcoming the limitations of traditional techniques and improving overall video visibility.

Keywords: low light, video enhancement, deep learning, visibility, noise reduction

1. INTRODUCTION

Insufficient illumination significantly degrades image quality, leading to low contrast, reduced visibility, and increased noise, which in turn hampers the performance of high-level visual tasks like object detection, image recognition, and semantic segmentation, as well as real-world applications such as autonomous driving and visual navigation. Traditional image enhancement techniques—such as contrast stretching, gamma correction, and histogram equalization—often produce overexposed or unnatural results and fail to adapt to dynamic lighting, motion blur, or variable noise levels. These methods also treat video frames independently, causing temporal inconsistency and flickering, and struggle to distinguish between fine details and noise, leading to detail loss. In contrast, recent deep learning approaches have shown great promise by learning to enhance and denoise images simultaneously in a context-aware manner. With the increasing reliance on visual data in areas like surveillance, healthcare, transportation, and consumer electronics—especially in countries like India, where poor lighting and power outages are common—there is a pressing need for intelligent, adaptive enhancement methods. Deep learning models can generalize across varying lighting conditions, utilize both spatial and frequency domain features, and process video in real-time, making them ideal for modern applications. The availability of large-scale datasets and GPU resources further enables the development of such solutions. This project aims to address the limitations of traditional techniques by building a deep learning-based system capable of delivering consistent, high-quality low light video enhancement across diverse environments and devices, ultimately improving the accuracy, reliability, and user experience of video-based systems.

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.

Zhang, Weidong, et.al. (2022) [12] proposed an efficient and robust underwater image enhancement method, called MLLE. Specifically, they first locally adjust the color and details of an input image according to a minimum color loss principle and a maximum attenuation map-guided fusion strategy. Afterward, they employ the integral and squared integral maps to compute the mean and variance of local image blocks, which are used to adaptively adjust the contrast of the input image. Meanwhile, a color balance strategy is introduced to balance the color differences between channel a and channel b in the CIELAB color space. Our enhanced results are characterized by vivid color, improved contrast, and enhanced details. Extensive experiments on three underwater image enhancement datasets demonstrate that our method outperforms the state-of-the-art methods. Our method is also appealing in its fast processing speed within 1s for processing an image of size 1024×1024×3 on a single CPU. Experiments further suggest that our method can effectively improve the performance of underwater image segmentation, keypoint detection, and saliency detection.

Peng, Lintao, et.al. (2022) [13] constructed a large-scale underwater image (LSUI) dataset including 4279 image pairs, and reported an U-shape Transformer network where the transformer model is for the first time introduced to the UIE task. The U-shape Transformer is integrated with a channel-wise multi-scale feature fusion transformer (CMSFFT) module and a spatial-wise global feature modelling transformer (SGFMT) module specially designed for UIE task, which reinforce the network's attention to the color channels and space areas with more serious attenuation. Meanwhile, in order to further improve the contrast and saturation, a novel loss function combining RGB, LAB and LCH color spaces is designed following the human vision principle. The extensive experiments on available datasets validate the state-of-the-art performance of the reported technique with more than 2dB superiority.

Zhou, Jingchun, et.al. (2022) [14] proposed a visual quality enhancement method for underwater images based on multi-feature prior fusion (MFPF), achieved by extracting and fusing multiple feature priors of underwater images. Complementary multi-features enhance the visual quality of underwater images. They designed a color correction method based on self-adaptive standard deviation, which realizes the color offset correction based on the dominant color of the underwater image. A gamma correction power function and spatial linear adjustment were also applied to achieve a set of artificial exposure map sequences obtained from a single degraded image and enhance the dark area's brightness and structural details. This design makes full use of the advantages of white balance, guided filtering, and multi-exposure sequence technology. And it uses a multi-scale fusion of various prior features to enhance underwater images. The experimental results show that by applying the multi-feature prior fusion scheme, this design comprehensively solves various degenerated problems, removes over-enhancement, and improves dark details.

Liu, Wenyu, et.al. (2022) [15] proposed a novel Image-Adaptive YOLO (IA-YOLO) framework, where each image can be adaptively enhanced for better detection performance. Specifically, a differentiable image processing (DIP) module is presented to take into account the adverse weather conditions for YOLO detector, whose parameters are predicted by a small convolutional neural network (CNN-PP).They learn CNN-PP and YOLOv3 jointly in an end-to-end fashion, which ensures that CNN-PP can learn an appropriate DIP to enhance the image for detection in a weakly supervised manner. They proposed IA-YOLO approach can adaptively process images in both normal and adverse weather conditions. The experimental results are very encouraging, demonstrating the effectiveness of our proposed IA-YOLO method in both foggy and low-light scenarios.

Jiang, Qiuping, et.al. (2022) [16] proposed an effective No-reference (NR) Underwater Image Quality metric (NUIQ) to automatically evaluate the visual quality of enhanced underwater images. Experiments on the constructed SAUD dataset demonstrate the superiority of our proposed NUIQ metric, achieving higher consistency with subjective rankings than 22 mainstream NR-IQA metrics.

Liu, Risheng, et.al. (2022) [17] proposed an object-guided twin adversarial contrastive learning based underwater enhancement method to achieve both visual-friendly and task-orientated enhancement. Concretely, they first develop a bilateral constrained closed-loop adversarial enhancement module, which eases the requirement of paired data with the unsupervised manner and preserves more informative features by coupling with the twin inverse mapping. In addition, to confer the restored images with a more realistic appearance, they also adopt the contrastive cues in the training phase. To narrow the gap between visually-oriented and detection-favourable target images, a task-aware feedback module is embedded in the enhancement process, where the coherent gradient information of the detector is incorporated to guide the enhancement towards the detection-pleasing direction. To validate the performance, we allocate a series of prolific detectors into our framework. Extensive experiments demonstrate that the enhanced results of our method show remarkable amelioration in visual quality, the accuracy of different detectors conducted on our enhanced images has been promoted notably. Moreover, they also conduct a study on semantic segmentation to illustrate how object guidance improves high-level tasks.

Jiang, Qun, et.al. (2022) [18] presented an underwater image enhancement method that does not require training on synthetic underwater images and eliminates the dependence on underwater ground-truth images. Specifically, a novel domain adaptation framework for real-world underwater image enhancement inspired by transfer learning is presented; it transfers in-air image dehazing to real-world underwater image enhancement. The experimental results on different real-world underwater scenes indicate that the proposed method produces visually satisfactory results.

[19] Zhou, Jingchun, Tongyu Yang, and Weishi Zhang. "Underwater vision enhancement technologies: A comprehensive review, challenges, and recent trends." Applied Intelligence 53.3 (2023): 3594-3621.

Zhou, Jingchun, et.al. (2023) [19] proposed to improve the visual quality of underwater images in the past few decades, which is the focus of this paper. Specifically, they review the theory of underwater image degradations and the underwater image formation models. Meanwhile, this review summarizes various underwater vision enhancement technologies and reports the existing underwater image datasets. Further, we conduct extensive and systematic experiments to explore the limitations and superiority of various underwater vision enhancement methods. Finally, the recent trends and challenges of underwater vision enhancement are discussed. They wish this paper could serve as a reference source for future study and promote the development of this research field.

[20] Wang, Fei, et al. "Far-field super-resolution ghost imaging with a deep neural network constraint." Light: Science & Applications 11.1 (2022): 1.

Wang, Fei, et.al. (2022) [20] proposed a far-field super-resolution GI technique that incorporates the physical model for GI image formation into a deep neural network. The resulting hybrid neural network does not need to pre-train on any dataset, and allows the reconstruction of a far-field image with the resolution beyond the diffraction limit. Furthermore, the physical model imposes a constraint to the network output, making it effectively interpretable. They experimentally demonstrate the proposed GI technique by imaging a flying drone, and show that it outperforms some other widespread GI techniques in terms of both spatial resolution and sampling ratio. They believe that this study provides a new framework for GI, and paves a way for its practical applications.

Zhou, Jingchun, et.al. (2022) [21] developed a restoration method based on backscatter pixel prior and color cast removal from the physical point of view of underwater image degradation. The proposed method used only a single underwater image as an input to estimate various parameters accurately, such as depth map, backscatter map, and illuminant map. Specifically, a backscatter estimation algorithm based on a depth map was proposed to improve the contrast of underwater images. Then, an algorithm was designed to remove color deviation based on the illuminant map. In particular, a color compensation strategy was created that could completely eliminate red artifacts in underwater images that were generated by the strong attenuation of the red channel. They designed comparative experiments from multiple angles on different real underwater image datasets. Experiments showed that the proposed method improved the contrast and removed the color deviation of light absorption compared to several reported methods. Even on underwater images with severe attenuation, the proposed method showed a significant positive effectiveness and stability on color cast removal.

Tavakkoli Yaraki, Mohammad, et.al. (2022) [22] development of nano-photosensitizers and nanoplasmonic strategies to enhance the SOG efficiency for better PDT performance. Firstly, they explain the mechanism of reactive oxygen species generation by classical photosensitizers, followed by a brief discussion on the commercially available photosensitizers and their limitations in PDT. They then introduce three types of new generation nano-photosensitizers that can effectively produce singlet oxygen molecules under visible light illumination, i.e., aggregation-induced emission nanodots, metal nanoclusters (< 2 nm), and carbon dots. Different design approaches to synthesize these nano-photosensitizers were also discussed. To further enhance the SOG rate of nano-photosensitizers, plasmonic strategies on using different types of metal nanoparticles in both colloidal and planar metal-PS systems are reviewed. The key parameters that determine the metal-enhanced SOG (ME-SOG) efficiency and their underlined enhancement mechanism are discussed. Lastly, they highlight the future prospects of these nanoengineering strategies, and discuss how the future development in nanobiotechnology and theoretical simulation could accelerate the design of new photosensitizers and ME-SOG systems for highly effective image-guided photodynamic therapy.

Gao, Peng, et.al. (2022) [23] reviewed various resolution enhancement approaches in DHM and discuss the advantages and disadvantages of these approaches. It is our hope that this review will contribute to advancements in DHM and its practical applications in many fields.

Wu, Yunpeng, et.al. (2022) [24] proposed a new rail boundary guidance network (RBGNet) for salient RS detection. First, a novel architecture is proposed to fully utilize the complementarity between the RS and the RE to accurately identify the RS with well-defined boundaries. The newly developed RBGNet injects high-level RS object information into shallow RS edge features by a progressive fused way for obtaining fine edge features. Then, the system integrates the refined edge features with RS features at different high-level layers to predict the RS precisely. Second, an innovative hybrid loss consisting of binary cross entropy (BCE), structural similarity index measure (SSIM), and intersection-over-union (IoU) is proposed and equipped into the RBGNet to supervise the network and learn the transformation between the input and ground truth. The input and ground truth then further refine the RS location and edges. Conveniently, an image-based model for RSD detection and quantification is also developed and integrated for an automatic inspection purpose. Finally, experiments conducted on the complex unmanned aerial vehicle (UAV) rail dataset indicate the system can achieve a high detection rate with good adaptation capability in complicated environments.

3. PROPOSED METHODOLOGY

This proposed methodology focused on improving the visibility and quality of videos 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 videos, making them clearer and more visually appealing. It employs a deep learning-based approach to enhance low-light videos. It utilizes techniques from computer vision, video to frame conversion, frame processing, and deep neural networks to achieve its objectives. Overall, this research is designed to address the challenges posed by low-light videos by applying deep learning-based techniques to enhance video quality, improve visibility, and provide visually appealing results. It finds applications in a variety of fields where low-light video enhancement is critical for obtaining meaningful and usable visual data.

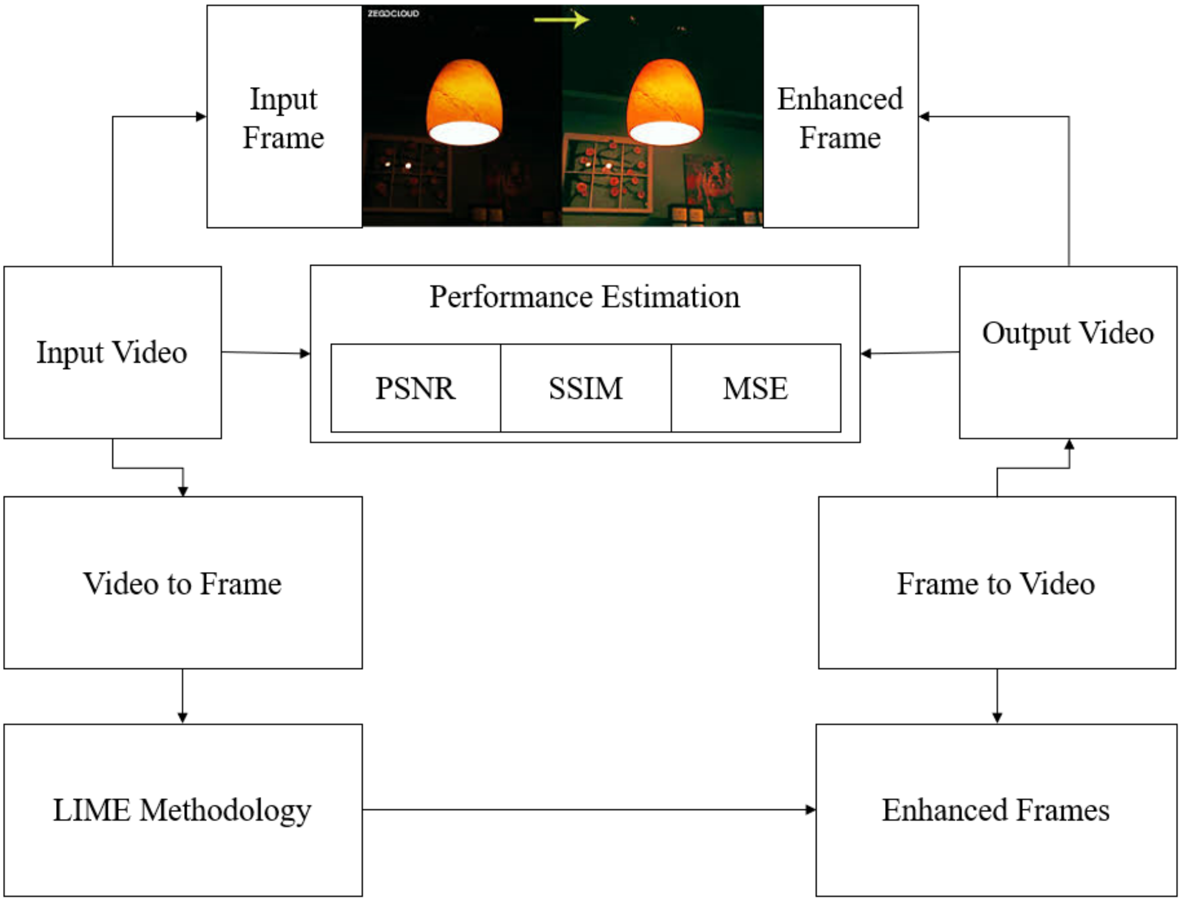

Fig.1: Proposed LIME Video Enhancement system.

The proposed methodology typically includes the following key components:

- Input Video: The initial step in the low-light video enhancement process involves providing the system with a target video captured under challenging lighting conditions. This video serves as the input to the proposed model, containing scenes that require enhancement to improve visibility and overall visual quality.
- Video to Frames Conversion: Following the acquisition of the input video, the next stage involves converting the video into individual frames. This process entails breaking down the video into a sequence of frames, where each frame represents a specific moment in the video timeline. The frame extraction allows for the application of the proposed model on a per-frame basis, enabling targeted enhancement of each frame in isolation. The conversion from video to frames can be achieved through standard video processing techniques. This involves extracting frames at a consistent frame rate from the input video. The resulting frames serve as the input data for the subsequent stages of the enhancement process. This frame-by-frame approach is crucial for ensuring that the proposed model can effectively process and enhance each individual frame in the video sequence. It facilitates the fine-tuning of details, contrast, and visibility in a frame-specific manner, contributing to the overall improvement of the low-light video content.
- Illumination Map Estimation: LIME often starts by estimating an illumination map for the input frame. This map highlights regions of the frame that require enhancement to improve visibility.

- Frame Enhancement: Based on the illumination map, LIME applies frame enhancement techniques to brighten dark regions, improve contrast, and enhance details while minimizing noise.
- Conversion of Enhanced Frames to Video: Following the Frame Enhancement, the enhanced frames are then aggregated and converted back into a video format. This conversion process involves reconstructing the video sequence using the enhanced frames. The resulting video showcases the cumulative impact of the proposed model on the entire low-light video, with improvements in visibility, noise reduction, and detail enhancement evident throughout the reconstructed video.
- Metric Evaluation: To assess the quality of the enhancement, the project often calculates various Video 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 frames.
- 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 frame. This enhanced frame should exhibit improved visibility, reduced noise, and enhanced details.
- Evaluation and Benchmarking: LIME's performance is often evaluated against benchmark datasets of low-light Frames. It aims to outperform or match existing state-of-the-art low-light enhancement methods in terms of frame quality metrics.

4. RESULTS AND DISCUSSION

4.1 Results description

Figure 2 shows a the original video that are taken in low-light conditions or have poor lighting quality. The videos are then converted to image/frame. And the frames 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.

Fig.2: Sample low-light Frams fed to the proposed model.


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PSNR 10.171815771384654
SSIM 0.18386150146633054
MSE 1.0857190890301478
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Fig. 3: Illustrating the obtained enhanced Frames using proposed model with quality metrics as PSNR, SSIM, and MSE.

Figure 3 displays a set of frames 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 1. It also includes quality metrics such as PSNR, SSIM, and MSE, which are used to quantitatively assess the quality of the enhanced frames. These metrics are numerical values that provide insights into the frame quality, with higher PSNR and SSIM values and lower MSE values indicating better video quality after converting the frames to video. The purpose of this figure is to visually demonstrate the effectiveness of the proposed image enhancement model by showing the enhanced video and providing quantitative metrics that measure the improvement in image quality.

The **Peak Signal-to-Noise Ratio (PSNR)** is a widely used metric for evaluating the quality of a video frame by comparing the original and enhanced frames to measure the level of noise or distortion relative to the maximum possible signal quality. Calculated using the peak_signal_noise_ratio function, PSNR produces a numerical value, typically in decibels (dB), where higher values indicate better visual quality. In parallel, the **Structural Similarity Index (SSIM)**, computed using the structural_similarity function, measures the perceptual similarity between two frames by assessing luminance, contrast, and structural information. SSIM returns a value between -1 and 1, with 1 indicating identical structural quality and values closer to -1 reflecting increasing dissimilarity. Both PSNR and SSIM are essential for objectively evaluating the effectiveness of video enhancement techniques.

5. CONCLUSIONS

This work represents a significant advancement in the domain of image processing and computer vision. By focusing on the challenge of enhancing images captured in low-light conditions, LIME offers a robust solution that improves image quality and visibility. Leveraging deep learning techniques, this project effectively addresses common issues encountered in low-light images, including noise, inadequate contrast, and the loss of critical details. One of the notable strengths is its versatility and adaptability. LIME provides users with the flexibility to fine-tune enhancement parameters, ensuring that the output aligns with specific requirements and preferences. Moreover, the integration of quality metrics such as PSNR, SSIM, and MSE enables a quantitative assessment of the success of the enhancement process. This ensures that the enhanced images not only look visually appealing but also maintain or exceed the quality of the original images. The impact of the LIME project extends across diverse domains. It finds application in fields like surveillance, where enhancing nighttime video quality is essential for security purposes. In astronomy, LIME aids in capturing the intricate details of stars and galaxies under challenging lighting conditions. Additionally, in consumer photography, the project enhances smartphone camera performance, particularly in dimly lit environments, offering users the capability to take high-quality photos even in adverse lighting conditions.

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