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Multi-Stacked Architecture for Low-Light Image Enhancement and Denoise

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ABSTRACT

Real-time image processing is usually associated with the problems of system slowness and image quality decline, especially in low-light conditions. This work proposes a novel approach utilizing a three-dimensional channel flexing mechanism for brightness enhancement and noise reduction. The channel flexing mechanism operates along three dimensions under a multi-stacked structure with the K-means clustering technique to enhance image brightness and minimize noise. The separation of the illuminated and dark images facilitates conversion to target pixels. The presented three-dimensional channel flexing technique employs triggers for dynamically swapping between the Red, Blue, and Green channels to avoid introducing luminous regions into oversaturation. The energy is allocated uniformly among respective clusters for higher PSNR. The standard assessment of the processed images has been done based on three major parameters: PSNR, SSIM, and MAE. The evaluation metrics show that this technique provides good visual quality and computation time, proving its adequacy for real-time image enhancement. The results imply that this strategy is particularly suitable for real-time visual enhancement in computer vision systems.

Keywords—Real-time image processing, Image enhancement, Denoising, Low-light conditions, MLS-UNET Model, Three-Dimensional Channel Flexing, K-means clustering, PSNR, SSIM, MAE.

I. INTRODUCTION

Enhancement is one of the basic issues associated with the application of visual perception and image interpretation in the world, as well as the improvement of image quality for the purpose of interpretation by humans and machines in the realms of autonomy. In general, two key issues, namely illumination adjustment and noise reduction, should be solved separately. Yet, existing approaches are good for particular applications but lack a holistic approach. Although these methods make sense from certain perspectives, none alone is sufficient for the cases where it is necessary to represent all effective adaptations as to the brightness and contrast for integrated image improvement with fewer steps.

To overcome this gap, we introduce an innovative approach, which will be called the Multi-Layer Stacked U-Net (MLS-UNET) model. This model combines a double preprocessing step—brightness adjustment and filter noise suppression—into a single model, dramatically improve the efficiency pictures improving in this steps. The MLS-UNET utilizes three-dimensional channel flexing algorithm for brightness enhancement and denoising. In this approach, the image is separated into red, green, and blue channels, enabling effective manipulation of image brightness and contrast. This guarantees better visualization while simultaneously consuming fewer computational resources.

The principal focus of this study is to focuses on obtaining defined and crisp images across diverse environmental scenarios including low lighting and extensive noise levels. Experimental research confirms that the proposed MLS-UNET model operates efficiently while producing satisfactory objective outcomes that use three primary evaluation factors including PSNR, SSIM, and MAE. The proposed system performs this image enhancement task using fewer computational resources than other alternative visual processing techniques. The MLS- UNET model achieves breakthrough research by uniting illumination enhancement with noise reduction tasks within one integrated program.

II. LITERATURE REVIEW

Zhe Li, H., Liu, H., Cheng, L., and Jia, X. introduced an noise reducing algorithm for an image that is a hybrid of basic methods such as BM3D and NSST as well as gradient domain guided filtering for effective image denoising. It puts forward a new hybrid soft thresholding approach to mitigate adverse effects of conventional approaches of thresholding. Use of experimental results reveals that the proposed approach has remarkably better PSNR and SSIM than other techniques for denoising. This model keeps a good level of interpretability, and it has lower computational costs than deep learning solutions. But this could bring more challenges and possibly increase the sensitivity when tuning the parameters, and in some cases, over-smoothing can be a problem [1]

Matsui, T., and Ikehara, M. propose a new LLIE method based on a relatively simple end-to-end network structure directly derived from the U-Net. Unlike existing CNN-based works, it is efficient in that aspect by not requiring a heavy amount of time and equally balancing color, illumination, and noise enhancements. Recent studies shown that the proposed method performs significantly better and has much lower processing time than other related methods. It also compares visuals and highlights its efficiency of producing natural colour images and does retain details. Altogether, the work focuses on optimization of low-light images singularity [2]

Zhang, Q., Zou, C., Shao, M., and Liang, H. introduced an unsupervised, single-stage denoising low-light images are presented in this paper using Swin-Transformer and CNNs to enhance performance without carrying out experiments with paired datasets. It also has a patch merging module that allows the system to reduce the number of features of an image while maintaining necessary details. The increase in the number of network nodes is accompanied by great denoising, increasing brightness and general picture quality. The method has been tested in numerous experiments with state-of-the-art techniques, proving that it provides higher visual quality and better scores than previous approaches. In total, this approach minimizes the difficulties that low-light image processing usually involves effectively [3]

Yang, S., Zhou, D., Cao, J., and Guo, Y. presented a new framework of integrating image enhancement technique called LightingNet, which offers a machine learning model for tackle the problem of improving low light quality images that traditional methods including histogram equalization and images recovered by Retinex models lack proficiency. This format has a Vision Transformer (VIT) sub-part that extracts high-level local feature and a sub-learning part for comprehensive features. While decoding, the VIT employs an enhanced self-attention technique; likewise, the complementary network helps provide features through pre-trained models. Substantial experiments prove that the proposed LightingNet has better subjective and objective measures than 14 benchmark methods. The paper focuses on the model useful in civil and industrial applications and any setting that demands unobstructed imaging in environments with low light levels. In conclusion, LightingNet is an improvement of image light enhancement in low light conditions [4]

Yu, T., Wang, S., Chen, W., Yu, F.R., Leung, V.C.M., and Tian, Z. introduced in this work is about enhancing the illumination of low light image, hence its goal is oriented towards increasing image brightness and decreasing noise. The given proposal comprises adaptive estimation of illumination, calibration of the model for footage reactions and the denoising in accordance with illumination. This method puts great emphasis on contrast enhancement with the avoidance of color shifts. Limitations of existing techniques are shown to point out the importance of self-supervised learning. It presents quantitative evaluation metrics that compare this method to others. On the whole, the document assembles the potential proposed approach for real-world applications [5]

Panagiotou, S., and Bosman, A.S. outlined a LPDM for boosting the quality of the picture captured in low light areas. LPDM can also be used to effectively suppress noise and improve image detail and color fidelity and is not a drawback of previous low-light pictures improvement techniques. Estimation of the LPDM leverages the reliant chances of underexposure for normal exposure in enhancing images with low lighting. Avoids the use of complex diffusion processes. The experimental results further substantiate LPDM capability of delivering better perceptual quality performance than conventional denoising methods. The method effectively deals with different types of artifacts and color anomalies and fully reflects its potential in the enhancement of low light pictures. Finally LPDM can be used as post processing for various different image enhancers [6]

Demir, Y., and Kaplan, N.H. developed a technique is revealed in the paper for improving the low-light images by a multi-scale decomposition, SSIF and CLAHE techniques. The approach further convert images from RGB space to HSV color space with specific emphasis on V channel for visibility enhancement. It act as a way of filtering out the information details while at the same time filtering out some of the noises. Algorithms used in experiments show the higher effectiveness relative to other methods in regards to the proposed method concerning the criteria such as visual quality, details preservation and color similarity. The method can be used in a number of conditions therefore it is applicable in different low light situations. In aggregate, it copes with the difficulties inherent in the processing of images in conditions of low illuminance, including the presence of noise, and insufficient contrast [7]

Xin, Y. described the difficulties in improving photos in low light poses challenges like image darkness colour distortion and noise. We introduce a creative method for improving images in low light. Improvement Procedure with nested skip connections based on unet++. This Layout propagates finer Characteristics improving brightness reducing distortion and retaining details. to mitigate noise from skip connections a residual block based on instance normalization (in) is introduced. IN Adjusts to each image lighting and noise. also we propose a hybrid loss Role that Highlights multiple image attributes. Our Procedure achieves state-of-the-art Effectiveness on the LOL Informationset with PSNR 23.0047 and SSIM 0.8682 demonstrating its superiority [8]

Jiang, Y., and Xue, Y. Inadequate light strongly impacts The level of the received pictures. A new CNN called DEANet is developed based on Retinex in an effort to address the issue of improving images in low light. Three subnetworks make up DEANet, which aggregates image frequency and content data. The networks for decomposition, improvement, and adjustment detect images by decomposing them, reducing noise, and improving contrast and details, and the generation networks adjust and generate images. This model learns from the public LOL dataset, and as evidenced by the subsequent test results, this model is superior in terms of visual presentation and image quality than the previous models [9]

Zhao, Q. detailed a low-light image improvement (LIE) that has gained significant attention recently, with Retinex theory-based deep learning methods showing promise due to their physical explainability. Notwithstanding present methods going to purchase conventional understandings, the accommodation measure is much either besides obtuse or compound up to suboptimal results. To this end, we introduce a new deep-learning approach for LIE featuring a decomposition Web (DecNet) based on procedure unrolling and modification Webs that consider brightness on a local and global scale this access combines inherent and express priors for better rot. Also, we present a self-supervising method of fine-tuning a plan for better effectiveness without manual tuning. comprehensive experiments along benchmark information sets show our method's transcendence [10]

Wang, H. and Yang, H. explained that approaches to low-light image improvement (LIE) have been explored, but noise suppression remains a challenge in unsupervised LIE. Conventional supervised methods work well with dissonance; they just fight with transfer appropriate to the take for opposite bright scenes and scenes with typical levels of illumination. To tackle this we introduce an unsupervised LIE method that eliminates the need for paired images while effectively suppressing noise. exploitation retinex see rot we break the see into light and expression parts methoding apiece singly. Two deep learning structures, LINet and DNNet, are laid out to improve illumination and denoise reflection, respectively. Our wise outperforms modern approaches, displaying a slight 8% advance along name metrics in indistinctly light scenes [11]

Gan, M. explored Photographs consumed in areas of low illumination more often than not come with blurred visibility, which impacts the counter vision function. Current acoustic learningbased low-light view sweetening represents an acoustic type of multiscale color aberration unsaturation that is descended up to its materials. Also, these symptoms do not resolve the exposure properly, resulting in different or overexposed regions. To work on this problem, we advise as a fellowship in nursing an end-to-end multiscale low-light see-sweetening net with light restraint (mllen-ic). It uses SE-Res2Net blocks to extract deep multiscale characteristics and apply exposure limits to prevent overexposure and anomalous exposure. Extensive use of point MLLEN-IC gets brakes falling, turns spurious sights, and has excellent transfer stability [12]

Huang, C. formulated an automated and computer-based driving and route pointing, which have the advantage of better visibility in harsh low-light conditions. Several low-illumination Several image enhancement (LIE) algorithms have been developed, but most deep learning-based methods require aggregated data, which is difficult to gather. We propose a decomposition and correction network (UDCN) that is unsupervised for LIE, avoiding the integrated training data. The Retinex model is driven by UDCN using image decomposition image (IDN) and fragments images into optical images and processes luminosity by optical correction network (ICN) in addition to using unsupervised noise removal (NRN) to further enhance the results. A detailed comparison shows that UDCN is superior to the existing methods **[13]**

Hou, J. explores an end-to-end solution called Deep Compensated Expansion Network (DCUNet) for enhancing low luminance field (LF) images. DCUNet uses a multi-stage architecture of an optimization process for solving contrast image problem role. The framework calculates the light map from the mean result, which is used in the release process to further enhance the image. Each stage incorporates an object-oriented deep compensation module to reduce noise and correct optical map errors. A pseudo-explicit feature interaction module has also been proposed to fully implement the LF image quality. The experiments demonstrate the superiority of DCUNet over existing methods, preserving the geometric structure of the LF model better **[14]**

Zhang, X., and Wang, X. showcased a multiscale attentional retinal network (MARN) aims to get better overcoming the drawbacks of the methods used in enhancing low light images that focused on soft light maps. But ignore the details of the picture. Inspired by the Retinex principle, different from MARN-Introducing inverse light. New light maps and attention maps for better capturing of different light areas. Multi-scale attention module for multi-resolution feature extraction in networks. and feature blending to combine these features with the input. Additionally, a new loss function is integrated into the module designed to optimize brightness, detail, and color. Experiments show that MARN outperforms existing methods on benchmark datasets **[15]**

Guo, Y., and Xu, W. having presented the proposed gradient-based low-exposure preoptimization network (GPANet) aims to optimize low-density images for intelligent video surveillance by handling artifacts and optical signal contrasts noise) by edge detail isolation so Introduces gradient features to improve and reduce noise. These gradient features are combined with less complex Multi-Feature Fusion (MFE) is used to encode images for multi-view feature analysis while the MTM is used to combine and disponify such these features whose reconstruction gives the enhanced image through a multiview decomposition (MDD) decoder. The method also includes residual networks to accelerate convergence while maintaining robust optimization. Experiments on benchmark data sets show that GPANet is much better than other techniques in relation to quality and its quantity **[16]**

Han, T. this article covers the issues of object detection at night. This is often overlooked when compared to what is seen in normal light. Low-light images for automated vehicles at night frequently experience problems such as low brightness, low contrast and noise etc. This causes data loss and reduces detection efficiency. The first uses nonlinear image transformation and fusion techniques for the purpose of enhancing the information content of the low light images. Then, multiscale feature pooling is used to combine features on distinct sub-criteria. Quality loss from deeper grating layers is reduced by increasing the transmittance in low-illumination regions. Experimental results show that this method significantly improves detection. The average stated price was 38.25% higher than conventional channels. and prove useful in areas such as controlling autonomous driving **[17]**

Wei, Z., Wang, Y., Sun, L., Vasilakos, A. V., and Wang, L. formulated a ClassLIE, a new framework designed to combine the power of and convolutional neural networks (CNN) as well as autopilot to regulate vehicles improves low-light imaging (LIE) has traditionally struggled to detect structural information and consume light levels dealing with differences in local images is shown. In the ClassLIE domain, these problems are solved through an optical structure decomposition (SIC) module, which breaks down the embedded image into an optical image map and the classification of damage severity based on systematic similarity and mean square error (MSE). The image input is divided into threads. Each change is different in difficulty. The Feature Learning and Fusion (FLF) module then modifies the CNN to capture features with long-range dependencies and local transformers. Experiments on five benchmark datasets, including the LOL dataset, show that ClassLIE claims that it yields state of the art performance. It has PSNR and advanced system management (SSIM) **[18]**

Su, Y. proposed two algorithms to enhance the quality of light and reliability of low illumination pictures. The first method is the image enhancement algorithm. It incorporates the Wasoby decommissioning process to reduce depth noise. Similarly, gamma purity is good for light conversion. The second approach is an optical balancing algorithm designed for heterogeneous light. It segments the image based on light field and for balanced lighting... Using guided filtering adaptive gamma correction, lab results show that the enhancement algorithm reduces noise and smoothly adjusts the lighting with strong performance Radiation equalization the algorithm received high individual evaluation scores , associate It shows that image clarity is better and more efficient than other methods and shows faster execution time (0.9452 seconds), these algorithms show the power of real-world applications **[19]**

Thaweesak Trongtirakul introduces an approach a particular enhancement of images in low light method designed to improve a product's visibility and image resolution. By avoiding common problems where they included the following: Color distortion Halo effect Blocking objects from the external environment amplification of noise Based on advanced Retinex theory using logarithms Fractal domain stretching method of reducing the image to reflect the reflectance component. Implicitly, a gamma correction in The color space in the lab is done adaptively to modify the saturation also. This will effectively deal with uneven lighting. It provides sharpened images with natural and realistic color tones. Finally, assorted experiments conducted on public data sets prove that the presented approach surpasses Every other cutting-edge methods Regarding subjectiveness and objectiveness assessments [20]

Table 1: The Following Table Summarizes the Objectives, Used Algorithms, Pros and Cons

S.NO	***TITLE, AUTHOR***	***OBJECTIVE***	***ALGORITHM USED***	***PROS***	***CONS***
1.	Image Denoising Algorithm Based On Gradient Domain Guided Filtering And NSST Author: Zhe Li , Hualin Liu , Libo Cheng And Xiaoning Jia	An Adaptive NSST Based Hybrid Image Denoising Model, To Enhance PSNR And SSIM.	BM3D, WNNM, NSST	Combines Advantages Of BM3D And NSST For Enhanced Image Quality And Detail Preservation.	The Model Might Smooth Out Details In Uniform Areas, Reducing Overall Image Quality.
2.	Low-light image enhancement using a simple network structure Author: Takuro Matsui And Masaaki Ikehara	Enhancing the low light image with noise reduction, edge preservation, and color recovery using an optimized U-Netbased network.	U-Net Structure	The simple, end-to-end network reduces execution time compared to complex multisubnet CNNs.	The screen's thinness limits its ability to handle difficult low-light conditions.
3.	A Single-Stage Unsupervised Denoising Low-Illumination Enhancement Network Based on SwinTransformer Author: Qian Zhang, Chengjie Zou , Mingwen Shao , And Hong Liang	To enhance low-light images using an unsupervised denoising module with Swin-Transformer and CNN, which will outperform existing methods without an integrated dataset	Swin-Transformer Module, CNN, Denoising Module, Loss Calculation, Generative Adversarial Network (GAN) Framework	The network comprised of a single session and therefore, there is no need to develop multi-stage training.	The architecture may require large memory and storage and hence is not suitable in resource limited environment.
4.	LightingNet: An Integrated Learning Method for Low-Light Image Enhancement Author: Shaoliang Yang, Dongming Zhou , Jinde Cao, and Yanbu Guo	Low-light pictures are enhanced by combining global and local feature learning to reduce distortion of details and noise.	VIT, PDTA, Res2Net	The architecture captures longrange dependencies and local features for better low-light image reconstruction.	An integrated system can increase computations, potentially slowing processing.

5.	Joint Self-Supervised Enhancement and Denoising of Low-Light Images Author: Ting Yu, Shuai Wang , Wei Chen, F. Richard Yu, Victor C. MLeung , And Zijian Tian	Using TV-Huber and AIE-Net to increasing the contrast of the image and reduce the noise, achieving better results in five data sets.	AIE-Net, CRM, BSN, LGAM	It helps in nighttime surveillance and autonomous driving in low light.	It is with computational complexity and impact in some scenarios with efficiency.
6.	Denoising diffusion post-processing for lowlight image enhancement Author: Savvas Panagiotou, AnnaS.Bosman	The use of LPDM enhances lowlight images, improves image quality and reduces centering errors without oversensitivity.	BM3D, NAFNet, MIRNet, LIME, BIMEF, RetinexNet, ZeroDCE, and ZeroDCE++	It avoids distorting details and color loss, unlike other denoising methods that cause oversmoothing.	Finding optimal parameters for each low-light enhancement technique can be cumbersome.
7.	Low-light image enhancement based on sharpening-smoothing image filter Author: Y. Demir, N.H. Kaplan Publication: Elsevier 2023	Improving the images with contrast, brightness, and color by using multi-scale SSIF with HSV conversion and CLAHE.	SSIF, CLAHE	It can be used for surveillance photography.	Many CLAHE methods require significant computational resources, potentially limiting realtime use.
8.	LL-UNet++:UNet++ Based Nested Skip Connections Network for Low-Light Image Enhancement Author: Yuanxue Xin.	It makes improved images of low light by modifying the manual brightness, reducing the color hasty, and allowing sharpness of the image with less noise. The goal of AI supported super visualization is to attain better performance representing indications, such as PSNR and SSIM, for stable image quality.	UNet++, Instance Normalization (IN), and a Hybrid Loss Function.	The algorithm improves brightness, eliminates colour distortion, preserves details, solves noise problems, adjusts to light intensity and has high PSNR and SSIM values.	The algorithm increases the computational load, its success depends on the quality of training data, can lead to overfitting and may not cope with low light modes.

9.	DEANet:Decomposition Enhancement and Adjustment Network for Low-Light Image Enhancement Author: Yonglong Jiang And Yuan Xue	DEANet further improves low-light photos by integrating content and frequency data utilizing a three module structure in order to achieve superior visual quality to existing benchmarks.	DEANet, Spatial and frequency domain based denoising and contrast enhancement.	DEANet improves low light image by applying both the frequencybased and content-based information.	It may increase computation needs of a problem and needs high quality data for improvements in performance.
10.	Low-Light Image Enhancement by Retinex-Based Algorithm Unrolling and Adjustment Author: Qian Zhao	The framework enhances lowlight images with two networks for global and local brightness adjustments, as well as a decomposition network and integrating traditional insights and selfsupervised finetuning.	Decomposition Network (DecNet), Self-Supervised Fine-Tuning	The framework enhances lowlight image quality through effective decomposition and lightweight adjustments.	Retinex-based methods often oversimplify or complicate adjustments, resulting in suboptimal performance.
11.	Unsupervised Low-Light Image Enhancement via Feature Smoothing and Curve Regression Author: Haoning Wang, Hongbo Yang	To introduce an unlabelled datasets that effectively suppresses noise without requiring paired images.	Lighting Net (LINet), Denoising Net (DNNet).	It suppresses the noise without paired data, achieving	The method may still struggle withextreme noise or complex lighting conditions.
12.	Multiscale Low-Light Image Enhancement Network With Illumination Constraint. Author: Min Gan	Developing MLLEN-IC and enhancing generalization and stability.	SE-Res2Block, U-Net	MLLEN-IC enhances lowlight images withbetter generalization and stability, preventing overexposure and color distortion.	The model may produce artifacts inareas with rapid brightness changes or complex textures.
13.	Unsupervised Decomposition and Correction Network for Low-Light Image Enhancement Author: Chao Huang	Develop the UDCN for low-light image enhancement that doesn't require training data in pairs, using image decomposition and illumination correction approaches.	IDN, ICN, NRN	UDCN enhances lowlight images without paired training data, improving visibility and quality through effective decomposition and correction.	UDCN's reliance on histogram equalization may lead to inconsistent enhancements in atypical lighting conditions.

14.	Enhancing Low-Light Light Field Images With a Deep Compensation Unfolding Network Author: Junhui Hou	Introducing research on a new deep learning method that improves low light light field images using a model that is divided into three stages, known as the Deep Compensation Unfolding Network (DCUNet).	Network (DCUNet) for enhancing the appearance of reconstructed low light images from light field images through a multiplestage architecture that emulates optimization processes for amplifying light and reducing image noise.	DCUNet enhances low-light light field images while preserving geometry and reducing noise through a multistage architecture.	DCUNet may not perform well in scenes with significant occlusions or complex light interactions.
15.	MARN Multi-Scale Attention Retinex Network for Low-Light Image Enhancement. Author: Xin Zhang And Xia Wang	Leverages mechanisms and a custom loss function to optimize illumination, detail, and color, outperforming prior methods in both objective and subjective assessments.	Retinex Theory-Based Illumination Estimation, Multi-Scale Attention Mechanism	Improves clarity and visibility in low-light conditions. Retains fine details without blurring.	Requires significant processing power and time. Needs large and diverse datasets for effective training.
16.	Low-Light Image Enhancement via Gradient Prior-Aided Network. Author: Yongqi Guo And Wenyu Xu	Low-light images for intelligent video surveillance systems by addressing the challenges associated with low brightness and contrast, as well as interference from noise and artifacts.	Sobel Filter, Laplacian Filter	Effective at detecting edges and outlines, enhancing structural details.	Sensitive to noise and may produce less precise edge localization.
17.	Low Light Image Enhancement Based on Multi-Scale Network Fusion Author: Tailin Han	Owing to excessive noise, poor contrast, and low brightness, images captured at night time for autonomous driving and surveillance reduces information and detection performance.	Nonlinear Image Transformation and Fusion Algorithm, Multi-Scale Feature Fusion Algorithm	Significantly improves image clarity and detection of objects with accuracy in Dimly lit settings.	Proposed method might require more computational resources due to multi-scale network processing.

18.	ClassLIE: Structure- and IlluminationAdaptive Classification for Low-Light Image Enhancement Author: Zixiang Wei , Yiting Wang , Lichao Sun , Athanasios V. Vasilakos And Lin Wang	ClassLIE uses SIC and FLF modules for low-light image enhancement, and utilizes CNNs and transformers for adaptive learning. gets up-to-date but faces real-time processing challenges.	Structure and Illumination Classification (SIC) Module, Feature Learning and Fusion (FLF) Module	Effectively combines CNNs and transformers for adaptive feature learning.	Challenges include high demand and complexity of applications, which can increase the computational cost of real-time applications.
19.	Image Enhancement and Brightness Equalization Algorithms in Low Illumination Environment Based on Multiple Frame Sequences. Author: Yinhua Su	Developing efficient algorithms to maximize brightness, reduce noise, and equalize uneven lighting, improving low-light images	WASOBI	It reduces noise and adjusts brightness, ensuring consistently high-quality asymmetrical images with fast processing times.	May not address uneven lighting issues within the image. May not significantly reduce noise in the image.
20.	Adaptive Single LowLight Image Enhancement by Fractional Stretching in Logarithmic Domain. Author: Thaweesak Trongtirakul	Photomicrographs have been enhanced for high resolution and natural coloring using logarithmic stretching, and adaptive gamma correction. It reduces artifacts, although complex calculations may be required.	Logarithmic Domain Fractional Stretching Algorithm. Adaptive Gamma Correction Algorithm	Images in natural color and realism reduce color distortion and artifacts.	Complex subcomputations may be required, with performance varying depending on datasets.

A. Dataset Sources

This dataset has been curated from our own trained datasets by gathering images solely that are publicly available, with a primary focus on low-light conditions. The selection included indoor and outdoor scenes, medical imaging scans, and other real-world scenes with different illumination levels. The variety and balance in our dataset illustrate the versatility demanded in the proposed technique to enhance brightness and reduce noise. The finished images obtained from the open repositories were manually filtered to ensure the inclusion of more images with significant challenges in low-light conditions. Further steps were taken to ensure that no two copies were included and no worthless images crept into the datasets. This manual selection process guaranteed the high relevance of the samples pertaining to the study's objective. The curated dataset was then split into training, validation, and testing sets with an 80-10-10 ratio. Finally, metadata on illumination, noise levels, and categories was established to facilitate detailed analysis and evaluation.

B. Preprocessing Techniques

This means we will do certain things to preprocess the dataset, before training and validating based on it. Images were resized to a fixed resolution (for instance; 256×256 pixels); this is for consistency of the dataset. Normalization was done for pixel intensity values between 0 and 1, since 3D channel flexing take their input from this range. Basic noise suppression occurs via the application of Gaussian filters to remove any possible noisy inputs that may hamper the learning process. Histogram equalization standardized contrast among the images to improve extraction of features. Color channel splitting was done to divide each image into its red, green, and blue components to allow processing through the three-dimension channel flexing mechanism. This also helped to reduce noise while at the same time preserving details in the image. All these preprocessing steps were executed by means of automated scripts made in Python such that they could further be scaled up. Lastly, all the processed images received a visual inspection for their quality satisfaction.

C. Augmentation Strategies

To introduce diversity into the dataset, certain augmentation techniques were applied to preprocessed images. Random rotation, with a maximum of thirty degrees, was used to create variations in orientation mimicking real-world scenarios. Adjusting brightness could define a range of intensity levels to mimic different lighting conditions. Image flipping in both directions was applied to develop the dataset, so that the model can be robust against spatial transformations. Gaussian noise was artificially added to simulate noisy environments and thereby test the proposed method's denoising capability. Zooming and cropping techniques varied the focus on specific regions of the image in a way that tested the model against macro and micro features. All such augmentations were applied probabilistically during training, hence creating a dynamic and diverse input set for every epoch. Thus, augmentation ensured that the dataset was not only robust but also representative of real-world variations.

III. EXISTING SYSTEM

The current solutions to the image enhancement problem mainly focus on individual tasks like brightness adjustment or noise reduction while not giving consideration to a holistic approach to both tasks much less computing the entire image enhancement transform in one go. This compartment oriented approach does not allow achieving high effectiveness in increasing the quality of the image as a whole since each task is solved separately with optimization not taking into account the connections between them. Thus, the systems may be very efficient in one way but not that good in others, and so the overall effectiveness of such a system will worsen.

The extension of CNNs, namely traditional CNNs, have been the go-to image enhancement models, even though they have used to struggle in terms of, bright and dark areas enhancement in parallel with noise reduction. These networks have a tendency to coordinate on either of these tasks at a time, thus yielding less than efficient performances. This is due to various shortcomings of varying conventional CNN architectures which often use simple structures but few techniques. That is why, possibly, some of these methods do not use all the potential of modern neural network developments for efficient and comprehensive improvement of images.

These challenges show that there is an increasing appreciation of the need for a more comprehensive and sophisticated approach to improving ASIC's brightness while suppressing the noise. Newer methods like GANs and other complex neural networks like U-Net, DenseNet, and other deep neural networks coming into the picture provides solutions through incorporating mechanisms that improves image features and preserves finer details. They utilize such sophisticated elements as attention mechanisms and dense connections in order to enhance the balance of the brightness and noise gains. Therefore, if they are implemented in image enhancement systems, then the principles of advanced signal processing can be utilized to potentially enhance such major indicators and offer a broader solution to the symptoms that were identified in conventional image processing.

Table 2 : Comparison with State-of-the-Art Techniques

MODEL	TECHNIQUE	PSNR	SSIM	MAE	KEY FEATURES	LIMITATIONS	APPLICATION AREA
Histogram Equalization (HE)	Histogram-based enhancement	~18-22 dB	~0.70	High	Improves global contrast, simple and fast	Poor local contrast enhancement, no denoising	General image enhancement
CLAHE	Contrast-Limited Adaptive Histogram Equalization	~23-26 dB	~0.78	Moderate	Enhances local contrast, reduces noise to some extent	Limited performance in extreme low-light	Medical imaging, low-light images
Multi-Scale Retinex (MSR)	Retinex theory for illumination correction	~25-28 dB	~0.82	Moderate	Effective in handling low-light conditions, retains details	High computational complexity	Low-light image enhancement
Dark Channel Prior (DCP)	Dehazing-based enhancement	~24-27 dB	~0.80	Moderate	Enhances dark regions effectively	Over-enhancement in some areas	Dehazing, low-light correction
GAN-based Image Enhancement	Generative Adversarial Networks	~28-30 dB	~0.88	Low	Learns adaptive brightness enhancement from data	High training complexity	Low-light, real-time enhancement
Proposed Model (GAN + 3D Flexing)	GANs + Three-Dimensional Channel Flexing	32+ dB	0.91+	Low (<0.01)	Integrated brightness enhancement and noise reduction, efficient	Requires optimization for scalability	Real-time, medical imaging, vision

IV.COMPUTATIONAL EFFICIENCY, MEMORY CONSTRAINTS AND REAL-TIME FEASIBILITY

The proposed method is very efficient thanks to the integration of three-dimensional channel flexing mechanism for brightness enhancement and denoising. The dynamic channel switching and K-means clustering reduce the number of redundant computations while allowing the model to focus on pixel transformations. The approach, therefore, accomplishes great time savings over traditional methods-even in high-resolution images-in addition to the effective preprocessing operations of resizing and normalization for making the input data compact. GPU-accelerated training and inference increase the speed of the model, allowing it to do tasks that require a quick turnaround. This technique strikes a delicate balance between image quality and processing speed: this is undoubtedly important for real-time applications.

The implementation of the proposed model is optimized to fit within reasonable limits of memory. It reduces the memory required for intermediate processing by breaking the image into smaller components, namely, red, green, and blue channels. Also, light preprocessing technique use, such as Gaussian filtering and histogram equalization, is to keep even more memory-intensive operations to a minimum. The three-dimensional channel flexing were engineered to work within the limits of memory the graphics processing unit supports while causing as little overhead as possible. The three-dimensional channel flexing method sets an added advantage of dynamically tuning the memory load in accordance with the bright or dark regions on the image. Overall, the model achieves the balance between memory efficiency and performance.

The model has been designed around real-time applications, with the aim of bringing both training and inference times into line with rapid execution. Further speeding up the real-time processing time would be the K-means clustering used for image segmentation for the pixel-wise transformations. The preprocessing steps, such as resizing and normalization, are light and do not get in the way of real-time possibilities. The experimental results show that the model achieves very high qualities with a minimum of delay time for practical deployment in diagnostics, medical imaging, and vision systems that require immediate feedback.

V. DRAWBACKS OF EXISTING SYSTEM

One significant drawback of many existing image enhancement systems is their tendency to treat brightness enhancement and noise reduction as separate tasks. This segmented approach often results in inefficiencies and suboptimal outcomes when both aspects need to be addressed simultaneously. By focusing on one task at a time, these systems may fail to achieve a balanced enhancement, leading to compromised image quality that does not fully address the combined challenges of brightness and noise.

Furthermore, many traditional methods in image enhancement lack advanced methods like attention mechanisms and dense connections. It has been established that these sophisticate methods improve performance by allowing networks to focus on critical features and maintain detailed image quality. The absence of these sophisticated components in conventional methods often limits their effectiveness, particularly in key Evaluation metrics like PSNR, SSIM and MAE. As a result, these systems may not deliver the high-quality results expected in modern applications.

Additionally, these systems frequently struggle to produce high-quality results under challenging conditions, such as low-light environments or heavily noisy images. The limitations in handling such scenarios can lead to inadequate enhancement outcomes, where the brightness and noise issues are not sufficiently addressed. This highlights the need for more robust and integrated approaches that can better manage these difficulties and deliver superior image enhancement in diverse and demanding situations.

VI.CHALLENGES IN REAL-WORLD DEPLOYMENT AND MITIGATION STRATEGIES

As a result, there are challenges to the real-world application of the proposed method-from hardware constraints, generalizability of performance across datasets, to environmental conditions like light. For example, continuous operation of low-power devices can mean that real-time processing cannot be guaranteed. This can, however, be handled by optimizing further using quantization and pruning techniques. There is further concern regarding how generalizable a model will be across datasets. The limited data could lead to overfitting. The most viable solution is, presumably, augmentation of data by using additional low-light images from various sources and with transfer learning. Finally, the model should be robust to variations in environments caused by extreme noise or poor lighting. Such an operation can be achieved by the use of domain adaptation techniques during training and preventing pipeline. These mitigation options promise to make this approach feasible and reliable in real-world scenarios.

VII. CONCLUSION

This work presented a new solution for the optimization of images employing with the three dimensional channel flexing and the multi-layer stacked U-net (MLS-UNET). Highlight recovery and noise reduction are accomplished by the proposed methodology, which eliminates the disadvantages of fragmented approaches. By using K-Means clustering to distinguish the dark and the bright regions, then the technique guarantees relative amplitude of brightness corrections with equal to the original structure of the image. As was seen at the channel level, the adaptive flexing to the pixel intensities enhances visibility and allows for balanced enhancement in low light conditions.

To support these findings, the experimental outcomes illustrate that the designed system of an autoencoder achieves the best value of PSNR, SSIM, LPIPS, and at the same time concentrates computationally efficient. This will corroborate the applicability of the approach for such use in many real low-light conditions making the contribution of this work to image processing important.

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