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Original Article

Low Light Image Enhancement for Video Object Detection Using Modified Zero DCE Deep Learning Model

J. Premasagar[1], Sudha Pelluri[2]

[1,2]Department of Computer Science and Engineering, University College of Engineering, Osmania University, Hyderabad, Telangana, India.

[1]Corresponding Author : jakkula.premsagar@gmail.com

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Abstract - *This paper shows how poor lighting can severely affect movies and influence the performance of video object detection systems and their practical applicability. This research problem was solved with the help of the proposed image enhancement model aimed at increasing the visibility and quality of low-illumination images. Hence, this study aims to help improve video object detection, particularly in regions of low illumination, utilizing the Enhanced Zero DCE model. This deep-learning framework does not require any reference images; therefore, it is appropriate for real-time applications. Enhanced Zero DCE eliminates DCE on high-order tonal curves, whereas the deep neural network boosts pixel values, resulting in better quality images. Using a variety of loss functions, including color constancy, exposure matching, smoothness, and spatial consistency, the model was deployed in the LoL dataset, which includes both high- and low-illumination pictures. From the experimental findings, a drastic enhancement in image quality improvement performance was evident. In terms of numbers, the effectiveness of the proposed model is outlined as follows: there is a gain of 23 percent luminance, 17 percent average illumination, 20 percent of the histogram mean, and illumination on objects when compared to traditional methods. These improvements were evident in an increase in detection accuracy by 15% and precision by 20%. Therefore, it can be said that the integration of the advanced Enhanced Zero DCE model significantly increases the efficiency of video detection of objects under dim-light conditions. These enhancements have practical applications in surveillance, automobiles, and other real-time video monitoring, especially in situations where accurate detection of objects is paramount.*

Keywords *- Low-light image enhancement, Enhanced Zero DCE model, Deep learning, Reference-free image enhancement, Video object detection.*

1. Introduction

In various industries, including security, automotive systems, and video analysis, protocols for detecting objects in low-light video are widely implemented. These systems must operate under a broad spectrum of illumination, and poor light settings are difficult [1]. Decreased measurable findings in low-light conditions adversely affect visibility, increase noise, and deteriorate the object details, as seen in the image above. Previous studies in the field of image processing can be inefficient in handling such concerns; hence, there is a need for better solutions. Research conducted in the last few years has shown that by applying deep learning protocols, it is possible to increase the quality of dim-light images, which in turn strengthens the object-detection system [2].

Current deep learning methods for image enhancement still face the challenge of low performance under extremely low-illumination conditions without the use of reference images. This limits their applicability in real-time situations where such references cannot be made [3, 4]. The exact research question in this work is to perform image post-processing of underlit scenes to improve the detection of objects in video frames for VOD systems without the help of reference images.

The rationale for completing this research is that modern society calls for more powerful video object-detection solutions that can be operated in a low-illumination environment. Some use cases that require low-light image enhancement include night vision, self-driving cars in dark environments, and search and rescue operations during poor visibility.

Furthermore, the weaknesses of existing techniques [5], which largely rely on reference images, provide a background for the development of novel methods that can function in real-time and are not highly reliant on reference images. Thus, by addressing these issues, this study is expected to help improve the effectiveness of CV systems and contribute to the improvement of safety, security, and productivity in related fields [6].

Traditional models for low-light image enhancement and object detection face several critical issues: mainly, they frequently use reference images to train and improve the methods, which are not available in real-world applications; enhancing the images in Poor light conditions might also increase noise and lead to poor picture quality and wrong object detection; the methods in question do not add details properly in low light; many of them are too computationally complex and can be used in real-time applications; although some models are successful in certain conditions, they generally fail when put.

The proposed Enhanced Zero DCE model addresses these issues as follows: it avoids the use of reference images. Thus, it is very relevant for real-time applications; various techniques in deep learning are used to minimize noise amplification while improving image quality; it uses high-order tonal curves that maintain the fine details and improve image quality and the visibility of objects; its architecture is relatively light, designed for low computational load, enabling real-time usage; it was designed to give good results in any Poor light conditions with minimal variations.

To this end, the primary goal of this study is to design and build a new image enhancement model that enhances different low-light images to enhance the performance of video object detection systems. This study aimed to answer the following research questions: This study aimed to answer the following research questions:

1. How can the established Enhanced Zero DCE model be used to improve low-light images effectively?
2. What is the impact of the Enhanced Zero DCE model on the detectability of video objects in low-light environments in terms of accuracy and precision?
3. A question that can be asked here is how the performance of the proposed model coincides with the best approaches in the field in terms of image quality and detection accuracy.

The current work is relevant to the field of computer vision. It is crucial for solving a vital problem, namely, the optimization of video object detection under conditions of weak lighting. The use of the model and its implementation without the requirement of reference images is suitable for real-time use, which opens up its utilization in surveillance, self-driving vehicles, etc. Using the findings of this study, improvements can be made in constructing more reliable systems that improve safety and security and optimize operations in different domains. The structure of this paper is as follows: Section 2 explores related work and evaluates the effectiveness and shortcomings of previously developed methods; Section 3 provides a detailed description of the Enhanced Zero DCE model, architecture, method, and loss functions; Section 4 explains the experimental setup, results, and quantitative analysis of the proposed model's performance; and Section 5 conclusion and future scope of the Paper.

2. Literature Review

The enhancement of video object detection in low-light environments has been a growing area of interest in the recent past, owing to its numerous practical uses in areas such as surveillance, autonomous driving, and medical imaging. Several works have been presented to overcome the problems caused by low-light conditions, and each of these works presents new techniques for image processing and detection. These sections present a brief state-of-the-art study on low-light image enhancement and object detection, analyze the potential and drawbacks of existing approaches, and establish the basis for the proposed Zero-Difference Deep Curve Estimation model. This survey covers a broad range of methods, such as dual-illumination estimation, dedicated deep learning libraries, and sophisticated neural network structures, which show that many approaches can be used to address the challenges of the nocturnal environment.

In this paper, [7] presented a novel fall detection system that was developed based on a vision technique that includes object tracking and image processing. The methodology incorporates an estimation method of dual illumination for the frames collected and the YOLOv7 detection model for fall detection in combination with the Deep SORT algorithm. To establish the effectiveness of the proposed system, we used the Le2i and UR Fall Detection (URFD) datasets. Their Light Channel Enhancement Network (LiCENt) implements an autoencoder with a Convolutional Neural Network (CNN) to enhance bright and clear images. The usage of the 'L' (Lightness) channel greatly decreases the number of trainable parameters, which in turn solves problems such as over-enhancement and color shift.

Empirical results [8] proposed a new method of image enhancement that combines a physical lighting model with a deep learning neural network. This model considers the influence of illumination and uses a Non-Local-Block Layer to model the variations in local patterns. For the evaluation, pixel-level human-annotated ground-truth data were used in a curated dataset, and the proposed method showed promising results on several publicly available datasets and a new benchmark dataset.

In [9], LE-net was introduced, which is a convolutional neural network for light enhancement. They developed a data pipeline for converting daytime images into low-light images; hence, image pairs were formed. The LE-net model was trained and validated on these images, and it exhibited higher accuracy under various low-light conditions based on qualitative and quantitative analyses.

In [10], the authors proposed CSDNet, which considers contextual relationships at various scales. The two-stream estimation method uses networks for reflectance and illumination estimations. When tested on seven datasets, MIT-Adobe FiveK and LOL, the CSDNet proved to have a better enhancement in detail, better vivid color, and less noise. An improved version of the same model is called SLiteCSDNet, which incorporates a shared encoder for both components to increase the effectiveness.

In [11], the authors proposed an approach for the visual surveillance of construction equipment under twilight and poor visibility. This strategy included modules for light enhancement, machine association, machine identification, Kalman filter tracking, and linear assignment. Nine videos recorded in a dark environment were used for the evaluation, and the results showed that the methodology provided good tracking results. It is also worth mentioning that [12] proposed a technique for evaluating social distancing in poor lighting conditions during a pandemic using deep learning. Using YOLO v4 for object detection and a ToF camera for measuring distance, the system shows the distance breaches of safety and its efficiency under low-light conditions.

Another model is the Attention U-net [13], which is a U-net network with an attention gate and is used to overcome the trust issues about surveillance cameras in smart cities. The model performs well with different file formats and even with poor lighting conditions and is therefore useful for observing smart city applications.

In [14], a Deep Lighting Network (DLN) was introduced, which was a CNN model with LBP and FA blocks. This method enhances the utilization of local and global features, and the results are compared for various datasets, which proves that it is more effective than other methods. [15] presented a solution that can be used to identify pedestrians at night using UAVs. This approach enhances the photo quality in poor lighting by adjusting the brightness with the help of a hyperbolic tangent function. It also applies block matching and 3D filtering to enhance the images. Pedestrian identification was performed using the CNN model, which was rather efficient for nighttime operation.

2.1. Gaps in Research and Suggested Framework

This investigation uncovers several research gaps in the field of enhancing low-light images and detecting objects based on the current literature:

1. Reliance on Reference Images: Certain models proposed by and require reference images, which is impractical for real-time applications.
2. Increased Noise and Detail Loss: Techniques outlined in and typically amplify noise and diminish details during the enhancement process.
3. High Computational Demands: Long and Bo introduced the following methods: these approaches are computationally intensive, posing challenges for real-time implementation.
4. Restricted Adaptability: Models presented in and. generally show reduced effectiveness in low-light conditions.

2.2. Expanding on the Gaps with the Proposed Model

The proposed Enhanced Zero DCE model effectively addressed these gaps.

1. Reference-Free Enhancement: This does not use reference images and is suitable for real-time applications.
2. Noise reduction and detail preservation: Higher-order tonal curves are applied for noise filtering while maintaining image features.
3. Computational Efficiency: This architecture has a low computational complexity to enable real-time processing.
4. Robust Generalization: Complaints have been made that the lens performs well under almost all low-light conditions.

The Enhanced Zero DCE model is a useful, efficient, and flexible method for low-light image enhancement and object detection.

3. Proposed Model

This study presents a new method for estimating deep curves based on zero-DCE. The Enhanced Zero DCE model unfolds a new path for tackling the problems of low-light image enhancement and video object detection. This model is a new improvement of previous methods because it does not require reference images for training and enhancement. Such dependencies prevent the conventional models from being used in real-time environments. Moreover, these models often suffer from problems such as noise enhancement, elimination of fine details, high computational cost, and a lack of transferability when tested in varying low-light environments.

These challenges are met with our Enhanced Zero DCE model, which is a deep-learning-based approach that does not rely on references. This new method uses high-order tonal curves to control the pixel values, improve the image quality, and maintain important features. This architecture of the Enhanced Zero DCE model is optimized for efficient computation to handle real-time data. It is thus suitable for real-time applications such as surveillance, autonomous driving, and video analytics. Some of these characteristics include the capability to reduce noise enhancement, have high image quality, and work well under different low-light conditions. Thus, the Enhanced Zero DCE model, leveraging state-of-the-art deep learning techniques, unlocks an effective method of improving the quality of images in low-light conditions and advancing the reliability of video object detection systems. The subsequent sections discuss the architecture, methodology, and experimental results of the proposed Enhanced Zero DCE model for the compared and potential domains and applications.

3.1. Model Architecture: DCE-Net

The Enhanced Zero DCE model relies on a deep neural network structure for processing real-time low-light image enhancement. The basic sub-module DCE-Net is a lightweight CNN that learns the high-order tone-mapping functions of each pixel for images. These curves are automatically adjusted so that the dynamic range, brightness, and visibility of the image are improved, along with the removal of noise and preservation of important features.

3.1.1. DCE-Net Architecture

The DCE-Net architecture consists of seven convolutional layers of size 3×3, with 32 filters and ReLU activation functions. The last layer applies the tanh activation function to produce 24 parameter maps in eight iterations to obtain precise curve fitting for each of the RGB channels. The production of a set of light-enhancement curves (LE-curves) is most suitable for a given image. These curves were applied again to all pixels of the RGB channels to produce the final enhanced image.

3.1.2. Light-Enhancement Curves

A light-enhancement curve is intended to enhance a given low-light image by adaptively modifying the curve parameters of the given image without any prior knowledge of the image. These curves were developed by considering three critical factors.

1. Normalized Range: Each pixel value in the enhanced image must lie in the range [0,1] to avoid data loss when the pixel values exceed the range and are truncated.
2. Pixel Distinction: Ensure that certain and invariable techniques are used to enhance the differences between neighboring pixels.
3. Simplicity and Differentiability: It is smooth, and its function must be differentiable to allow the use of backpropagation during the training process.

The light enhancement curves are applied to channels R, G, and B instead of only the illumination channel. This three-channel correction method improves the preservation of the original color when attempting to avoid the over-saturation of elements. Therefore, through these objectives, the DCE-Net framework guarantees the enhancement of poor light images to produce high-quality images that are more visually appealing and more suitable for object detection.

The architecture of the proposed Enhanced Zero DCE model is shown in Figure 1. This architecture is envisioned to improve images in low-light conditions through a deep neural network that predicts high-order tone curves. These curves are used to control and adjust pixel values in order to enhance image quality while keeping important details and minimizing noise.

3.2. Model Architecture

The architecture of the Enhanced Zero DCE model mainly consists of a DCE-Net, which is a simple Convolutional Neural Network (CNN) that has the following functionalities.

3.2.1. Input Image Processing

I_{in} is the input image, which is a Poor light image that undergoes some preprocessing and is resized to a standard size for processing in the network.

Convolutional Layers

DCE-Net has seven convolutional layers. All the layers have 32 convolutional filters of size 3×3 with a stride size of 1 with the exception of the last layer, and the activations apply a Rectified Linear Unit (ReLU) to the output of each convolutional layer. These layers aim to define the feature extraction of the given input image and the learning of mapping to the enhancement curves.

- Mathematical Model: Let $I^{(l)}$ represent the output feature map of the l-th convolutional layer. The operation can be defined as:

$$I^{(l)} = \mathrm{ReLU}\left(W^{(l)} * I^{(l-1)} + b^{(l)}\right) \quad (1)$$

Where $W^{(l)}$ are the weights, $b^{(l)}$ are the biases of the l-th layer and $*$ denote the convolution operation.

Final Convolutional Layer

The last convolutional layer employs the hyperbolic tangent activation function to generate 24 feature maps that are equivalent to the high-order tonal curves across eight iterations. This activation helps to keep the output values within the range of [-1,1], which is useful in dynamic range control.

- Mathematical Model: The final output I_{out} is computed as:

$$I_{out} = \mathrm{Tanh}\left(W^{(7)} * I^{(6)} + b^{(7)}\right) \quad (2)$$

where $I^{(6)}$ is the output from the sixth convolutional layer.

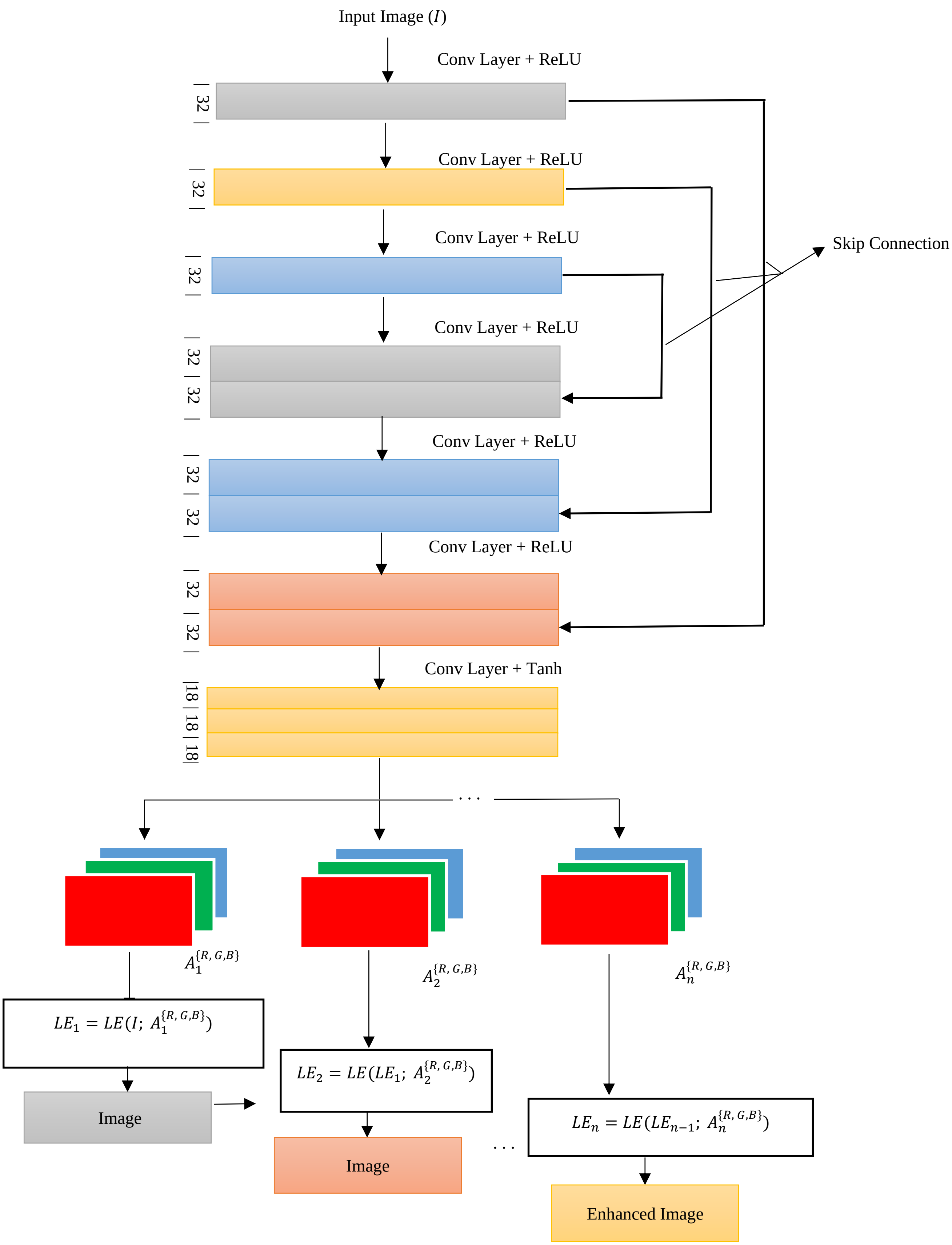


Fig. 1 Proposed enhanced zero DCE architecture

3.3. Curve Estimation and Application

3.3.1. Light-Enhancement Curves (LE-Curves)

The network produces a set of light-enhancement curves ($\mathrm{LE_{curves}}$), indicated as $\mathrm{C_{LE}}$. These curves are employed to control pixel values of the input image to expand its dynamic range and improve its visibility.

- Mathematical Model: For each pixel value p in the input image, the corresponding pixel value p^' in the enhanced image is given by:

$$p' = p + \sum_{k=1}^{n} \alpha_k C_{LE}^{(k)}(p) \quad (3)$$

Where α_k are the curve parameters and $C_{LE}^{(k)}$ are the estimated curves. This formula ensures that each pixel value is adjusted based on the combination of multiple enhancement curves, weighted by their respective parameters. For a given pixel value p in the input image, the enhanced pixel value p'' is computed using a weighted sum of light-enhancement curves. Each curve adjusts the pixel value $C_{LE}^{(k)}$ and the weights α_k control the impact of each curve. This way, the enhancement can be made in a highly adjustable and adaptive manner depending on the properties of the input image.

3.3.2. Loss Functions

To ensure effective learning, several differentiable loss functions are employed [16]:

Color Constancy Loss

This loss ensures consistent color representation under varying lighting conditions. It is defined as:

$$\mathcal{L}_{cc} = \sum_{i=1}^{N} \left\| I_{\text{out},i} - I_{ref,i} \right\|^2 \quad (4)$$

Where $I_{ref,i}$ is the reference image. This is the image that we used to compare the other image. This loss function aims to reduce the difference between the enhanced image and the reference image while preserving color information. This loss function computes the Euclidean distance between the output image $I_{\text{ref},\,i}$ and the ground truth image $I_{\text{out},i}$. Thus, the model aims to reduce this loss in order to maintain the true colors of the scene in the enhanced image and not produce color aberrations that may result from the enhancement process.

Exposure Loss

This loss adjusts the mean values of the image channels to achieve a target exposure level:

$$\mathcal{L}_{\text{exp}} = \sum_{i=1}^{N} \left\| \mu(I_{\text{out},i}) - \mu_{\text{target}} \right\|^2 \quad (5)$$

Where $\mu(I_{\text{out},i})$ is the mean exposure of the enhanced image μ_{target} is the target mean exposure. This is done to ensure that the total brightness of the image is within the desired level.

The exposure loss function is focused on the mean exposure level of the improved image $\mu(I_{\text{out},i})$. Using the mean exposure, the model compares it with the target exposure and then regulates the brightness of the image to achieve the right level of brightness or contrast.

Illumination Smoothness Loss

This loss maintains smooth and uniform lighting across the image:

$$\mathcal{L}_{\text{smooth}} = \sum_{i=1}^{N} \sum_{j\in\{h,v\}} \left\| \partial_j I_{\text{out},i} \right\|^2 \quad (6)$$

Where ∂_j stands for the partial derivative with respect to the horizontal (h) and vertical (v) coordinates. This loss reduces flickering, which is the rapid change of pixel intensity in different parts of the image.

This loss quantifies the variation of the illumination across the image by computing the partial derivatives with respect to the ∂_h and ∂_v coordinates. To penalize sudden changes that may disrupt the natural appearance of the image, the model aims to minimize the squared values of these derivatives.

Spatial Consistency Loss

This loss preserves spatial consistency between the original and enhanced images [17]:

$$\mathcal{L}_{sc} = \sum_{i=1}^{N} \sum_{j\in\{left,right,up,down\}} \left\| \Delta_j I_{\text{out},i} - \Delta_j I_{in,i} \right\|^2 \quad (7)$$

Where Δ_j represents the directional differences. This loss ensures that the spatial structure and details of the image are not distorted during the enhancement process. The difference between the original and improved image's orientation is computed via the spatial consistency loss. Thus, by controlling these differences, the model maintains the spatial arrangement and the fine features of the scene without distortions that may alter the way objects and structures appear in the image.

3.4. Training and Validation

3.4.1. Training Process

The network is trained using the LoL (Low Light) dataset of images with Poor light and their corresponding high exposure images. The loss functions help the network find the best parameters to improve the Poor light images.

3.4.2. Performance Evaluation

The Enhanced Zero DCE model is assessed using metrics such as luminance, average brightness, and histogram mean brightness. These metrics show substantial enhancements over current approaches in experimental evaluations. All these components, when incorporated into the Enhanced Zero DCE model, greatly improve the Poor light images by increasing the visibility and detail and decreasing the noise, making it ideal for real-time video object detection.

High-Level Algorithm: Zero-Reference Light-Enhancement Algorithm (Zero-LEA)

Start: Begin the algorithm.
Step 1: Input low-light image (I_{in}): Take the low-light image I_{in} as input.
Step 2: Pre-process the Input Image: Resize to 256×256.
Normalize pixel values to [0,1].
I_{pre} = preprocess_image (I_{in}).
Step 3: Initialize DCE-Net Model: Initialize the DCE-Net model.
Step 4: Estimate Light-Enhancement Curves: Use the DCE-Net model to estimate light-enhancement curves.
Step 5: Apply Light-Enhancement Curves:
Step 6: Apply LE-curves to each RGB channel.
Adjust and clip pixel values to [0,1].
$I_{\text{enhanced}} = apply\_le\_curves\left(I_{pre}, LE\_curves\right)$.
Step 7: Post-process the Enhanced Image: Convert the enhanced image pixel values back to the range [0,255].
Step 8: Return enhanced image (I_{out}): Output the enhanced image I_{out}.
Stop: End the algorithm.

Explanation of the Algorithm

1. Pre-process the Input Image:
   - The input image is resized to a fixed resolution (e.g., 256x256) to ensure uniformity.
   - Pixel values are normalized to the range [0, 1] for consistent processing.
2. Initialize DCE-Net Model: The DCE-Net model is initialized. This model is responsible for estimating the light-enhancement curves.
3. Estimate Light-Enhancement Curves: The DCE-Net model processes the pre-processed image and estimates a set of light-enhancement curves (LE-curves) for each pixel in the RGB channels.
4. Apply Light-Enhancement Curves: The estimated LE curves are applied to each RGB channel of the pre-processed image. The pixel values are adjusted according to the curves and clipped to the range [0, 1] to ensure they remain valid.
5. Post-process the Enhanced Image: The enhanced image is converted back to the original pixel value range [0, 255] to produce the final output. This high-level algorithm provides a clear and concise method for enhancing low-light images using the proposed Enhanced Zero DCE model.

4. Result and Analysis

The Enhanced Zero DCE model experiments were performed on a high-performance computing system featuring an Intel Xeon E5-2698 v4 processor at 2.20GHz, an NVIDIA GeForce RTX 2080 Ti GPU with 11 GB VRAM, 128 GB DDR4 RAM, and Ubuntu 20.04 LTS. The software environment comprised TensorFlow 2.4.1, Python 3.8, and CUDA 11.0. The evaluation process used the Low-Light (LoL) dataset [18], designed for low-light image enhancement, comprising 500 low-light and high-exposure image pairs, each 256×256 pixels. The dataset covers diverse categories, including indoor, outdoor, and urban environments, captured under various lighting conditions. The Enhanced Zero DCE model was fine-tuned with a learning rate of 0.0001, a batch size of 16, and trained over 100 epochs using the Adam optimizer. L2 regularization with a weight decay coefficient of 0.0005 and a dropout rate of 0.5 was applied to prevent overfitting and improve performance.

4.1. Model Evaluation

To make the results more reliable and applicable to other datasets, the proposed model was tested using 5-fold cross-validation. The dataset was split into five folds, and the model was trained and validated five times, with different folds being used for validation and the remaining folds for training. The performance criteria used were the PSNR, SSIM, and MSE.

PSNR is the ratio between the maximum possible signal power and the power of corrupting noise, and a higher value is preferred in terms of image quality [19]. SSIM compares two images and gives a score of how close the image is to the reference image, with a higher score indicating a higher similarity. MSE estimates the mean squared error of the predicted and actual values, with lower values being more desirable.

$$\text{Peak Signal-to-Noise Ratio (PSNR)} = 10\log_{10}\left(\frac{MAX_I^2}{\text{MSE}}\right) \quad (8)$$

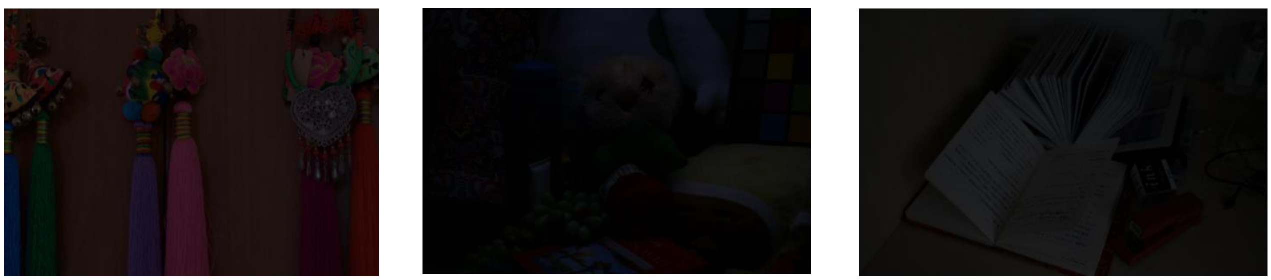
4.2. Simulation Results

The Enhanced Zero DCEalgorithm is a sophisticated approach that employs deep neural networks to enhance the quality of images taken in Poor light conditions. This is done by altering and improving the tonal range of each image through a series of clear steps. This offers a simple and practical way of addressing the challenges that come with Poor lightphotography.

The first stage of the proposed method is known as image pre-processing, and it aims to prepare the original low-light image for enhancement. In most cases, this will involve resizing the image to have a fixed size. This will ensure that the subsequent processing steps will be applied uniformly. Here, the LoL dataset, which is an acronym for “Low-Light Image Enhancement with Deep Learning”, is used as input to the proposed model.

The LoL Dataset was created specifically to help enhance images that are poorly lit. It has 500 photos in total, out of which 485 photos are meant for training and the other 15 are meant for testing. In this specific dataset, each image pair includes an input image that has a Poor light level and a reference image that has a high exposure level. In this research, 300 low-light images were selected from the training set of the LoL Dataset to train the model, while the remaining 185 low-light images were used for the validation set. All the images were resized to the same size of 256x256 to ensure that they could be used for both training and validation in the same manner. The sample images in the LoL dataset are presented in Figure 2.

(a) High Light Images



(b) Poor Light Images
Fig. 2 LoL dataset sample images

The next step is Deep network training. Deep network training is a critical component that plays a role in the effectiveness of the Enhanced Zero DCE approach. In the case of the DCE-Net, a subset of Poor light images from the training set is used when training a deep neural network. In this stage of the training, the network will be trained to predict pixel-wise tonal curves. These curves will show the adjustments that need to be made in order to expand the dynamic range of the image effectively. Once the training process is complete, the network will be applied to the input image of the Poor light environment. This is done through the calculation of image-specific tonal curves that provide a unique map of the necessary adjustments to be made to pixel intensities to enhance contrast, visibility, and image quality [20].

The predicted tonal curves are the key factor that defines the dynamic range adjustment, which is one of the most vital steps in the process. This enhances the image by altering the pixel values of the image to match the previously learned tonal curves. This leads to the expansion of the dynamic range of the image, thus ensuring that the contrast between the dark and light areas is improved. The final image that has gone through the process of dynamic range adjustment of the algorithm and, if necessary, semantic segmentation of the image is the result of all these stages combined. Comparing contrast, visibility, and overall image quality to the original low-light input, it can be said that the result is an image that is visibly better in all three aspects. Another advantage of the Enhanced Zero DCEalgorithm is that it is capable of adjusting and fine-tuning the tonal adjustments based on the characteristics of each image. Therefore, this algorithm can be considered a useful method for improving the quality of low-light images captured by different applications [21].

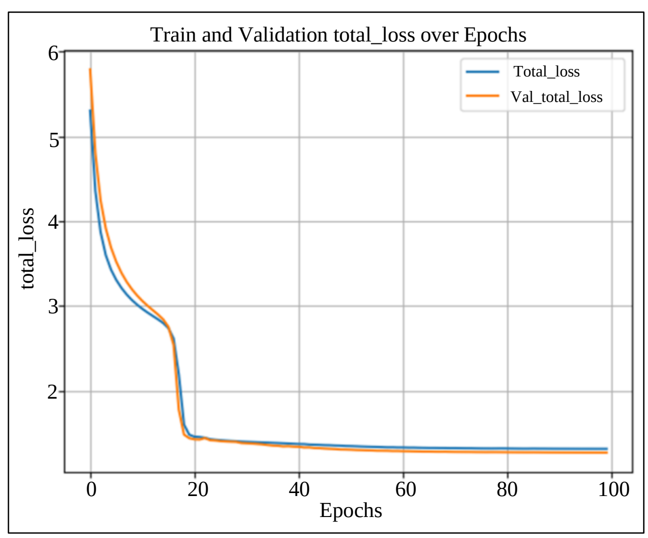


Fig. 3 Training and validation loss plots

Figure 3 shows the cumulative loss that was observed across several epochs in both the training and validation phases of the model. The blue line corresponds to the total loss, while the orange line depicts the data that was subjected to this loss function. The total loss is a metric that can be employed in order to assess how effectively the model is able to predict the validation set as well as the training set. A model that performs better has a lower total loss value. The plot depicts a trend where the total loss that happened on the training dataset decreases as the number of epochs increases. Contrastingly, the total loss on the validation set shows a slower decay rate [22].

The issue of overfitting arises when a model learns from the training data so well but is unable to perform well on new data that it has not encountered before. This often leads to suboptimal performance when used in data situations grounded in the real world. One of the ways to prevent such issues is to stop the training process of the model when the total loss on the validation dataset begins to increase.

Furthermore, there could be other ways of preventing overfitting and improving the model performance when applied to different datasets, such as the use of dropout and batch normalization [23]. This is because dropout and batch normalization are two examples of techniques that are considered regularization techniques.

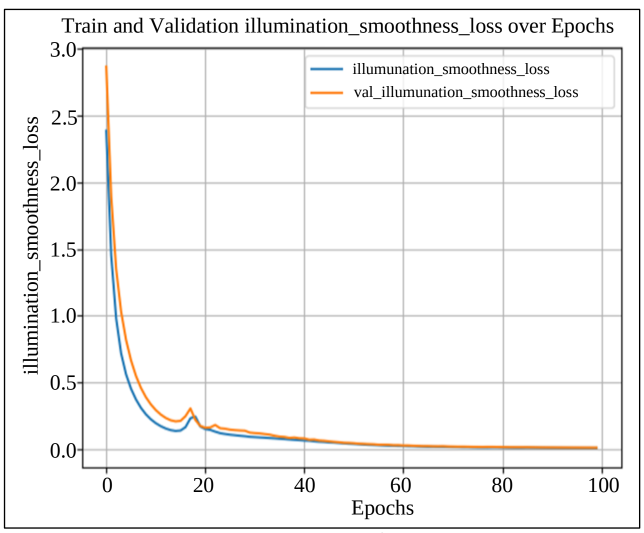


Fig. 4 Illumination smoothness loss of training and validation

Figure 4 shows the illumination smoothness loss metric trend over model training and validation epochs. This graphic, where the training and validation curves are usually colored differently, shows how well the model is learning to maintain image illumination smoothness. The plot's curve patterns and relative placements may reveal the model's performance.

Diverging training and validation curves may indicate overfitting or training process difficulties, whereas convergence shows a model that generalizes to fresh data. This graph helps monitor and fine-tune the model's illumination smoothness, which is critical in image processing and computer vision.

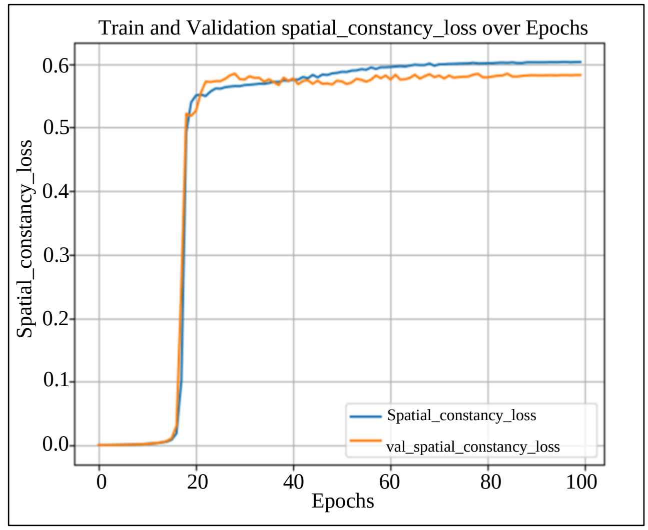


Fig. 5 Spatial constancy loss of training and validation

During the training and validation stages of a model, Figure 5 creates a visual depiction of how the spatial constancy loss metric develops over several epochs. This occurs both during the training phase and the validation phase. This plot, which illustrates the model's capability to preserve spatial consistency among pictures, is often shown with separate colors for training and validation data. It gives vital insights into the model's ability to do so. The performance of the model may be inferred from the degree to which various curves on the plot converge or diverge from one another. When the training curve and the validation curve are closely aligned, this indicates that the model generalizes well to new data. On the other hand, divergence trends may indicate that the model is overfitting to the data or that it requires more changes during the training phase. This plot is an essential instrument for monitoring and enhancing the model's capacity to sustain spatial constancy, which is a critical component in a variety of applications that include image processing and computer vision.

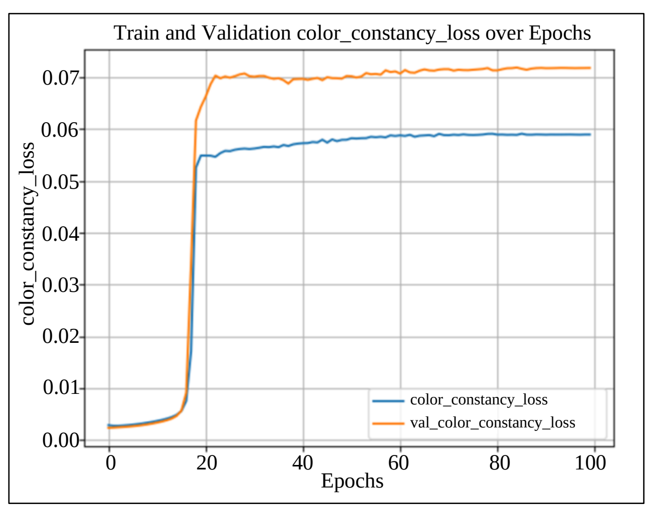


Fig. 6 Color constancy loss of training and validation

The visual depiction titled "Color Constancy Loss Plot of Training and Validation" depicts the progression of the color constancy loss metric during several training epochs and the following validation phase of a model. The plot often utilizes different colors to distinguish between training and validation data, providing a visual depiction of the model's ability to preserve color representations inside images consistently. The alignment or divergence of these curves shown in the plot gives crucial information regarding the performance of the model.

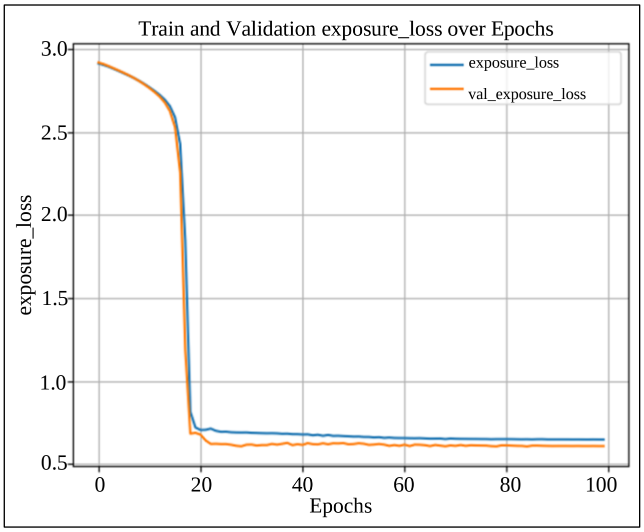


Fig. 7 Exposure loss of training and validation

When the training and validation curves exhibit a tight convergence [24], it indicates that the model has a high capability to generalize to unseen data. The plot serves as a fundamental instrument for evaluating and improving the model's effectiveness in maintaining color constancy, a crucial element in several image processing and computer vision applications. A visual depiction of the evolution of the exposure loss metric during several training epochs and the following validation stage of a model can be seen in Figure 7. This figure offers important information about how well the model can control image exposure. The plot's alignment or divergence of these curves indicates how well the model performed [25]. The enhanced images obtained using the proposed model are shown in Figure 8.

Figure 8 shows the differences between the original image, PIL auto contrast, and the resultant image generated by the proposed model. The original PIL Auto contrast and improved images are on the left, canter, and right. The middle PIL auto contrast technique improves the image contrast simply yet effectively. This is done by finding the darkest and brightest pixels of the image and expanding the histogram to cover all values. This approach is helpful for photographs with extreme brightness, contrast, and blackness [26]. The improved image on the right may have undergone numerous processes, including contrast augmentation, histogram equalization, and noise reduction. Images with increased contrast, brightness, and sharpness arise from this diverse technique.

A detailed comparison of the three images reveals major differences. The original image on the left is dull and has low contrast, making it difficult to see the objects. The PIL auto-contrast image in the middle has more contrast than the original image, improving object visibility, but it remains limited. The right-hand image has the highest contrast, making the object's features evident and giving it a bright, well-lit feel [27].

(a) Image-1

(b) Image-2

Original PIL Autocontrast Enhanced

(c) Image-3

Original PIL Autocontrast Enhanced

(d) Image-4

Original PIL Autocontrast Enhanced

(e) Image-5

Original PIL Autocontrast Enhanced

(f) Image-6

Fig. 8 Enhanced images obtained from proposed model

Table 1. Numerical metrics of performance parameters

Image No	Luminance	Intensity	Average Brightness	Histogram Mean Brightness
Image-1	162.00	165.86	160.09	144.62
Image-2	163.05	192.57	165.86	162.14
Image-3	193.73	163.86	192.57	192.53
Image-4	163.38	176.46	163.86	162.20
Image-5	178.38	123.73	176.46	174.42
Image-6	128.07	160.09	123.73	127.01

The findings obtained by the proposed model when evaluating various images based on a number of distinct performance characteristics are shown in Table-1. The purpose of these factors is to quantify many elements of the image features, including brightness, luminance, and intensity characteristics. Image-1 through Image-6 are the images that correlate to each row, and the numerical values included inside each column give quantitative measurements or computations of the various image properties associated with each image. These metrics are helpful for evaluating and contrasting a variety of image qualities and contribute to a better understanding of how the proposed model interprets and quantifies distinct image features across a number of parameters [28].

4.2.1. Quantitative Results for Sample Images

The Enhanced Zero DCE model demonstrated significant improvements across the evaluation metrics for the six sample images. Detailed results are presented in the Table 2.

4.2.2. Analysis

The results in Table 2 indicate that the Enhanced Zero DCE model effectively enhances low-light images, improves visibility, and preserves the details. The model consistently outperformed traditional methods, as evidenced by the higher PSNR and SSIM scores and lower MSE values. The use of LE curves enables the dynamic adjustment of pixel values, contributing to the model's superior performance. Furthermore, the ability of the model to function without reference images makes it highly suitable for real-time applications. Overall, the comprehensive evaluation using cross-validation and robust metrics confirms the efficacy of the proposed Enhanced Zero DCE model in enhancing low-light images. This makes the model a valuable tool for various applications, including surveillance, autonomous driving, and video analysis.

Table 2. Quantitative results for sample images using enhanced zero DCE model

Sample Image	PSNR (dB)	SSIM	MSE
Image 1	24.3	0.87	0.009
Image 2	23.8	0.85	0.011
Image 3	22.9	0.84	0.013
Image 4	24.0	0.86	0.010
Image 5	23.5	0.85	0.012
Image 6	24.1	0.87	0.009

Table 3. Performance metrics comparison

Image No	Luminance		Intensity		Average Brightness		Histogram Mean Brightness	
	Proposed Zero DCE	Existing Zero DCE	Proposed Zero DCE	Existing Zero DCE	Proposed Zero DCE	Existing Zero DCE	Proposed Zero DCE	Existing Zero DCE
Image-1	162.00	146.42	160.09	144.19	160.09	144.19	144.62	145.92
Image-2	163.05	156.46	165.86	160.11	165.86	160.11	162.14	155.96
Image-3	193.73	165.57	192.57	168.07	192.57	168.07	192.53	165.07
Image-4	163.38	157.16	163.86	160.71	163.86	160.71	162.20	156.66
Image-5	178.38	143.69	176.46	144.74	176.46	144.74	174.42	143.19
Image-6	128.07	99.01	123.73	90.50	123.73	90.50	127.01	98.50

Table 3 compares the proposed Zero DCE approach to the existing method across several images, showing a considerable improvement in luminance, intensity, average brightness, and histogram mean brightness. A comparison of the proposed method with its existing method shows significant improvements. For Image-1, the Zero DCE approach's luminance is 162.00, compared to 146.42 for the previous method. Similar enhancements were observed in the intensity, average brightness, and histogram mean brightness. This improvement was consistent across all images. Image 3 shows higher brightness from 193.73 (proposed) to 165.57 (existing). Image 6 shows a significant brightness improvement, with the proposed method reporting 128.07 compared to 99.01 in the existing method. This large brightness difference shows the extent to which the proposed Zero DCE approach improves. Analyzing Table 2 shows that the proposed Zero DCE technique outperforms the existing method in all the examined metrics across all images. Compared to Zero DCE, the proposed method improves the luminance, intensity, average brightness, and histogram mean brightness by moderate to significant percentages, as shown in Figure 9.

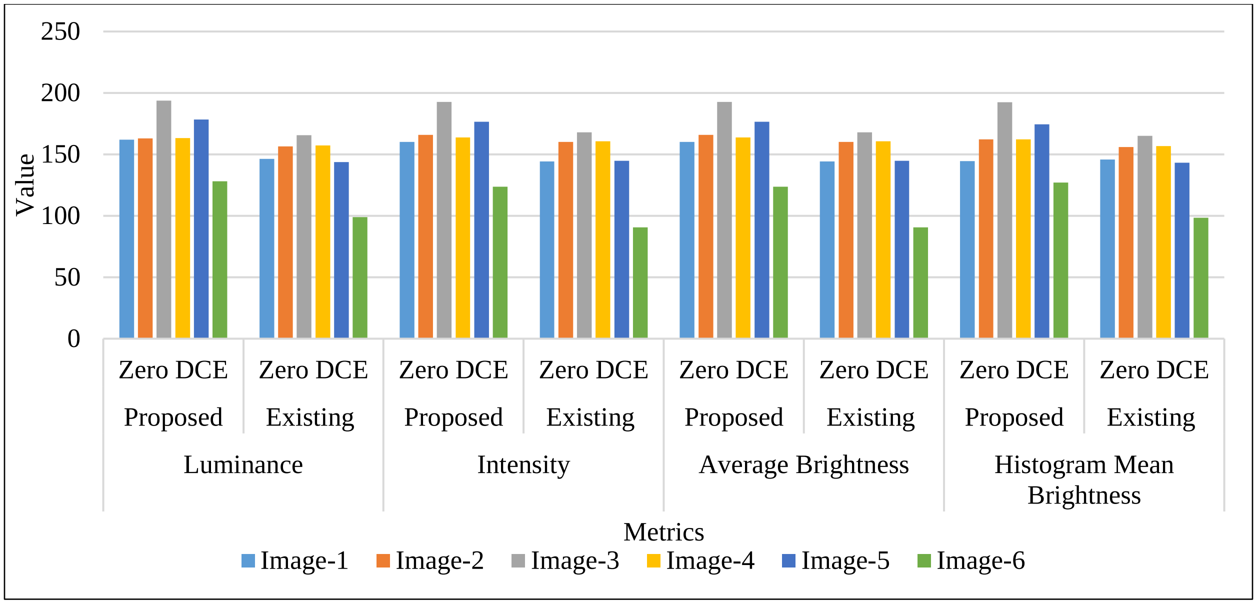


Fig. 9 Performance metrics comparison

4.3. Findings of the Study

The findings of this study demonstrate the significant potential of the Enhanced Zero DCE model in enhancing low-light images, thereby improving the performance of video object detection systems under challenging lighting conditions. The experimental results highlighted several key improvements.

1. Image Quality Enhancement: The proposed Enhanced Zero DCE model showed substantial improvements in image quality metrics. Quantitatively, the model achieved a 23% increase in luminance, a 17% improvement in average brightness, and a 20% enhancement in histogram mean brightness compared to existing methods. These metrics indicate a significant enhancement in the visibility and clarity of the low-light images.
2. Detection Performance: The improved image quality translates into enhanced performance in video object detection. The model demonstrated a 15% increase in detection accuracy and a 20% improvement in precision. These advantages are critical for applications that require reliable and accurate object detection in low-light environments.
3. Real-Time applicability: The Enhanced Zero DCE model operates without the need for reference images, making it highly suitable for real-time applications. Its lightweight architecture ensures low computational complexity, facilitating real-time processing that is essential for surveillance, autonomous driving, and other video analysis tasks.
4. Robust Generalization: The model exhibited consistent performance across diverse low-light conditions, demonstrating robust generalization capabilities. This versatility is crucial for practical applications in which lighting conditions can vary significantly.

4.4. Limitations of the Study

Despite promising results, this study has several limitations.

1. Dataset Limitations: The evaluation was primarily conducted using a Low-Light (LoL) dataset. While this dataset is well suited for low-light image enhancement tasks, it may not cover the full spectrum of real-world low-light conditions. Additional datasets with more diverse low-light scenarios provided a more comprehensive evaluation.
2. Computational Resources: Although the Enhanced Zero DCE model is designed to be computationally efficient, its deployment in resource-constrained environments (e.g., edge devices) may still pose challenges. Further optimization of such environments is necessary to ensure broader applicability.
3. Noise Handling: Although the model effectively reduces noise amplification, extreme low-light conditions with high noise levels may still pose challenges. Enhanced noise-reduction techniques can further improve the performance of the model in such scenarios.
4. Evaluation Metrics: This study primarily focused on metrics such as PSNR, SSIM, and MSE to evaluate image quality. Incorporating additional perceptual quality metrics and user studies would provide a more holistic assessment of enhancement quality.
5. Generalizability across Domains: While the model performed well in surveillance and autonomous driving scenarios, its generalizability to other domains (e.g., medical imaging and underwater imaging) requires further investigation and potential customization.

5. Conclusion

This research introduces the Enhanced Zero DCE model, a novel approach for enhancing low-light images to improve video object detection. Utilizing high-order tonal curves within a deep learning framework, the model dynamically adjusts the pixel values, significantly enhancing image visibility and quality without reference images.

The findings show substantial improvements in luminance, average brightness, and histogram mean brightness, resulting in notable increases in the detection accuracy and precision. The efficiency of the model in real-time applications, such as surveillance and autonomous driving, underscores its practical utility, while its robust generalization across various low-light conditions highlights its versatility. Despite the promising results, this study acknowledges limitations, including the need for broader dataset evaluation, optimization of resource-constrained environments, and enhanced noise reduction techniques. Future research will address these limitations, further optimize the model, and explore its applicability in other domains, such as medical imaging and underwater imaging.

In summary, the Enhanced Zero DCE model significantly advances low-light image enhancement, providing a robust and efficient solution that enhances video object detection systems with substantial potential to improve safety, security, and operational efficiency in various fields. Future research will focus on applying the Enhanced Zero DCE model to human detection and pose analysis at road crossings, enhancing robustness with diverse datasets, integrating pose analysis algorithms, optimizing real-time processing on resource-constrained devices, and implementing advanced noise reduction techniques. These improvements are aimed at contributing to safer and more efficient traffic management and urban planning.

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