LOW-LIGHT IMAGE ENHANCEMENT USING A CONVOLUTIONAL ATTENTION MECHANISM IN THE ZERODCE FRAMEWORK

Thesis Submitted
in Partial Fulfillment of the Requirements for the Degree of

MASTER OF TECHNOLOGY

in

Data Science

by

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May, 2026



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ACKNOWLEDGEMENT

I would like to express my sincere gratitude to Dr.Sanjay Patidar, Assistant Professor, Department of Software Engineering, Delhi Technological University, for his invaluable guidance, support, and encouragement throughout the preparation of this seminar report. His insights and expertise were instrumental in shaping the direction of my research.

I am grateful to the faculty members and my peers at the Department of Software Engineering, Delhi Technological University, for their continuous encouragement and constructive feedback.

Finally, I would like to thank my family and friends for their unwavering support and motivation during the course of this work.

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The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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Low-Light Image Enhancement Using a Convolutional Attention Mechanism in the ZeroDCE Framework

Sumit Singh

ABSTRACT

Image exposure correction and low-light image enhancement are important problems in computer vision due to their significant impact on image quality and downstream vision applications. Existing enhancement approaches often suffer from issues such as noise amplification, color distortion, loss of structural details, and limited adaptability to varying illumination conditions. Although recent deep learning-based methods achieve improved enhancement quality, many of them rely on computationally expensive architectures and large-scale paired datasets for training. The current thesis provides an in-depth discussion of methods used for exposure correction and introduces two efficient zero-reference enhancement models based on the ZeroDCE framework. While the former is extended using the CBAM for more precise spatially-adaptive feature refinement, the latter one utilizes a new technique called the Exposure Guided Attention (EGA). Both models rely on the self-supervised training using the losses without the need for pair-supervision during the process. Experimental results show that the use of the introduced architectures leads to improvements in terms of image quality, preservation of the image structure and perceptual similarity while being computationally-efficient. In particular, the newly-proposed framework based on the utilization of EGA achieves significant improvements compared to the baseline ZeroDCE method as it increases the value of PSNR by 6.85 dB (from 10.57 dB to 17.42 dB) and the SSIM score by 0.249 (from 0.233 to 0.482).

List of Publications

1. Sumit Singh, ZeroDCE-CBAM: Lightweight Spatial-Channel Aware Illumination Enhancement for Images, 9th International Conference on Innovative Computing and Communication (ICICC), 2026.

2. Sumit Singh, Image Exposure Correction: A Comprehensive Review, 7th International Conference on Data Analytics & Management (ICDAM), 2026.

3. Sumit Singh, EGA-Enhanced Zero-DCE for Low-Light Image Enhancement, International Conference on Intelligent Computing, Control & Communication (ICICCC), 2026. (Under-consideration)

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List of Symbols

$I(x)$	Input low-light image
$LE_n(x)$	Enhanced image after the n^{th} enhancement iteration
$A_n(x)$	Pixel-wise enhancement curve parameter estimated by ZeroDCE
F	Intermediate feature representation extracted from the network
F_{ega}	Exposure-guided refined feature representation
$M_c(F)$	Channel attention map generated by CBAM
$M_s(F)$	Spatial attention map generated by CBAM
M_{ega}	Exposure Guided Attention map
$D(x)$	Darkness-aware guidance mask
σ	Sigmoid activation function
$\otimes$	Element-wise multiplication
$Conv(\cdot)$	Convolution operation
L_{total}	Total composite loss function
L_{spa}	Spatial consistency loss
L_{exp}	Exposure control loss
L_{col}	Color constancy loss
L_{tvA}	Illumination smoothness loss
$PSNR$	Peak Signal-to-Noise Ratio
$SSIM$	Structural Similarity Index
$CBAM$	Convolutional Block Attention Module
EGA	Exposure Guided Attention
LOL	Low-Light dataset
$ExDark$	Exclusively Dark dataset
GPU	Graphics Processing Unit

Chapter 1

INTRODUCTION

The task of enhancing images under difficult lighting conditions poses one of the key problems in computer vision since it impacts both visual quality and the success of related tasks such as surveillance, robotics, automation, object detection, and so on. The problem of enhancement arises from the presence of low contrast, color cast, noise, and lack of structure in the case of images taken under insufficient illumination, while saturated and distorted images can be obtained during overexposure of the scene. Consequently, efficient enhancement procedures should work for various lighting conditions.

Prior enhancement approaches involved manually developed statistical and physical-based algorithms. In particular, retinex-based approaches, e.g., SSR & MSR [1] and lightness correction methods [2], were used for dealing with nonuniform illumination. Recent advances in deep learning brought new promising approaches such as EnlightenGAN [3] and zero-reference methods like ZeroDCE [4]. They demonstrate improved visual quality and computational efficiency in comparison to previous solutions; however, they either demand heavy computational resources or use globally operating algorithms which do not work well under spatially variant lighting conditions.

In this regard, researches have been conducted in Retinex-based deep models [1], Transformer architectures [5], and diffusion-based methods [6, 7, 8, 9]. These methods show impressive results regarding the image's perceptual quality but require more computational complexity. Besides, unified exposure correction approaches [10, 11, 12, 13, 14] aim to solve both issues of over- and under-exposed regions simultaneously. However, this approach is accompanied by extra architecture and computational overheads. However, despite progress in these fields, several issues still remain unsolved including noise amplification, inconsistent colors, and low cross-dataset performance [15].

In order to solve the mentioned shortcomings, the thesis first introduces an attention-guided enhancement framework called *ZeroDCE-CBAM*, where the Convolutional Block Attention Module (CBAM) [16] is embedded within the ZeroDCE framework. With the introduction of channel and spatial attention modules, the proposed framework is capable of enhancing region-wise with the properties of lightweight and zero-reference



Figure 1.1: Comparison between low-light input image and enhanced output image.

enhancement. In addition, an enhanced ZeroDCE framework called *EGA-Enhanced ZeroDCE* is introduced with an additional illumination-aware module called *Exposure Guided Attention (EGA)*. The EGA module leverages the darkness-aware feature modulation in order to enhance only the severely underexposed areas while suppressing unreliable features. It is worth mentioning that this enhancement allows for more spatially adaptive and consistent features without increasing computation and being zero-reference.

Experimental evaluations conducted on benchmark data sets have revealed the improved efficiency of the proposed approaches in retaining structural information, improving perceptual quality, and achieving uniform illumination. It is worth mentioning that the EGA-optimized model has achieved significant improvement in the performance of the ZeroDCE base algorithm without affecting its feasibility for real-time operations.

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Several experiments conducted on benchmark datasets have revealed that the presented approaches show improved efficiency in terms of structure preservation, perceptual quality improvement, and constant illumination. Importantly, the architecture based on the EGA method has shown impressive improvements in the performance of the ZeroDCE baseline technique while retaining its applicability for real-time process-

ing.

1.1 Background

The issue of image exposure correction has witnessed great improvements, progressing from the classical image processing approach to advanced machine learning approaches that handle low light conditions and excessive exposures. Classical methods involved statistical and physics-based models used to generate images, where Retinex theory [1] formed the basis of the theoretical framework. The concept involved representing an image as a product of two factors, namely illumination and reflectance, hence giving rise to variations of the technique known as Single-Scale Retinex (SSR) and Multi-Scale Retinex (MSR) used in visibility improvement through illumination modeling and dynamic range correction. Some of the classical techniques include histogram equalization, gamma correction, and illumination map estimation methods such as LIME [17]. Such techniques involve enhancing the brightness and contrast of an image using transformation of intensity levels globally. Nonetheless, these algorithms failed to preserve colors, created artifacts, and could not be applied in more complex illumination environments [2, 18]. Even comparative studies conducted on classical methods showed their weaknesses in handling real-world illumination changes [19, 20].

The development of deep learning approaches facilitated the usage of learning-based algorithms that could accurately approximate challenging illumination scenarios from raw data. Supervised learning-based methods such as deep Retinex decomposition [21] and CNN-based image enhancement algorithms [22] relied on the usage of paired data to learn the function of transforming dark images into bright ones. An alternative to the above approaches was the use of GANs for improving the perceptual quality of images. Among the most sophisticated solutions, there was EnlightenGAN [3]. Another application area of GANs is night-to-day image translation [23, 24]. Transformer-based approaches such as RetinexFormer [5] and semantic-aware image enhancement [25], and even more sophisticated approaches based on diffusion models [6, 7, 26, 8] represent promising alternatives for illumination transfer in complex and highly exposed cases. Despite the effectiveness of the approaches described above, they are usually very resource-intensive and unsuitable for real-time applications.

The problem of the need for paired data is addressed through the advent of zero-reference learning approaches. One such zero-reference approach is known as Zero-

Reference Deep Curve Estimation (ZeroDCE). In this framework, the image enhancement problem is converted to a curve estimation problem through a loss function which does not require any paired data for training. Some other developments in this domain include light-weight models such as Zero-DCE++, Zero-DCE Tiny, and DA-Zero-DCE that also make use of attention-based image enhancement techniques. These approaches have been applied to tasks like object detection [27, 28, 29] and night vision surveillance [30]. However, most zero-reference approaches operate on a global level and thus are unsuitable for illumination adaptation tasks.

Simultaneously, unified exposure correction algorithms have proposed methods that address exposure issues in both overexposed and underexposed areas at once [10, 11, 12, 13, 14]. Moreover, more recent research on exposure correction has focused on the issue under dynamic conditions as well as challenging environments with harsh lighting [31, 9]. However, while such techniques enhance robustness, they also add complexity and computational cost. Therefore, efficient high-resolution enhancement models have become increasingly popular [32].

Recently, it has been observed that attention mechanisms play an important role in enhancing the feature representation capabilities of deep learning models. The Convolutional Block Attention Module (CBAM) [16] uses sequential channel and spatial attention to emphasize on useful features and suppress the unnecessary ones. It leads to increased spatial adaptability. The saliency guided enhancement schemes [33, 34, 35, 36] and attention based object detection methods [37, 38, 39] provide examples for the usefulness of attention mechanisms in enhancing feature representations. Moreover, integrating attention mechanisms in lightweight networks can be used to compensate for the weaknesses of global feature enhancement approaches. This motivated us to propose the *ZeroDCE-CBAM* framework which combines zero-reference learning with spatial feature enhancement.

Despite the benefits provided by CBAM-enhanced ZeroDCE in dealing with spatially varying illumination conditions, severe underexposures still affect its performance negatively due to lack of reliable feature representations and inadequate illumination guidance in image enhancement. Traditionally, attention-based methods depend only on learned feature representations and ignore the role of illumination in guiding feature enhancement. For this reason, enhancement in highly dark regions is often associated with texture blurring, noise corruption, and inconsistent feature propagation.

In order to overcome these drawbacks, some research works have been directed towards the development of illumination-aware and exposure-guided feature enhance-

ment mechanisms. In the light of the ZeroDCE-CBAM framework, we propose the *EGA-Enhanced ZeroDCE* model, which employs an *Exposure Guided Attention (EGA)* mechanism to enhance the feature representation of severely underexposed regions using darkness-aware feature modulation. Through the introduction of illumination knowledge to the attention model, our framework addresses spatial inconsistencies, eliminates unreliable activations, and preserves image structures without compromising lightweight and zero-reference properties.

However, in most cases, the development process of exposure correction methods indicates that there is always some sort of balance between perceptual quality improvement, flexibility, and computational cost. While deep learning models can generate outstanding results, they require enormous amounts of computing power, making them hard to apply in practice, where lighting conditions may vary too widely for simple solutions. Therefore, efficient illumination-aware image enhancement techniques will emerge.

1.2 Motivation

Image exposure correction and low-light image enhancement continue to be significant challenges in computer vision because of the diverse illumination conditions experienced in real-world settings, which include low-light, over-exposed, and mixed-exposure images. Images taken in such conditions often lack good contrast, contain noise, have poor color, and structural information losses that negatively impact their appearance and the performance of the vision applications using them. Although conventional techniques like histogram equalization, gamma correction, and Retinex model enhance the illumination conditions to an extent, they cause artifacts, add more noise, and struggle to cope with illumination conditions varying across space.

Advancements in deep learning have greatly enhanced the quality of enhancement through zero-reference models, GAN-based models, Transformer-based models, and diffusion models. Nevertheless, many current methods still suffer from several shortcomings such as computational complexity, dependence on paired data, poor generalization capability between datasets, lack of consistent evaluation protocol, and incapability of handling severely under-exposed areas. Zero-reference models like ZeroDCE allow efficient enhancement in a way that does not need paired supervision; however, their dependence on global feature representation makes them less adaptable to different illumination conditions. In addition, current enhancement methods based

on attention mechanism enhance feature refinement; however, they fail to consider illumination-awareness in the enhancement procedure.

This justifies the necessity of conducting a thorough investigation on exposure correction methods as well as the design of efficient and adaptive enhancement systems, which can work effectively under difficult illumination situations while remaining computationally affordable. It is in this context that the current thesis is motivated to propose efficient zero-reference enhancement systems based on spatial attention and illumination-dependent feature adjustment for enhancing images in severely low-light and non-uniform illumination scenarios.

1.3 Problem Statement

Image enhancement in various lighting situations such as low lighting, high exposure, and mixed exposure settings is still an open issue in computer vision. Images taken under such settings are prone to lack of contrast, color aberration, noise, and structural information, and have a negative impact on human perception and computer vision applications. Enhancement techniques based on histogram equalization, gamma correction, and Retinex theory [1] use hand-crafted priors and global operations, and hence are limited in complex lighting scenarios [2].

Recent deep learning methods, especially those based on generative models like EnlightenGAN [3], zero-reference models like ZeroDCE [4], Transformer models, and diffusion models [5, 6, 7] have been shown to produce better enhancement results. However, most of these methods are characterized by high computational complexity, need for paired datasets, and low generalization capability across different datasets and illumination conditions. In addition, unified exposure correction techniques that correct under-exposure and over-exposure tend to add extra architectural complexities [10, 11, 12, 13, 14].

Even though zero-reference models that are computationally light such as ZeroDCE offer efficient enhancement without the need for paired supervision, they depend on global features and hence limit the adaptation capabilities to spatially varying illumination conditions. Models such as ZeroDCE-CBAM that utilize attention mechanisms to improve spatial adaptability lack illumination-based guidance for underexposed regions.

The key challenges in this research are summarized as follows:

- Traditional enhancement techniques cannot effectively process illumination vari-

ations in complex scenarios.

- Deep-learning techniques are usually based on paired datasets and large-scale models that are difficult to apply to real cases.
- Light-weight zero-reference techniques are not sufficiently adaptive under extremely low-light illumination.
- Illumination-aware enhancement techniques are not considered in current attention modules.
- Underexposed image areas may suffer from unreliable feature representation and loss of details and noise in the enhancement procedure.
- Lack of standardized datasets and evaluation measures makes the comparison between enhancement techniques very hard.

The motivation of this thesis is to develop efficient, adaptive, and illumination-aware enhancement frameworks to improve visibility, structure recovery, and perceptual quality. To solve the above issues, this thesis presents attention-guided zero-reference enhancement frameworks based on the ZeroDCE framework, including spatial feature refinement using CBAM and illumination-aware enhancement using Exposure Guided Attention (EGA).

1.4 Objectives

The overall goal of this research is to propose effective and adaptive image enhancement algorithms that could improve images obtained under different conditions, namely low illumination, overexposure, and a combination of these issues. In addition, the proposed framework should be computationally efficient, enabling its applicability in a wide range of practical tasks.

The research will be carried out under the following objectives:

1. Investigate and compare different traditional and deep learning-based exposure correction algorithms under varied lighting scenarios in order to determine their advantages, disadvantages, and challenges in research.
2. Design efficient image enhancement algorithms that can cope with non-uniform lighting and also possess the capabilities of computational efficiency and zero-reference learning.

3. Assess the developed algorithms through quantitative and qualitative evaluations.

1.5 Technology Used

1.5.1 Self-Supervised Learning

Conventional supervised low-light image enhancement techniques require paired datasets that contain dark and well-lit instances of the same scene. However, obtaining such paired observations under similar illumi- nation and exposure conditions is often challenging, cumbersome, and impractical. Furthermore, benchmark datasets (LOL, SICE) lack scales and variety in scenes, which can lead to overfitting and poor generaliza- tion when trained models are applied to different lighting environments. For this reason, we consider a self-supervised learning framework, which is where the model can directly train and utilize large amounts of unpaired or unlabeled low-light images, becomes applicable.

Self-supervised learning (SSL) allows the model to learn meaningful illumination representations without any explicit ground-truth supervision. The model does not rely on labeled dark and well-lit pairs. Instead, SSL exploits constraints and objectives defined internally (which are derived from the input image) to learn self-regularization. In the low-light image enhancement task, a network could be trained to improve visibility while preserving natural color balance and structural invariance. It does this by minimizing task-specific loss functions that measure for qualities of illumination, exposure uniformity, and spatial smoothness.

In the proposed framework, the ZeroDCE-CBAM model follows a self-supervised paradigm that estimates an illumination adjustment curve directly from the input image. The Convolutional Block Attention Module (CBAM) is a attention mechanism embedded in ZeroDCE architecture in order to introduce a spatial and channel based attention to the model that can help the model to predict the curve based on different regions of the image. Different self-supervised losses are used in order to train the model such as exposure control loss, color constancy loss, illumination smoothness loss, and spatial consistency loss. These objectives collectively ensure that the network learns to restore the illumination of the image and preserve fine image details without requiring any paired supervision.

By employing this self-supervised approach, the proposed method does not rely on

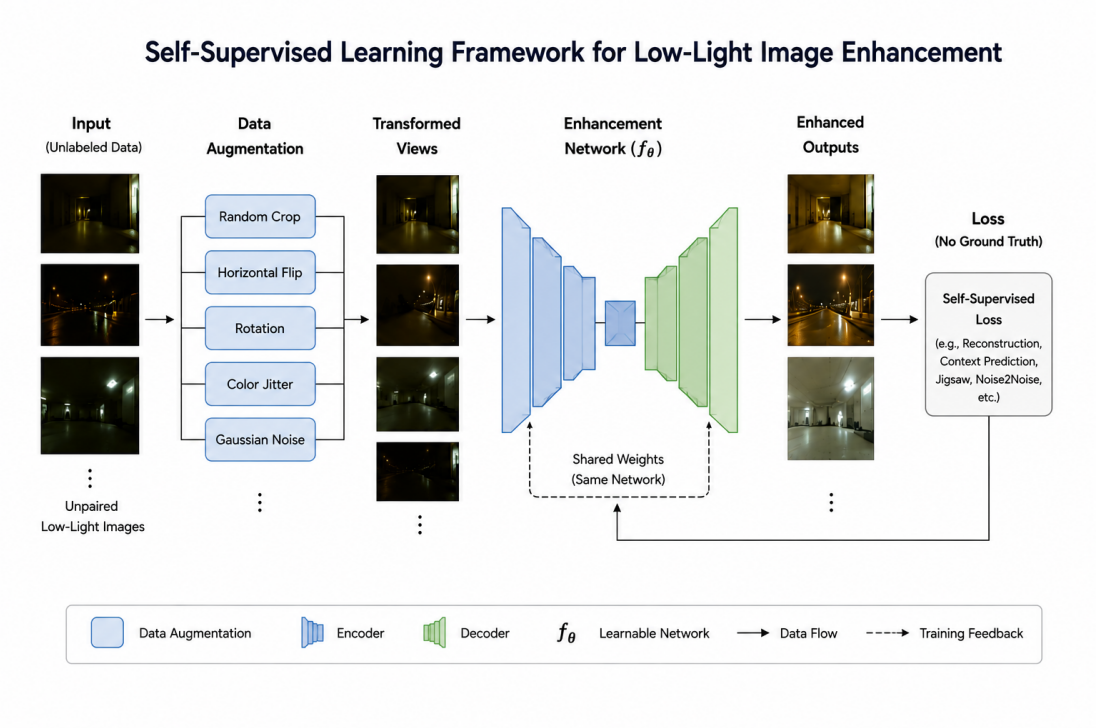


Figure 1.2: Self-supervised learning framework for low-light image enhancement using unlabeled low-light images and enhancement consistency learning.

labeled training data, yet allows for greater generalization across different real-world lighting conditions. The network learns the structure, color, and illumination relationship from the input image itself and through the various losses demonstrates better visual quality through even the most complex environments such as glare, shadows, or uneven lighting.

1.5.2 Image Enhancement Framework

The proposed image enhancement framework uses a generative framework to enhance low-light images by recovering their original illumination and color balance without requiring paired data. Generative models can learn to produce well-illuminated representations of low-light images without compromising the structural and chromatic integrity of the scene. Recent developments in generative modeling include the estimation of illumination curves, attention-based feature learning, and illumination aware refinement, which greatly improve the output of enhanced low-light images.

In our study, we use a hybrid enhancement network using the Zero-DCE model framework. The model learns the per-pixel illumination correction curves in a self-supervised manner and applies them iteratively to enhance the luminosity of the im-

ages without altering the contrast and textures. In order to boost spatial adaptability, a Convolutional Block Attention Module (CBAM) is used to enhance the learned features with spatial and channel-wise attention. This helps in focusing on the informative parts of the input image. Based on the above framework, a new Exposure Guided Attention (EGA) module is employed to boost the enhancement performance on severely underexposed regions. Unlike the traditional attention modules that consider only the learned importance of the features, our EGA module adopts a new dark-aware feature modulation scheme with the inclusion of illumination priors through the guidance of exposure level of each region. Our model is capable of refining the unreliable feature responses while ensuring structural coherence in regions with extreme illumination issues. As a result, our network can preserve fine-grained textures and edges as well as semantic details even while retaining the lightweight nature of our baseline ZeroDCE.

In conclusion, we have shown how our enhancement framework combines curve estimation interpretability, attention-guided feature refinement, and illumination-aware enhancement techniques to provide an effective solution to enhancing images acquired in low-light and unbalanced illumination scenarios.

1.5.3 Loss Function Design

The proposed **ZeroDCE-CBAM** model is a zero-reference, self-supervised model trained using different loss functions that guides the network to generate bright, color-consistent, structurally integrity, and artifact-free enhanced images without the need for ground-truth images. Each component of the total objective function targets a distinct aspect of perceptual image quality.

Exposure Control Loss ($\mathcal{L}$exp) This loss controls the brightness of the overall image by ensuring that we expose each local patch $\mathbf{P}i$ of the image to a desired amount of exposure E_t (typically, we set this to 0.6). It treats the overexposed and underexposed parts independently:

$$\mathcal{L}\text{exp} = \frac{1}{M} \sum i = 1^{M} \left(\mu(\mathbf{P}_i) - E_t\right)^2 \tag{1.1}$$

Color Constancy Loss ($\mathcal{L}$col) This loss function makes certain that there is not any unnatural color shift in the generated image. The loss function penalizes the variability in mean intensities for different RGB channels (μ_c). This preserves stability in any

relative relationships between the channels:

$$\mathcal{L}_{\text{col}} = \sum_{(c_1,c_2)\in\{(R,G),(R,B),(G,B)\}} \|\mu_{c_1} - \mu_{c_2}\|_2 \tag{1.2}$$

Illumination Smoothness Loss ($\mathcal{L}$smooth) The regularization term promotes spatial smoothness in the estimated enhancement curve map $\mathcal{R}$, while crucial edge structures remain partially preserved. The penalty varies according to the gradients of the image **I**in with an edge-sensitivity parameter λ (which is set to 10 empirically).

$$\mathcal{L}\text{smooth} = \sum i, j\Big(|\nabla_x \mathcal{R} i, j| \exp\left(-\lambda |\nabla_x \mathbf{I}\text{in}, i, j|\right) + |\nabla_y \mathcal{R} i, j| \exp\left(-\lambda |\nabla_y \mathbf{I}\text{in}, i, j|\right) \Big) \tag{1.3}$$

Spatial Consistency Loss ($\mathcal{L}$spatial) This term diminishes the difference in their respective gradient fields to sustain structure stability between the input **I**in, in, and the enhanced output, **I**enh. This term preserves texture and boundary detail present in the input that is relevant to perceptual realism:

$$\mathcal{L}_{\text{spatial}} = \sum_{d\in\{x,y\}} \|\nabla_d(\mathbf{I}_{\text{in}}) - \nabla_d(\mathbf{I}_{\text{enh}})\|_2^2 \tag{1.4}$$

Total Objective Function: The overall training objective is defined as a weighted combination of all the above components:

$$\mathcal{L}\text{total} = \lambda_1 \mathcal{L}\text{exp} + \lambda_2 \mathcal{L}\text{col} + \lambda_3 \mathcal{L}\text{smooth} + \lambda_4 \mathcal{L}_{\text{spatial}} \tag{1.5}$$

In this instance, λ_1, λ_2, λ_3, and λ_4 has been defined as balancing coefficients to modulate the relative importance of each term, empirically set to 10, 25, 200 and 1 respectively. This composite loss function facilitates perceptually meaningful enhancement through optimizing brightness, color balance, structural smoothness and spatial coherency in a single unified term in an unsupervised learning setting.

1.5.4 Evaluation Metrics Used

The quantitative enhancement performance of the conventional algorithm and proposed **ZeroDCE-CBAM** model are evaluated on the **LOL dataset** using both full-reference and no-reference image quality metrics. The metrics used collectively measures the brightness restoration, structural integrity, and naturalness of the image converted from low light conditions.These metrics not only measures the objective of the

model but also measures the prospective improvement and fidelity of the model.

1. Peak Signal-to-Noise Ratio (PSNR): PSNR is a full-reference metric that measures the ratio between the maximum possible power of a signal and the maximum amount of corruption that can happen in a signal affecting its fidelity. In our case its the intensity value and the mean squared error (MSE) between the enhanced and reference (well-illuminated) images. A higher PSNR value indicates better reconstruction quality and fewer distortions introduced during enhancement of the input image.

$$\text{PSNR} = 10 \log_{10} \left(\frac{MAX_I^2}{MSE} \right) \tag{1.6}$$

2. Structural Similarity Index Measure (SSIM): SSIM is another full-reference metric that measures the similarity between the input image and output image considering the luminance, contrast and structure. SSIM values range from 0 to 1, with values closer to 1 representing higher structural fidelity.

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{1.7}$$

3. BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator): BRISQUE is a measurement that automatically scores the quality of image without the need of a reference image ie original image.

It computes Mean Subtracted Contrast Normalized (MSCN) coefficients:

$$\hat{I}(i, j) = \frac{I(i, j) - \mu(i, j)}{\sigma(i, j) + C} \tag{1.8}$$

where $\mu(i, j)$ and $\sigma(i, j)$ denote local mean and variance computed over a Gaussian window, and C is a small stabilizing constant. The distribution of MSCN coefficients and their pairwise products are modeled by a Generalized Gaussian Distribution (GGD):

$$p(x; \alpha, \sigma^2) = \frac{\alpha}{2\beta\Gamma(1/\alpha)} \exp\left[- \left(\frac{|x|}{\beta} \right)^{\alpha} \right] \tag{1.9}$$

where α controls the shape and $\beta = \sigma \sqrt{\frac{\Gamma(1/\alpha)}{\Gamma(3/\alpha)}}$. The final BRISQUE score is obtained by evaluating these features using a trained regression model:

$$\text{BRISQUE} = g(\mathbf{f}_{\text{BRISQUE}}) \tag{1.10}$$

4. PIQE (Perception-based Image Quality Evaluator): PIQE objectively assess the

output image on how the human will perceive the image's quality without the need of reference image.

For each block B_k of the image I, a local distortion measure is defined as:

$$D(B_k) = w_k \cdot \frac{\sigma_{B_k}}{\mu_{B_k} + \epsilon} \tag{1.11}$$

where μ_{B_k} and σ_{B_k} are the block mean and standard deviation, w_k is a perceptual weighting factor, and ϵ is a small positive constant. Overall PIQE is calculated as follows:

$$\text{PIQE} = \frac{1}{N_v} \sum_{k=1}^{N_v} D(B_k) \tag{1.12}$$

As can be seen from the use of both full-reference (PSNR, SSIM) and no-reference (BRISQUE, PIQE) metrics, this research presents a detailed assessment of the model's performance through quantitative measures. PSNR and SSIM reflect the pixel-based precision and structural similarity in relation to the illumination of the reference image. BRISQUE and PIQE evaluate the perceptual realism and naturalness of the output images. All these metrics prove that the suggested **ZeroDCE-CBAM** model produces high-quality results.

1.6 Thesis Structure

The remaining part of the thesis is structured as follows:

- **Chapter 2 – Literature Review:** Explains prior work related to image exposure correction and low-light image enhancement, including traditional enhancement methods, zero-reference frameworks, GAN-based approaches, Transformer and diffusion-based models, along with commonly used datasets and evaluation metrics.

- **Chapter 3 - Methodology:** Gives a brief overview of the research methodology that has been used in this thesis. This includes literature review, data set selection, evaluation metrics, model architecture, training, attention module integration, and the proposed ZeroDCE-CBAM and EGA-Enhanced ZeroDCE models.

- **Chapter 4 - Experimental Setup:** Discusses the experimental setup used in implementing the proposed enhancement frameworks. This includes information about datasets, training parameters, evaluation metrics, and frameworks used.

- **Chapter 5 - Results and Analysis:** Analyzes both the qualitative and quantitative results obtained using the proposed enhancement frameworks. This chapter also includes comparisons between the results of the proposed framework and other state-of-the-art methods.
- **Chapter 6 - Conclusion and Future Work:** Includes the summary of this thesis, its contributions, and the future scope of research on image exposure correction and low-light image enhancement.

Chapter 2

LITERATURE REVIEW

Image correction and enhancement under low lighting are among the most actively studied topics in computer vision due to their practical significance for image quality and subsequent vision tasks. Pictures taken in difficult light conditions often feature reduced contrast, heavy noise, distorted colors, poor visibility, and lack of structure, thus having negative consequences for applications in surveillance, robotics, medicine, and other areas where automatic vision plays a significant role. As natural lighting is both non-stationary and uncontrollable, the creation of adaptive and robust image enhancement techniques is of great importance for today's vision-related research.

Early methods for enhancing images focused on manually constructed image processing methods based on statistics and illumination models of physics. Conventional methods such as histogram equalization, gamma correction, and Retinex-based enhancement were proposed to enhance visibility through global intensity adjustments and illumination decomposition. The Retinex model [1] emerged as one of the first illumination correction methods, giving rise to single-scale retinex (SSR) and multi-scale retinex (MSR) methods. Illumination correction using lightness-chrominance decomposition was further investigated by Guo et al. [2] in order to correct exposure. Despite being efficient, these methods often led to noise amplification, color discrepancies, and halos under varying illumination.

With the continuous development of deep learning techniques, the traditional image enhancement methods have been increasingly evolving towards data-driven approaches that can learn the complicated lighting conditions directly from image samples. These include GAN-based approaches such as EnlightenGAN [3], zero-reference approaches such as ZeroDCE [4], and recently Transformer and diffusion-based approaches [5, 6, 7]. The lightweight zero-reference approaches exhibited high efficiency in computation while the Transformer and diffusion-based approaches showcased excellent capabilities of contextual modeling and lighting recovery.

Recent studies also explored attention-guided enhancement strategies for improving spatial adaptability and feature refinement. Attention-based frameworks utilizing channel attention, spatial attention, and feature modulation [16, 34, 35] demonstrated improved structural preservation and perceptual enhancement under low-light conditions. However, many existing enhancement approaches still suffer from limitations

such as high computational complexity, dependency on paired datasets, poor generalization, and inadequate handling of severely underexposed regions.

This chapter presents a comprehensive review of existing exposure correction and low-light image enhancement methods, including traditional image enhancement techniques, deep learning-based frameworks, zero-reference enhancement methods, attention-guided feature refinement approaches, and illumination-aware enhancement strategies. The chapter also discusses commonly used benchmark datasets, evaluation metrics, and the major research challenges identified in the literature that motivate the development of the proposed ZeroDCE-CBAM and EGA-Enhanced ZeroDCE frameworks.

2.1 Traditional Image Enhancement Methods

Traditional image enhancement methods mainly relied on handcrafted image processing techniques such as histogram equalization, gamma correction, and Retinex-based illumination decomposition. These approaches aimed to improve image visibility through global intensity transformations and illumination normalization under low-light and exposure-degraded conditions.

The Retinex theory formulated by Rahman et al. [1] is considered one of the most important theories in illumination correction, which resulted in algorithms such as the Single Scale Retinex (SSR) and the Multi Scale Retinex (MSR). Guo et al. [2] used lightness chrominance decomposition in illumination correction to enhance exposure. These algorithms have been shown to work effectively in terms of enhancing brightness and contrast; however, they tend to amplify noise, distort colors, generate halos, and lack flexibility under spatially varying illumination.

Despite substantial advancement compared to the conventional approaches, most of these frameworks are subject to constraints such as paired datasets, heavy computational costs, and poor adaptability across varying illuminations.

2.2 Deep Learning-Based Enhancement Frameworks

Recent advancements in deep learning have significantly improved image enhancement performance by learning illumination transformations directly from image data. GAN-based frameworks such as EnlightenGAN [3] demonstrated strong perceptual enhancement capability without requiring paired supervision. More recent Transformer-based and diffusion-based methods [5, 6, 7, 8, 9] further improved contextual feature

learning and enhancement quality under complex illumination conditions.

Several unified exposure correction frameworks [10, 11, 12, 13, 14] were also proposed to simultaneously handle under-exposed and over-exposed regions within a single architecture. Although these methods improve enhancement flexibility and perceptual quality, they often introduce high computational complexity and reduced efficiency for real-time applications.

Despite significant improvement over traditional methods, many deep learning-based enhancement frameworks still suffer from dependency on paired datasets, computationally expensive architectures, and limited generalization under varying illumination conditions.

2.3 Zero-Reference Low-Light Enhancement

The concept of zero-reference enhancement has received much popularity in recent years owing to its capability to perform enhancement without requiring paired training datasets. Zero-Reference Deep Curve Estimation (ZeroDCE) [4] formulates image enhancement as a curve estimation technique based on illumination adjustment and non-reference loss functions.

Several lightweight models like Zero-DCE++ [40], Zero-DCE Tiny [41], and DA-ZeroDCE [42] were developed based on the ZeroDCE model to optimize computational efficiency and robustness to various illumination settings. Such approaches exhibited high computational efficiency and real-time performance, while maintaining independence from paired supervision.

However, due to their good performance, the majority of zero-reference algorithms mainly depend on global illumination correction and show less spatial adaptation capabilities when dealing with severe non-uniform lighting settings, which may influence enhancement performance in extremely dark areas.

2.4 Attention-Based Feature Enhancement Frameworks

Attention-based feature enhancement frameworks have recently been applied to low-light image enhancement for improving feature representation and spatial adaptability. The Convolutional Block Attention Module (CBAM) [16] improves feature learning through sequential channel and spatial attention mechanisms, enabling the network to focus on informative regions while suppressing irrelevant features.

Several enhancement frameworks [33, 34, 35, 36] employing attention mechanisms showed better structural preservation, perceptual quality, and spatial consistency when enhancing images taken under low-light conditions. There are many approaches that apply attention mechanisms for low-light object detection and night surveillance systems [43, 44, 45].

Nevertheless, the majority of current attention-based enhancement frameworks lack the capability of illumination guidance when refining features, which limits their ability to achieve enhancement consistency when processing severely underexposed regions.

2.5 Illumination-Aware Enhancement Frameworks

Different approaches have been suggested by illumination-aware enhancement frameworks to cope with challenging illumination scenarios while ensuring consistent enhancement of images captured under highly degraded illumination conditions. Both transformer-based and diffusion-based enhancement frameworks [5, 6, 7] showed impressive contextual learning and illumination modeling abilities that enable them to excel in low-light enhancement operations.

Other unified exposure correction models have been developed [10, 11, 13, 14] capable of solving both over-exposure and under-exposure challenges in a single network. While these frameworks have proven to offer superior enhancement and illumination consistency, they are usually inefficient in terms of computation when used in real-time scenarios.

Even with great strides having been made on the front of low light enhancement, there is still the problem of achieving a good balance between enhancing qualities, adaptability in space, and computational complexity using current algorithms. Efficient zero-reference methods achieve fast illumination correction, although their approach to global enhancement fails to enhance extremely under-exposed areas successfully. Such problems necessitate the need for more sophisticated frameworks, hence the proposed framework.

2.6 Datasets Used in Low-Light Image Enhancement

The effectiveness of any low-light image enhancement system is closely related to how rich its benchmark dataset is in terms of variation of illumination levels as well as scene

complexity. Currently available datasets vary in several ways, namely image type, lighting exposure condition, variety of scenes, and suitability for evaluation purpose. Datasets such as the former may offer paired low-light and normally exposed images, which can be used in supervised learning tasks and for full-reference evaluation.

Table 2.1 summarizes commonly used datasets employed in low-light image enhancement and exposure correction research.

Table 2.1: Summary of commonly used datasets for low-light image enhancement.

Dataset	**Image Type**	**Lighting Condition**	**Key Features**	**Limitations**
LOL Dataset	Paired real images	Indoor and outdoor	Provides real low-light and normal-light image pairs for supervised learning and quantitative evaluation.	Limited scene diversity and small dataset size.
ExDark Dataset	Real unpaired images	Nighttime and low illumination	Contains diverse object categories suitable for both enhancement and object detection studies.	No reference images; strong noise and exposure variations.
SICE Dataset	Synthetic and real images	Multi-exposure indoor and outdoor scenes	Includes multiple exposure levels per scene for HDR and exposure fusion research.	Synthetic exposure limits realism and may cause tonal bias.
DarkFace Dataset	Captured face images	Photos shot at night and on the streets	Specifically designed for face detection/recognition.	Focus only on face recognition; lacks variety of environment.
DICM Dataset	Real photographs	Indoor and outdoor environments	Captured using consumer-grade cameras under natural illumination variations.	Small dataset; limited dynamic range and diversity.
MEF Dataset	Multi-exposure scenes	Indoor and outdoor	Useful for multi-exposure fusion and HDR tone mapping tasks.	Not originally created for enhancement benchmarking.
SID Dataset	RAW sensor data	Extremely low illumination	Captures raw sensor images for training physics-based enhancement models.	Requires extensive preprocessing; computationally heavy.

LOL dataset has been popular among the frequently utilized benchmarking datasets because it includes paired low-light and high-light image datasets appropriate for use in full-reference evaluation methods like PSNR and SSIM. On the other hand, datasets such as ExDark are designed to address real-world low-light scenarios and scenes and thus are frequently utilized in enhancing robustness evaluations.

Table 2.2: Comparative review of representative exposure correction methods

Author	**Problem Solved**	**Approach**	**Datasets Used**	**Metrics**
Guo et al. [2]	Highlight clipping and colour loss in over-exposed photographs	CIELAB lightness-chrominance separation with gradient-domain compression	Custom natural images	Qualitative evaluation
Guo et al. [4]	Low-light enhancement without paired supervision	Zero-reference deep curve estimation	LOL, LIME, NPE, DICM	NIQE, LPIPS, PSNR
Li et al. [40]	Real-time low-light enhancement	Lightweight Zero-DCE++ with shared curves	LOL, SICE, MEF, NPE	PSNR, SSIM, FPS
Jiang et al. [3]	Unpaired low-light enhancement	GAN with global-local discriminators	Unpaired real images	NIQE, user study
Cai et al. [5]	Limited global illumination modelling	One-stage Retinex-based Transformer	LOL, LOL-v2, SID	PSNR, SSIM
Afif et al. [10]	Joint correction of under- and over-exposed images	Coarse-to-fine Laplacian pyramid CNN	MIT-Adobe FiveK, LOL, LIME	PSNR, SSIM
Nsampi et al. [11]	Spatial inconsistency in unified exposure correction	Exposure consistency modelling with global attention	MIT-Adobe FiveK	PSNR, SSIM
Baek et al. [13]	Colour distortion in mixed exposure scenes	Luminance-aware colour transform	SICE	SSIM, colour error

Author	Problem Solved	Approach	Datasets Used	Metrics
Jin et al. [14]	Balancing mixed exposure regions	Region-aware exposure consistency network	SICE, MSEC	PSNR, SSIM
Jiang et al. [6]	Dependence on paired data in LLIE	Unsupervised latent Retinex diffusion	LOL, LIME, MEF	PSNR, LPIPS
Wu et al. [7]	Weak conditioning in diffusion-based LLIE	Retinex-conditioned diffusion	LOL, LOL-v2	PSNR, SSIM, LPIPS

As observed from Table 2.2, recent enhancement frameworks have progressively shifted from traditional illumination correction approaches toward lightweight zero-reference methods, attention-guided architectures, and Transformer or diffusion-based frameworks. While complex models offer great perceptual quality and illumination modeling capability, they come with higher complexity and inefficiency.

On the other hand, lightweight zero-reference systems offer an effective way to enhance images without the need for paired training data, but they are less effective when dealing with severe non-uniform illumination scenes. In a similar vein, attention-based enhancement models improve the refinement of features and structures, but they do not explicitly consider illumination in the enhancement process. This demonstrates that there is a need for illumination-aware and computationally efficient systems that can improve spatial adaptability and preserve structure under low-light scenes.

Recent low-light image enhancement methods are further compared in Table 2.3 based on their core techniques, strengths, limitations, and benchmark datasets used for evaluation.

Table 2.3: Comparative Analysis of Recent Low-Light Image Enhancement Methods

Method	Core Technique	Strengths	Limitations	Dataset
Zero-DCE (2020)	Estimation of curve in deep network without paired supervision	Lightweight and fast, no reference images needed	Tends to increase noise in extremely dark regions	LOL

Method	Core Technique	Strengths	Limitations	Dataset
Zero-DCE++ (2021)	Enhanced curve estimation with improved color consistency and spatial awareness	Improved visual results and stable training convergence	Slight increase in computation complexity	LOL, ExDark
RetinexNet (2018)	Decomposition into illumination and reflectance maps using deep Retinex theory	Better contrast and texture recovery	May produce halo artifacts in extreme darkness	LOL, SICE
KinD (2019)	Deep neural network-based illumination adjustment and reflectance restoration	Balanced enhancement in terms of brightness and textures	Not effective on non-uniform lighting conditions	LOL, NPE
DA-Zero-DCE (2022)	Enhancement by using zero-reference enhancement technique	Improvement in generalization for unseen domains	Additional step of domain adaptation is required	LOL, SID, ExDark
Saliency-guided Fusion (2023)	Fusion of visible and thermal images based on saliency & multiscale features extraction	Better detail and contrast preservation	Requirement of multi-source input data	M3FD, TNO

In general, the analysis shows that enhancement frameworks developed recently have continuously made strides in improving perceptual quality and illumination consistency via attention mechanisms, zero-reference enhancement, and illumination-aware feature refinement. Nevertheless, issues related to efficient computation, spatial adaptation, and severe degraded illumination environments are some critical research problems that need to be addressed.

In summary, this chapter discussed various exposure correction and low-light image enhancement methodologies, including conventional image processing, deep learning, zero-reference enhancement, attention-guided feature refinement, and illumination-

aware enhancement methods. Various advancements in image enhancement methods were shown from early handcrafted illumination correction approaches towards more complex and sophisticated deep learning models such as GANs, Transformers, and diffusion models.

A review of the current enhancement methodologies shows that even though recent deep learning-based enhancement methods considerably increase enhancement performance and perceptual similarity, some of the enhancement approaches still suffer from limitations such as computational cost, spatial adaptation, and feature extraction based on lighting conditions. Although lightweight methods without requiring supervised training pairs offer efficient enhancement, they cannot handle illumination challenges.

The limitations obtained through reviewing the literature have encouraged the creation of computationally efficient and illumination-aware enhancement networks which can enhance low-light images more efficiently and effectively. The findings of the literature review constitute the motivations behind proposing ZeroDCE-CBAM and EGA-Enhanced ZeroDCE in upcoming sections.

Chapter 3

METHODOLOGY

This chapter discusses the method that was employed in designing the two low-light image enhancement models built on the ZeroDCE framework. The two enhancement methods considered are ZeroDCE-CBAM model and the newly proposed EGA-Enhanced ZeroDCE model. These methods aim at enhancing lighting, perception visibility, and structural consistency in severely under-exposed images with illumination variations in an energy-efficient manner.

The proposed framework is an extension of the ZeroDCE model, which has been enhanced with the use of attention-guided and illumination-aware feature refinement techniques. In the first stage, CBAM module is introduced in the ZeroDCE-CBAM model in order to improve the representation of spatial and channel features during the image enhancement process. In the second phase, the newly designed framework uses the illumination awareness and Exposure Guided Attention technique in order to improve illumination consistency.

The current chapter explains the datasets, preprocessing steps, architecture of the proposed frameworks, illumination-based feature tuning approach, loss functions, and experimental settings used. The entire process emphasizes on developing an efficient adaptive low light enhancement system that does not rely on any supervised paired data while maintaining structural and visual qualities.

3.1 Datasets Used

The current sub-section discusses the benchmark datasets utilized for training, validating, and testing the developed Zero DCE-CBAM and EGA-Enhanced ZeroDCE models. In order to have comparable results, the same benchmark datasets were used in all the experiments performed with both enhancement models.

Two benchmark datasets were employed in this study: the Exclusively Dark (ExDark) dataset and the Low-Light (LOL) dataset.

The **ExDark dataset** [46] contains 7,363 real low-light images captured under varying illumination conditions including ambient, low, and extremely dark environments. The dataset consists of multiple real-world object categories such as human beings, vehicles, and street scenes along with object-level annotations. Due to its di-

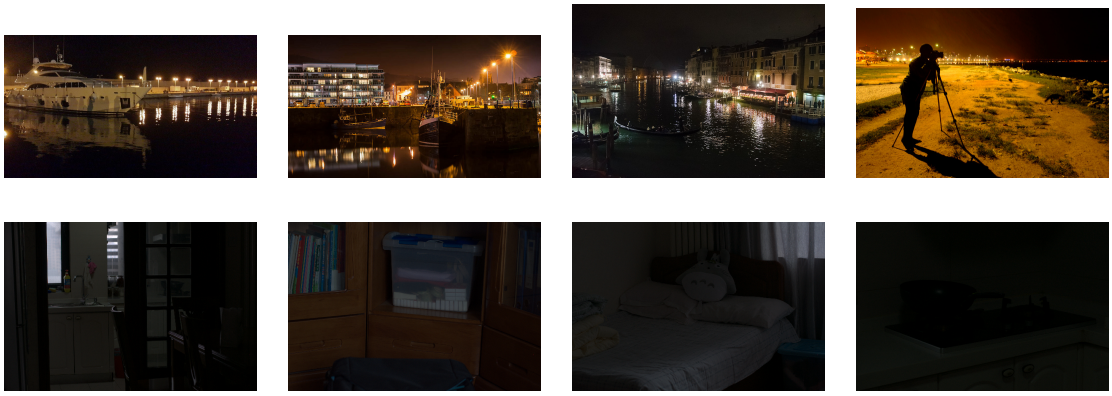


Figure 3.1: Sample images from ExDark (top row) and LOL (bottom row) datasets used in this study. The ExDark samples represent natural low-light scenes captured in real-world conditions, while LOL samples include paired low- and normal-light scenes for full-reference evaluation.

versity in scene composition, exposure levels, and illumination variations, the ExDark dataset is primarily used for training and qualitative evaluation under practical low-light environments.

The **LOL dataset** [21] contains 500 paired low-light and corresponding normal-light images captured under controlled indoor and outdoor lighting conditions. Since the dataset provides paired reference images, it is suitable for full-reference quantitative evaluation using metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). In this work, the LOL dataset is mainly utilized for validation and quantitative performance analysis.

Figure 3.1 shows some sample images taken from each dataset, emphasizing the variety of lighting situations, different levels of exposure, and types of scenes that have been considered to test our proposed frameworks.

3.2 Overall Enhancement Pipeline

Figure 3.2 illustrates the overall enhancement pipeline adopted in this thesis for low-light image enhancement. The proposed methodology combines two lightweight zero-reference enhancement frameworks, namely ZeroDCE-CBAM and EGA-Enhanced ZeroDCE, within a unified enhancement pipeline designed to improve illumination consistency, perceptual visibility, and structural preservation under severely low-light environments.

The pipeline begins with preprocessing of the input low-light image, where the im-

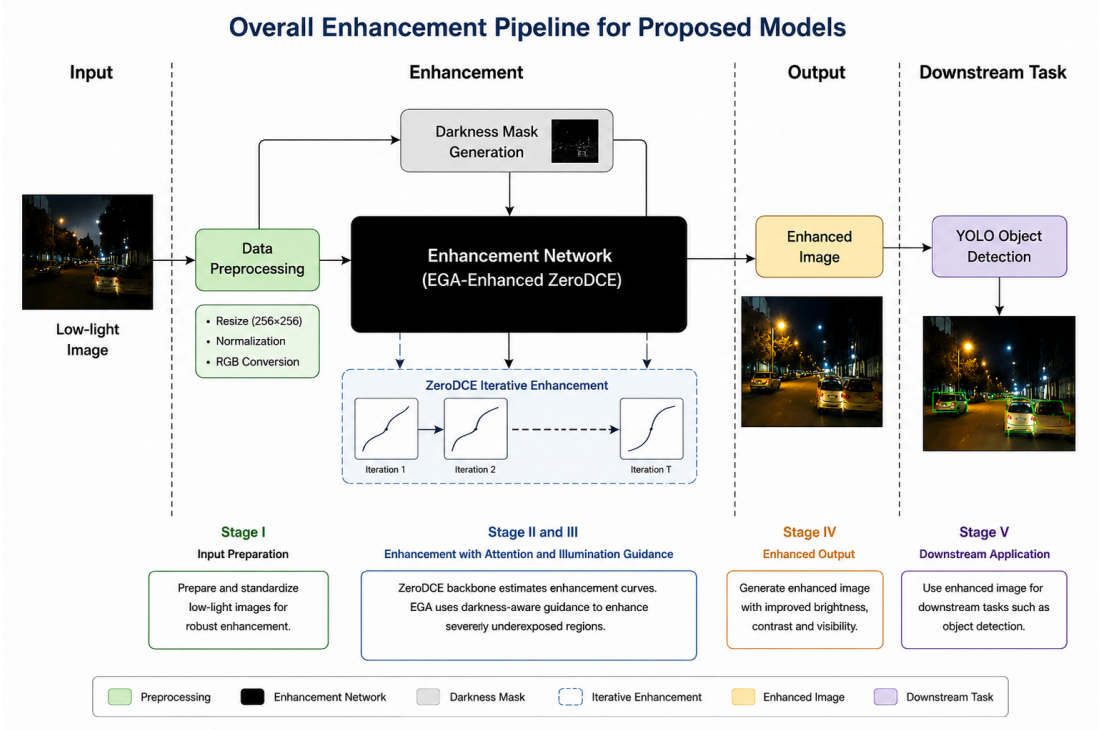


Figure 3.2: Overall enhancement pipeline of the proposed ZeroDCE-CBAM and EGA-Enhanced ZeroDCE frameworks.

ages are resized and normalized before being passed to the enhancement network. The ZeroDCE backbone is responsible for extracting hierarchical feature representations and estimating iterative enhancement curves for illumination correction. To improve feature representation and spatial adaptability, the ZeroDCE-CBAM framework integrates the Convolutional Block Attention Module (CBAM), which refines feature maps through channel and spatial attention mechanisms.

Building upon the ZeroDCE-CBAM framework, the proposed EGA-Enhanced ZeroDCE model further incorporates darkness-aware feature modulation and Exposure Guided Attention (EGA) for illumination-aware feature refinement. A darkness mask generated from the input image guides the network to selectively enhance severely underexposed regions while suppressing unreliable feature activations. The refined features are then utilized to generate enhanced images with improved brightness, contrast, structural consistency, and perceptual quality.

The enhanced outputs produced by the proposed frameworks can further be utilized for downstream computer vision tasks such as object detection and scene understanding under low-light conditions. The overall pipeline maintains the lightweight and computationally efficient characteristics of the ZeroDCE framework while improving

spatial adaptability and enhancement consistency under complex illumination environments.

3.3 ZeroDCE-CBAM Framework

The ZeroDCE-CBAM architecture represents the basic enhancement architecture of the proposed EGA-Enhanced ZeroDCE algorithm. The architecture enhances the Zero-Reference Deep Curve Estimation (ZeroDCE) architecture with the addition of Convolutional Block Attention Module (CBAM) to refine channels and spatial features in the images under the low light condition. The goal of the architecture is to enhance illumination consistency, structural preservation, and visual clarity while preserving the lightweight and zero-reference nature of the ZeroDCE architecture.

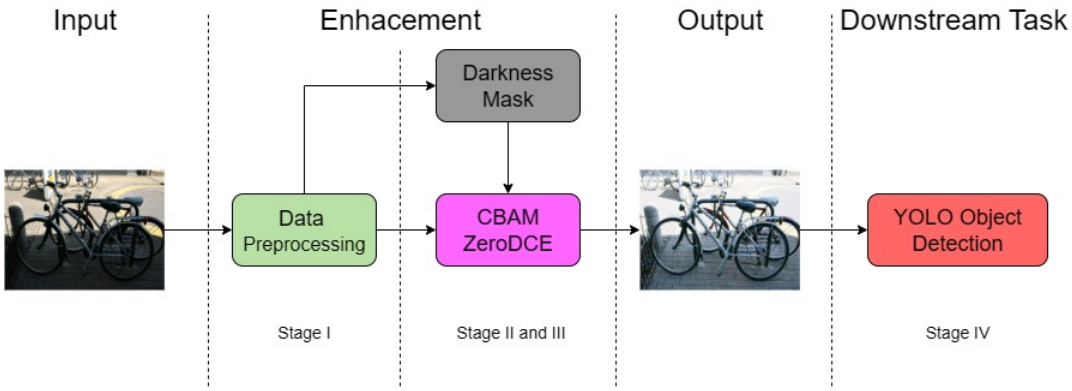


Figure 3.3: Overall pipeline of the proposed ZeroDCE-CBAM framework for low-light image enhancement.

As illustrated in Fig. 3.3, the framework consists of four major stages: *(i)* preprocessing of low-light images, *(ii)* feature extraction and illumination enhancement using the ZeroDCE-CBAM network, *(iii)* darkness-aware attention refinement, and *(iv)* generation of enhanced output images for perceptual evaluation and downstream computer vision applications.

The preprocessing stage standardizes the input images through resizing and normalization before they are passed to the enhancement network. The ZeroDCE backbone then extracts hierarchical feature representations and estimates pixel-wise enhancement curves that iteratively improve image illumination. Unlike the original ZeroDCE framework, the proposed architecture incorporates CBAM modules to improve feature representation using channel and spatial attention mechanisms.

As CBAM is embedded into the network, the network gains the ability to choose relevant regions of the image to enhance and eliminate activation of uninformative features. It provides better spatial adaptation capability in varying illumination environments, and more importantly, increases visibility in very dark regions without losing fine texture details. In addition, an awareness-based attention module is used to assist feature learning using illumination sensitive information from the input image.

The enhanced output from the framework can then be used for other computer vision tasks such as object detection, scene understanding, and even surveillance systems in low lighting environments. Our proposed scheme remains efficient and can run in real-time applications despite improvements made in enhancement results under difficult illumination scenarios.

3.3.1 ZeroDCE Enhancement Network

In the proposed scheme, we leverage Zero-Reference Deep Curve Estimation (ZeroDCE) [4] as the main backbone network for estimating illumination adjustment curves. The ZeroDCE algorithm formulates the image enhancement process as a problem of estimating pixel-wise enhancement curves, which are iteratively applied to the input image in order to improve illumination conditions.

The image enhancement process formulated through the iterative application of the enhancement curves can be expressed as:

$$LE_n(x) = LE_{n-1}(x) + A_n(x)LE_{n-1}(x)(1 - LE_{n-1}(x)) \tag{3.1}$$

where $LE_n(x)$ refers to the output image enhanced during the n^{th} iteration, $A_n(x)$ denotes the estimated pixel-wise enhancement curve parameter, and $LE_0(x)$ is the input low-light image.

Pixel-wise enhancement curves are learned via a lightweight convolutional neural network consisting of convolutional layers with skip connections. Iterative enhancement formulation allows us to apply smooth illumination changes while ensuring consistency of the resulting image structure.

While most supervised enhancement methods optimize the enhancement process by employing non-reference loss functions using pairs of low-light and normal light training images, ZeroDCE achieves this in an unsupervised manner, which increases training efficiency and enables real-time enhancement capabilities.

While the original ZeroDCE model proves to be computationally efficient and ef-

fective for illumination correction, its enhancement method depends mainly on global features with limited spatial adaptability in severely non-uniform illumination conditions. In order to solve this problem, the suggested framework employs attention-guided feature refinement through CBAM and illumination-aware enhancement via Exposure Guided Attention (EGA).

3.3.2 CBAM-Based Feature Refinement

To improve spatial adaptability and feature representation under non-uniform illumination conditions, the proposed ZeroDCE-CBAM framework integrates the Convolutional Block Attention Module (CBAM) [16] within the enhancement network. CBAM refines intermediate feature representations through sequential channel attention and spatial attention operations, enabling the network to focus on informative regions while suppressing irrelevant feature activations.

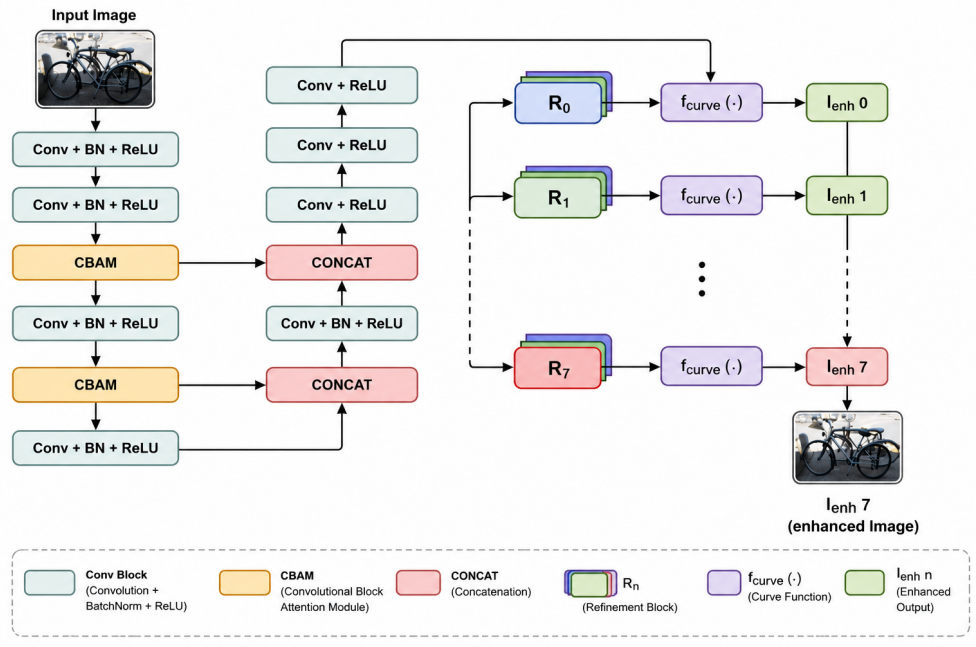


Figure 3.4: Structure of the Convolutional Block Attention Module (CBAM) integrated within the ZeroDCE enhancement framework.

As illustrated in Fig. 3.4, the CBAM module first applies channel attention to emphasize important feature channels and then applies spatial attention to selectively refine informative spatial regions. The refined feature maps are subsequently forwarded to the enhancement network for illumination curve estimation.

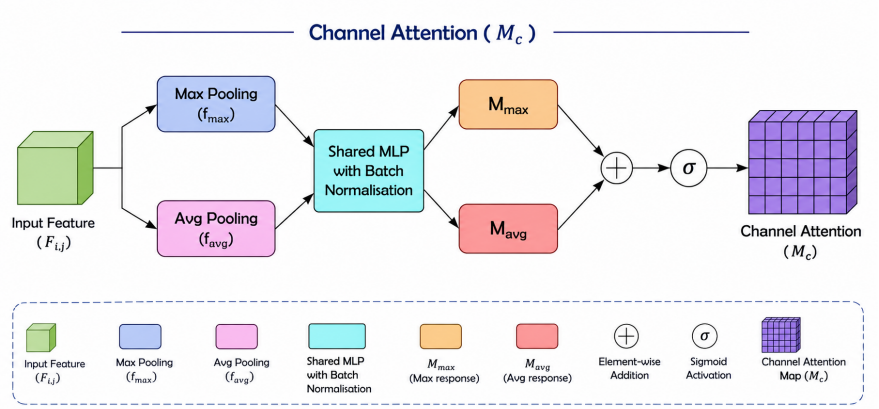


Figure 3.5: Architecture of the channel attention mechanism.

Channel Attention: Channel Attention makes use of global average pooling and global max pooling to learn the important feature channels. As shown in Fig. 3.5, the input feature map undergoes processing via two parallel branches using average pooling and max pooling. The pooled descriptors then go through a common Multi-Layer Perceptron (MLP), and the outputs are fused and activated by sigmoid activation to form the channel attention map. The generated attention map highlights the informative feature channels while ignoring the non-informative ones.

For an intermediate feature map $F \in \mathbb{R}^{C\times H\times W}$, channel attention is formulated as:

$$M_c(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F))) \tag{3.2}$$

where $M_c(F)$ denotes the channel attention map, σ represents the sigmoid activation function, and MLP corresponds to the shared multi-layer perceptron.

The refined feature representation after channel attention is obtained as:

$$F' = M_c(F) \otimes F \tag{3.3}$$

where $\otimes$ denotes element-wise multiplication.

Spatial Attention: After channel refinement, spatial attention is applied to identify the most informative spatial regions within the feature map. As illustrated in Fig. 3.6, average pooling and max pooling are first performed along the channel dimension to generate complementary spatial descriptors. These descriptors are concatenated and passed through a convolution layer with batch normalization to capture spatial dependencies. In the proposed framework, a darkness-aware guidance mask is additionally

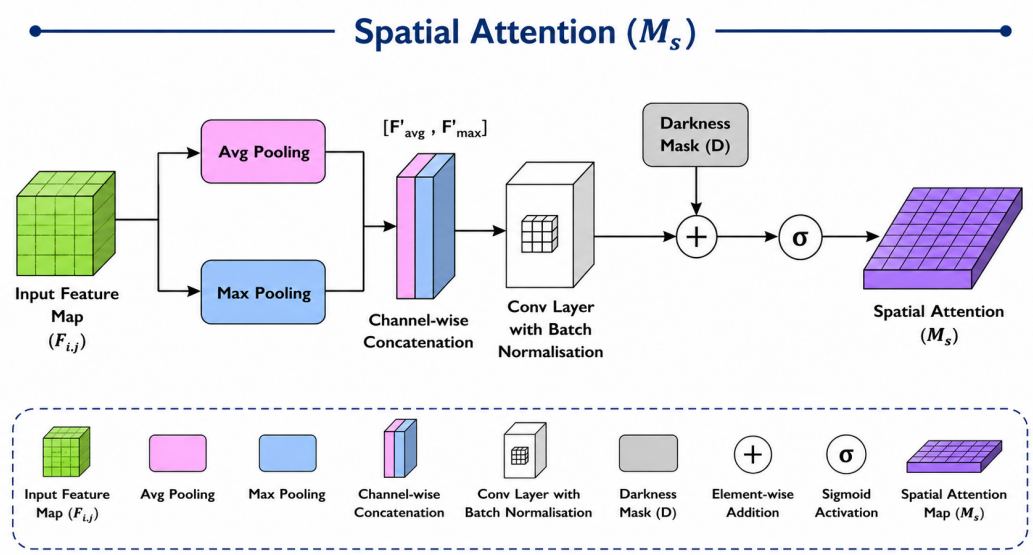


Figure 3.6: Spatial attention mechanism with darkness-aware guidance.

incorporated before sigmoid activation to emphasize underexposed regions and improve illumination-aware feature refinement.

Spatial attention is computed as:

$$M_s(F') = \sigma(f^{7\times7}([AvgPool(F'); MaxPool(F')])) \tag{3.4}$$

where $f^{7\times7}$ represents a convolution operation with a 7×7 kernel and $[\,]$ denotes channel-wise concatenation.

The final refined feature map after spatial attention is computed as:

$$F'' = M_s(F') \otimes F' \tag{3.5}$$

The integration of CBAM enables the enhancement network to improve feature refinement and spatial adaptability under low-light environments. By selectively emphasizing informative feature channels and spatial regions, the framework improves illumination consistency, texture preservation, and structural fidelity during enhancement.

3.3.3 Darkness-Aware Feature Refinement

In order to enhance the enhancement performance consistency under severely underexposed conditions, the framework proposed employs a darkness aware feature refining approach, which uses illumination sensitive information to guide the enhancement net-

work. The aim of the module is to enable enhanced emphasis on severely dark areas and suppress unreliable feature responses induced by illumination deterioration.

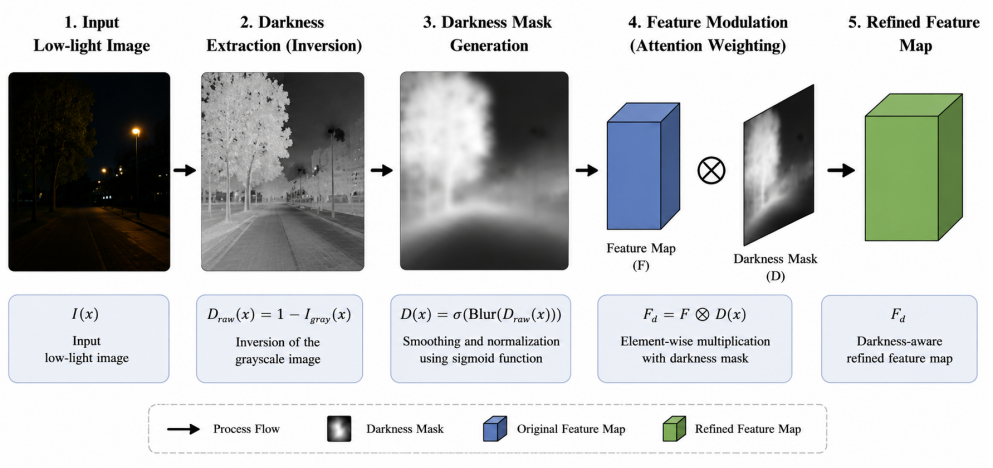


Figure 3.7: Generation process of the proposed darkness-aware feature refinement mask.

The darkness aware refinement procedure is shown in Fig. 3.7, where first a low light attention map is extracted from the input image. Since the lowly lit areas usually have relatively low illumination intensities, the representation of the image obtained is darkness sensitive in nature.

Given an input image $I(x)$, the darkness-aware mask $D(x)$ is computed as:

$$D(x) = 1 - I(x) \tag{3.6}$$

where $I(x)$ denotes the normalized image illumination value and $D(x)$ indicates the parts that suffer from low illuminations. Higher values in darkness mask indicate severe darkness regions that need more enhancement on their features.

The obtained darkness mask will be combined with intermediate feature representations for attention-based refinement as follows:

$$F_d = F \otimes D(x) \tag{3.7}$$

where F is the intermediate feature maps and F_d denotes the darkness-enhanced feature maps.

By using the above-mentioned strategy, the network will be able to enhance only those severely dark regions while ignoring other well-lit parts. This leads to an effective enhancement process in complex low-light conditions with spatially consistent, structurally preserved and perceptually high-quality images.

3.4 EGA-Enhanced ZeroDCE Framework

The proposed EGA-Enhanced ZeroDCE framework extends the ZeroDCE-CBAM architecture through the integration of Exposure Guided Attention (EGA) and illumination-aware feature refinement for improving enhancement consistency under severely underexposed environments. While the ZeroDCE-CBAM framework improves spatial adaptability using attention-guided feature refinement, enhancement performance in extremely dark regions may still suffer from unreliable feature activations and insufficient illumination-aware guidance.

To address these limitations, the proposed framework introduces an Exposure Guided Attention mechanism that explicitly incorporates exposure-sensitive information during feature refinement. The EGA module utilizes darkness-aware feature representations to selectively emphasize severely underexposed regions while suppressing degraded and unreliable activations caused by extreme illumination conditions.

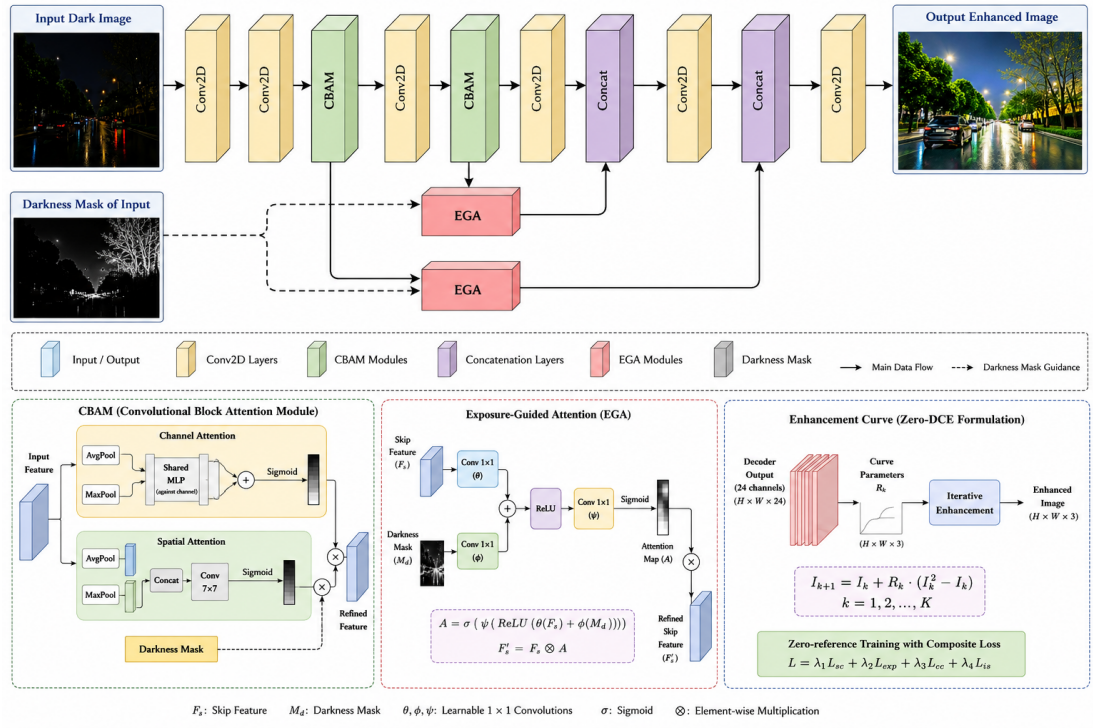


Figure 3.8: Architecture of the proposed EGA-Enhanced ZeroDCE framework.

As illustrated in Fig. 3.8, the proposed framework follows an encoder-decoder enhancement pipeline in which low-level and high-level feature representations are extracted using convolutional layers. The extracted features are refined using CBAM-based channel and spatial attention operations before being passed to the Exposure

Guided Attention module.

The EGA module generates illumination-aware attention maps using darkness-sensitive feature representations derived from the input image. These attention maps guide intermediate feature refinement by selectively increasing enhancement strength in severely underexposed regions while preserving structural consistency and texture information in well-illuminated areas.

Unlike conventional attention mechanisms that rely solely on learned feature importance, the proposed framework explicitly incorporates illumination priors during feature modulation. This enables adaptive enhancement under spatially varying illumination conditions and improves robustness under complex low-light environments.

The refined feature representations are subsequently utilized for iterative illumination curve estimation and enhancement generation using the ZeroDCE enhancement formulation. The overall framework maintains the lightweight and zero-reference characteristics of ZeroDCE while improving enhancement quality, spatial consistency, and perceptual visibility under severely degraded illumination conditions.

3.4.1 Exposure Guided Attention (EGA)

The Exposure Guided Attention (EGA) module is the primary contribution of the proposed enhancement framework and is designed to improve illumination-aware feature refinement under severely low-light environments. Unlike conventional attention mechanisms that primarily rely on feature importance, the EGA module explicitly incorporates exposure-sensitive information during enhancement to guide the network toward severely underexposed regions.

As illustrated in Fig. 3.9, the EGA module receives intermediate feature representations extracted from the enhancement network along with a darkness-aware guidance map generated from the input image. The module utilizes these illumination-sensitive features to selectively refine degraded regions while suppressing unreliable activations caused by severe illumination degradation.

Given an intermediate feature representation F, the exposure-guided attention map M_{ega} is computed using the darkness-aware representation $D(x)$ as:

$$M_{ega} = \sigma(Conv(F \oplus D(x))) \tag{3.8}$$

where σ denotes the sigmoid activation function, $Conv(\cdot)$ represents convolutional refinement, and $\oplus$ denotes feature concatenation between the extracted feature map

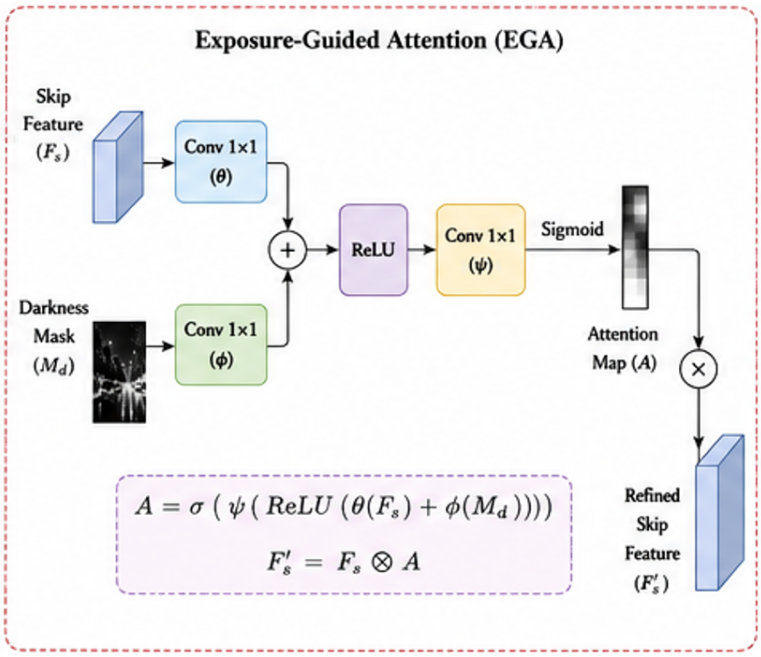


Figure 3.9: Detailed structure of the proposed Exposure Guided Attention (EGA) module.

and the darkness-aware guidance representation.

The refined feature representation generated by the EGA module is obtained as:

$$F_{ega} = M_{ega} \otimes F \tag{3.9}$$

where $\otimes$ represents element-wise multiplication and F_{ega} denotes the exposure-refined feature representation.

The generated attention maps guide the network to focus more strongly on severely underexposed regions requiring higher enhancement intensity while preventing excessive enhancement in already illuminated regions. This improves illumination consistency, texture preservation, and structural fidelity under spatially varying illumination conditions.

The integration of the EGA module significantly improves the robustness of the enhancement framework under extremely dark environments by introducing explicit illumination-aware feature guidance within the enhancement process. Furthermore, the module maintains computational efficiency and lightweight implementation characteristics suitable for real-time low-light enhancement applications.

3.5 Loss Function Formulation

The proposed ZeroDCE-CBAM and EGA-Enhanced ZeroDCE frameworks are optimized using the same non-reference loss formulation adopted in the original ZeroDCE framework [4]. Since the proposed enhancement approaches operate in a zero-reference setting, no paired low-light and normal-light supervision is required during training. Instead, the enhancement process is guided through multiple perceptual and illumination-related constraints that encourage natural illumination enhancement, structural consistency, and color preservation.

The overall loss function is defined as a weighted combination of multiple non-reference loss terms:

$$L_{total} = L_{spa} + W_{exp}L_{exp} + W_{col}L_{col} + W_{tvA}L_{tvA} \tag{3.10}$$

where L_{spa} denotes the spatial consistency loss, L_{exp} represents the exposure control loss, L_{col} corresponds to the color constancy loss, and L_{tvA} denotes the illumination smoothness loss. The weighting parameters W_{exp}, W_{col}, and W_{tvA} control the contribution of each loss component during optimization.

Spatial Consistency Loss: The spatial consistency loss preserves local structural relationships between the input and enhanced images to prevent structural distortion during enhancement. The loss is formulated as:

$$L_{spa} = \frac{1}{K}\sum_{i=1}^{K}\sum_{j\in\Omega(i)}(|Y_i - Y_j| - |I_i - I_j|)^2 \tag{3.11}$$

where Y and I denote the enhanced and input images respectively, and $\Omega(i)$ represents neighboring regions around pixel i.

Exposure Control Loss: The exposure control loss encourages the enhanced image to maintain balanced illumination intensity across local regions:

$$L_{exp} = \frac{1}{M}\sum_{k=1}^{M}|Y_k - E| \tag{3.12}$$

where Y_k represents the average intensity of a local region and E denotes the target exposure level.

Color Constancy Loss: The color constancy loss reduces color distortion and maintains consistency among RGB channels:

$$L_{col} = \sum_{(p,q)\in\varepsilon} (J^p - J^q)^2 \tag{3.13}$$

where J^p and J^q represent the mean intensity values of different color channels.

Illumination Smoothness Loss: The illumination smoothness loss constrains the estimated enhancement curves to maintain spatial smoothness and avoid abrupt illumination variations:

$$L_{tvA} = \frac{1}{N} \sum_{n=1}^{N} \sum_{c\in\xi} (|\nabla_x A_n^c| + |\nabla_y A_n^c|)^2 \tag{3.14}$$

where A_n^c denotes the estimated enhancement curve parameters for channel c, and ∇_x, ∇_y represent spatial gradients along horizontal and vertical directions respectively.

The combined optimization of these non-reference loss functions enables the proposed frameworks to improve illumination quality, preserve structural consistency, and maintain natural color appearance without requiring paired training supervision.

Chapter 4

EXPERIMENTAL SETUP

The current chapter will explain the experiment settings, implementations, evaluation process, and approaches to evaluate the performance of the two proposed models, which include ZeroDCE-CBAM and EGA-Enhanced ZeroDCE. In order to compare the results effectively, a unified preprocessing method and training and evaluation process is employed for the enhancement models.

4.1 Hardware and Software Configuration

All experiments were performed in the Google Colab environment featuring NVIDIA T4 GPU with 16 GB VRAM. TensorFlow 2.9 framework was used to implement the proposed enhancement model and PyTorch was used to implement EnlightenGAN. Lightweight architecture of the proposed model enables fast training and real-time enhancement performance for practical low-light scenarios.

4.2 Training Configuration

To maintain consistency across experiments, all input images were resized to 256×256 resolution and normalized within the range $[0, 1]$ prior to training and evaluation. The ExDark dataset was primarily used for training, whereas the LOL dataset was utilized for validation and quantitative evaluation.

Both the ZeroDCE-CBAM and EGA-Enhanced ZeroDCE frameworks were trained using the Adam optimizer with an initial learning rate of 1×10^{-4}, a batch size of 16, and a total of 100 epochs. Early stopping and model checkpoint callbacks were utilized during training to reduce overfitting and improve convergence stability.

The enhancement frameworks were optimized using the composite self-supervised loss formulation adopted from the original ZeroDCE framework, including spatial consistency loss, exposure control loss, color constancy loss, and illumination smoothness loss.

4.3 Evaluation Metrics

The performance of the proposed enhancement frameworks was evaluated using both full-reference and no-reference image quality assessment metrics.

- **Peak Signal-to-Noise Ratio (PSNR):** Evaluates reconstruction quality between enhanced and reference images.
- **Structural Similarity Index (SSIM):** Measures structural and perceptual similarity between enhanced and ground-truth images.
- **BRISQUE:** A no-reference perceptual quality metric used to evaluate naturalness and distortion in enhanced images.
- **PIQE:** Measures perceptual image quality without requiring reference images.

These evaluation metrics collectively assess illumination quality, structural preservation, perceptual consistency, and enhancement robustness under challenging low-light conditions.

4.4 Baseline Methods

For comparative analysis, several classical and deep learning-based enhancement methods were included as baselines:

- **Retinex-MSR and Retinex-SSR:** Traditional illumination decomposition methods used as classical enhancement baselines.
- **ZeroDCE:** Baseline zero-reference low-light enhancement framework based on iterative curve estimation.
- **EnlightenGAN:** GAN-based unpaired low-light enhancement framework optimized using adversarial learning.
- **ZeroDCE-CBAM:** Attention-guided enhancement framework integrating CBAM within the ZeroDCE architecture.

The proposed EGA-Enhanced ZeroDCE framework was evaluated against these methods using identical preprocessing conditions and evaluation settings to ensure fair comparison.

4.5 Experimental Protocol

To ensure unbiased evaluation, all enhancement frameworks were trained and evaluated under identical preprocessing and normalization conditions. The LOL dataset was utilized for quantitative evaluation using full-reference metrics, while ExDark was used for qualitative analysis and robustness evaluation under practical low-light conditions.

Both qualitative and quantitative analyses were performed to evaluate enhancement quality, structural consistency, texture preservation, and illumination balance. In addition to objective evaluation metrics, visual comparison experiments were also conducted to assess perceptual quality and enhancement consistency under severely low-light environments.

It should be noted that the experimental setting as a whole is aimed at demonstrating the advantages of CBAM-based feature enhancement and the proposed EGA approach in terms of achieving better illumination consistency and spatial adaptation capabilities, yet still remaining computationally efficient enough.

Chapter 5

RESULTS & DISCUSSIONS

In this chapter, the qualitative and quantitative analysis of the proposed EGA-Enhanced ZeroDCE system is presented in a low-light environment. The proposed EGA-Enhanced ZeroDCE framework is analyzed based on benchmark low-light data set compared to other traditional and deep learning-based enhancements.

5.1 Qualitative Analysis

The visual analysis is conducted to compare the quality of the illumination enhancement as well as texture, structure and perceptual realism of the enhanced output images generated by applying different low-light enhancement methods.

While ZeroDCE framework is capable of improving the overall image brightness and visibility in scenes captured under low-lighting condition, it still demonstrates some weaknesses in detail-preserving capability and balanced illumination generation. The proposed ZeroDCE-CBAM method, on the other hand, is able to provide superior enhancement quality and more accurate representation of local contrast and illuminations of the regions important for scene perception through the use of CBAM attention. The enhanced images produced by using ZeroDCE-CBAM are characterized by better detail preservation, structure definition and illumination consistency.

Further, the proposed EGA-Enhanced ZeroDCE model improves the enhancement quality through exposure-guided attention and darkness aware feature modulation. As can be seen in Fig. 5.2, the proposed method offers better illumination balance while preserving natural appearances of the scene in contrast with baseline enhancement framework. The model is also capable of improving visibility of severely dark regions in contrast with conventional low-lighting enhancement techniques.

The qualitative analysis verifies the effectiveness of both methods in improving the visibility of low-light images. Nevertheless, the addition of Exposure Guided Attention significantly contributes to the enhancement process in terms of illumination awareness, leading to better structure preservation, perceptual consistency, and adaptation ability under different low-light environments.

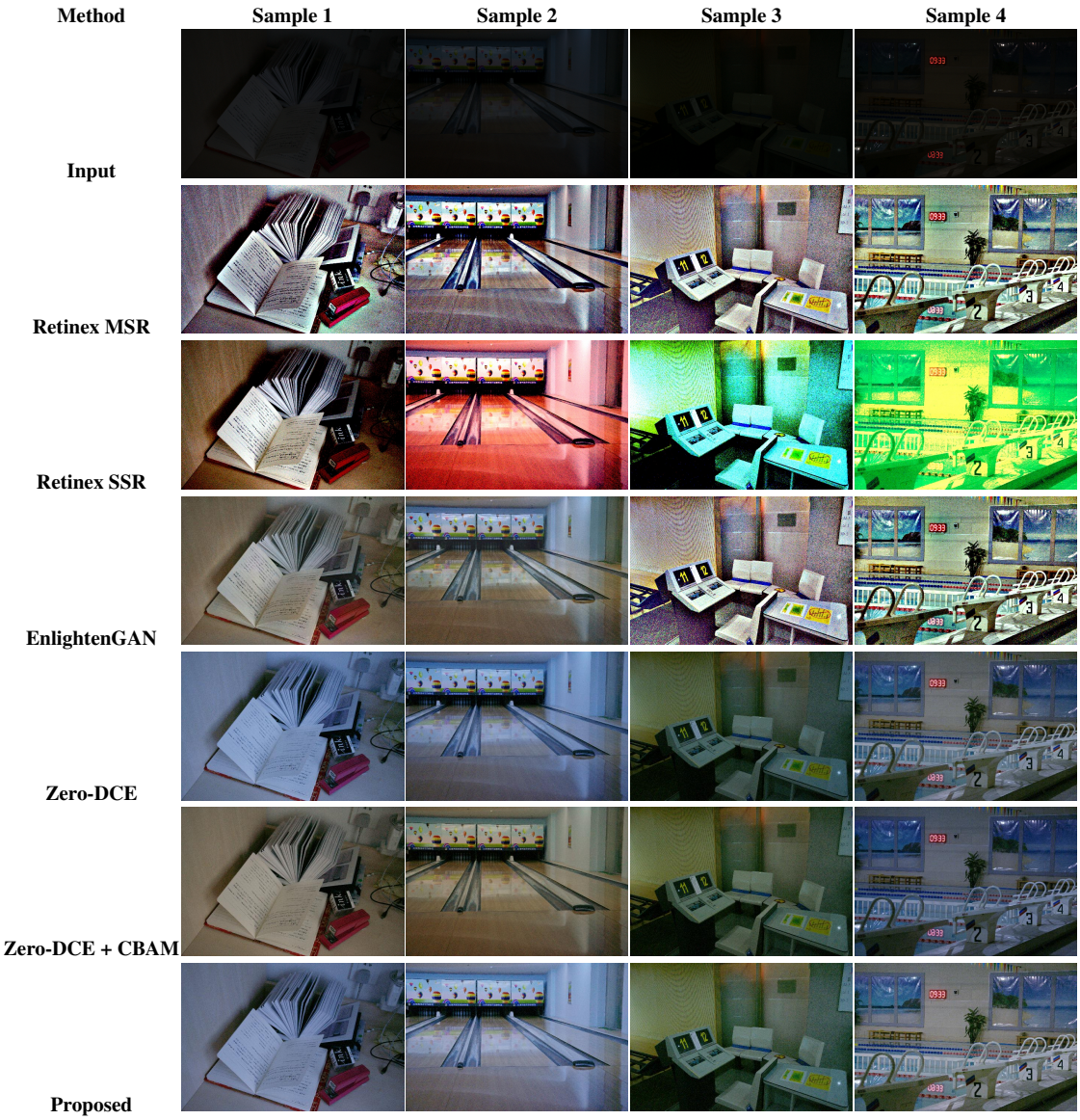


Figure 5.1: Qualitative comparison of low-light enhancement methods on different samples from the LOL dataset.

5.2 Quantitative Analysis

In the quantitave experiment, full-reference and no-reference measures were considered to evaluate the quality of image enhancement in low-light condition, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), BRISQUE, and PIQE. From the results presented, one can see that the proposed ZeroDCE-CBAM and EGA-Enhanced ZeroDCE models outperform the others in enhancing image qualities in challenging low-light illumination.

Table 5.1: Quantitative evaluation of the proposed EGA-Enhanced ZeroDCE framework on the LOL dataset.

Method	**PSNR** ↑	**SSIM** ↑	**BRISQUE** ↓	**PIQE** ↓
Retinex MSR	5.90	0.090	49.79	59.57
Retinex SSR	6.79	0.184	48.55	57.79
EnlightenGAN	10.13	0.189	**11.18**	**29.94**
Zero-DCE	10.57	0.233	29.32	41.60
Zero-DCE + CBAM	11.74	0.254	29.00	41.35
Proposed Model	**17.42**	**0.482**	21.49	35.73

Firstly, the proposed ZeroDCE-CBAM model makes improvement on the basic ZeroDCE model by considering attention refinement based on CBAM mechanism. With the consideration of attention mechanisms, the model is capable of making improvement on PSNR and SSIM values, which implies its superiority in preserving the images' structures and illumination consistency. Besides, the application of attention mechanism makes improvements on structural distortions and local contrast distribution in low-light images.

Secondly, the EGA-Enhanced ZeroDCE model makes further improvement on image enhancement performances through exposure-guided attention and darkness-aware features. In the comparison with other models, it gains the best PSNR and SSIM, implying its superiority in structural fidelity and illumination balancing. In addition, it outperforms the other in terms of BRISQUE and PIQE values.

In conclusion, the findings from the quantitative experiments prove that the ZeroDCE-CBAM framework and EGA-Enhanced ZeroDCE framework have been significantly beneficial for enhancing image consistency and quality in low-lighting conditions, with the latter being even more effective for illumination and structure adaptation.

5.3 Comparative Performance Analysis

The comparative analysis demonstrates the improvement achieved through the integration of attention-guided and illumination-aware refinement within the ZeroDCE framework. As shown in Fig. 5.2, the ZeroDCE-CBAM framework improves overall brightness and visibility under low-light conditions. However, certain dark regions still exhibit uneven illumination and limited structural clarity.

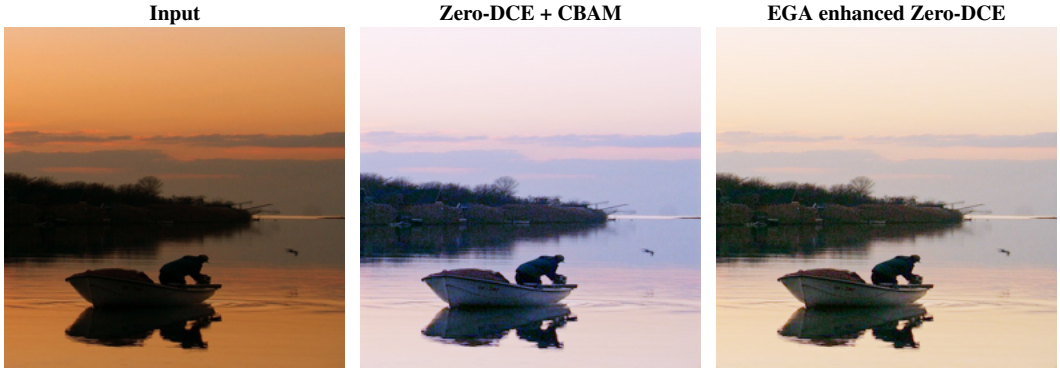


Figure 5.2: Visual comparison between the ZeroDCE-CBAM framework and the proposed EGA-Enhanced ZeroDCE framework on a representative low-light sample.

The proposed EGA-Enhanced ZeroDCE framework further improves illumination balance, texture visibility, and structural preservation while maintaining a more natural appearance of the scene. The enhanced output also shows reduced over-enhancement artifacts and improved perceptual consistency across foreground and background regions.

The quantitative results further support these observations, where the proposed framework achieves improved PSNR and SSIM values, indicating better structural fidelity and enhancement consistency under challenging low-light environments.

5.4 Limitations of the Proposed Framework

However, despite the progress made through the new framework, there are several shortcomings that should be highlighted as well. While EGA-Enhanced ZeroDCE framework enhances consistency within severe low-light conditions, its effectiveness under extremely noisy environment and exposure mismatched conditions may need some improvements as well.

Additionally, while EGA-Enhanced ZeroDCE framework concentrates on the problem of low-light enhancement, it does not cover the problem of unified exposure correction, which includes both underexposed and overexposed regions. Even though EGA-Enhanced ZeroDCE framework is less computationally complex than transformer-based or diffusion-based enhancement frameworks, the application of other, more complicated illumination models may help enhance robustness within extremely complex lighting conditions.

5.5 Practical Implementation

Due to its lightweight architecture and zero-reference properties, the suggested EGA-Enhanced ZeroDCE approach is well-suited for applications involving low-light image enhancements that are computationally efficient and enable real-time inference capability. Possible use cases are surveillance, autonomous driving, smartphone photography, object detection at night time, and scene understanding in the dark.

Use of CBAM for refining features along with the Exposure Guided Attention makes the process more robust to difficult illumination settings without compromising the computational efficiency required for resource-limited vision applications.

Chapter 6

CONCLUSION AND FUTURE SCOPE

This thesis aims to provide a thorough investigation of image enhancement in challenging illumination scenarios, especially for exposure correction schemes and the design of efficient and effective zero-reference low-light image enhancement systems. This dissertation is mainly structured in two significant sections, including the systematic review of current exposure correction schemes and the design of attention guided zero-reference enhancement frameworks based on ZeroDCE architecture.

In the review study, existing traditional and deep learning methods are analyzed with a focus on low-light enhancement, over-exposure correction, unified exposure correction, transformer-based schemes, and diffusion-based techniques. Several existing limitations and challenges in exposure correction research include the issue of poor generalization ability, high computation cost, inconsistent metrics, and the inconsistency in enhancement quality versus efficiency for complex illumination situations.

Considering these drawbacks in existing works, the novel ZeroDCE-CBAM framework, which is based on the ZeroDCE structure by the inclusion of channel-spatial attention mechanisms, is initially proposed in this thesis. In addition, an enhanced scheme called "Exposure Guided Attention Enhanced ZeroDCE" (EGA-Enhanced ZeroDCE), incorporating the exposure guided attention and dark-aware feature refinement scheme, is proposed to enhance the consistency in under-exposed areas.

According to results obtained through experiments conducted on benchmarking datasets such as LOL and ExDark, the frameworks proposed perform better than the current state-of-the-art lightweight enhancement models in terms of enhancement quality, structural fidelity, and consistency. For instance, the proposed EGA-Enhanced ZeroDCE framework performs better in terms of reconstruction effectiveness than ZeroDCE and ZeroDCE-CBAM.

Conclusion reached from the study carried out in this thesis indicates that the developed enhancement schemes provide an ideal balance between enhancement quality, spatial adaptability, and computational performance, hence making them fit for application in low-light vision systems such as surveillance, autonomous driving, and mobile imaging.

Future research could be directed towards developing unified approaches to correcting exposure which work effectively in both low-light and over-exposed situations.

Developing lightweight Transformers and diffusion models and using them in the proposed framework for video enhancement are also promising directions.

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Paper 1 Details

Conference Name: 9th INTERNATIONAL CONFERENCE ON INNOVATIVE COMPUTING AND COMMUNICATION (ICICC-2026) (https://icicc-conf.com/)

Title of Paper: ZeroDCE-CBAM: Lightweight Spatial-Channel Aware Illumination Enhancement for Images

Proof of Communication: Accepted

Submission Summary

Conference Name	9th INTERNATIONAL CONFERENCE ON INNOVATIVE COMPUTING AND COMMUNICATION (ICICC-2026)
Track Name	ICICC2026
Paper ID	365
Paper Title	ZeroDCE-CBAM: Lightweight Spatial-Channel Aware Illumination Enhancement for Images
Abstract	Low-light conditions pose a continual challenge for computer vision systems, frequently resulting in diminished image quality and impaired performance in subsequent tasks such as object detection and recognition. In this work, we present ZeroDCE-CBAM, a lightweight, completely unsupervised image enhancement framework that preserves colour balance and structural consistency while enhancing visibility in low light. This model is built on the ZeroDCE architecture by combining a Convolutional Block Attention Module (CBAM) to enable feature refinement that is both spatially and channel-aware. This enables the network to choose and highlight important regions during enhancement. Furthermore, the architecture introduces a darkness-aware spatial mask derived from luminance statistics to explicitly guide attention to severely underexposed areas. The model is optimized using a combination of zero reference loss functions, such as exposure control, spatial consistency, illumination smoothness, and color constancy, without requiring paired training data. The model consistently outperforms current approaches in full-reference measures like PSNR and SSIM as well as no-reference perceptual scores like BRISQUE and PIQE when tested on benchmark datasets like the LOL Dataset and ExDark Dataset. The proposed model with its compact architecture, strong interpretability, and consistent improvements over ZeroDCE, achieves an 11\% gain in PSNR and an 8\% gain in SSIM on the LOL dataset.
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Authors	**Sumit Singh** (Delhi Technological University) <sumit2023.cse@gmail.com> Sanjay Patidar (Delhi Technological University) <sanjaypatidar@dtu.ac.in>
Submission Files	Final_Draft.pdf (1.8 Mb, 2025-09-29 22:06:18 GMT+5:30) 365_CRC.pdf (1.8 Mb, 2025-10-11 23:41:53 GMT+5:30)

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Greetings from - ICICC 2026!

We congratulate you that your paper with submission ID **'365'** and Paper Title **'ZeroDCE-CBAM: Lightweight Spatial-Channel Aware Illumination Enhancement for Images'** has been accepted for publication in the **Proceedings of ICICC 2026- Springer LNNS Series** [Indexing: zbMATH, Scopus, DBLP, EI Compendex & SCImago - Approved]. This acceptance means your paper is among the top 15% of the papers received/reviewed.

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Prof. Prabhat Kumar
General Chair
National Institute of
Technology, Patna, India

Prof. A.K. Singh
Technical Program Chair
National Institute of Technology,
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Paper 2 Details

Conference Name: 7th International Conference on Data Analytics & Management (ICDAM-2026) (https://www.icdam-conf.com/)

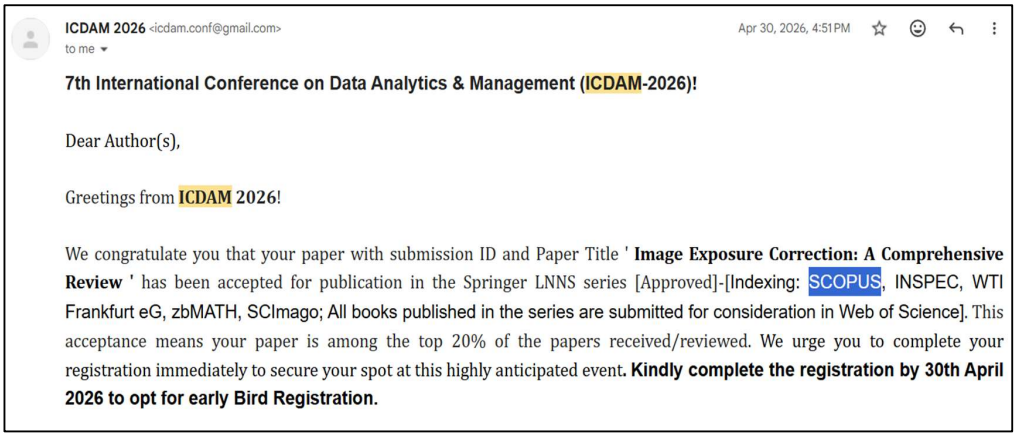
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Submission Summary

Conference Name	7th International Conference on Data Analytics & Management (ICDAM-2026)
Track Name	ICDAM2026
Paper ID	1188
Paper Title	Image Exposure Correction: A Comprehensive Review
Abstract	The problem of exposure correction plays a significant role in computational photography and computer vision, which focuses on improving image quality by addressing exposure-related problems like underexposure, overexposure, or even mixed exposure. Conventional image processing approaches were adopted to solve the exposure correction problem until now, while the latest developments have largely focused on solving exposure correction through deep learning. This work reviews existing techniques for exposure correction, starting from low light enhancement, overexposure correction, unified exposure correction, as well as novel applications, including extreme exposure and dynamic exposure. Apart from the existing datasets, common performance metrics are reviewed, indicating inconsistency with the learning paradigm. An analysis of existing works in terms of modeling, dataset, and efficiency is provided. Issues with the exposure correction process, namely information loss due to extreme exposure, inconsistency in performance metric, inefficiency of models, as well as the potential directions for future research are discussed.
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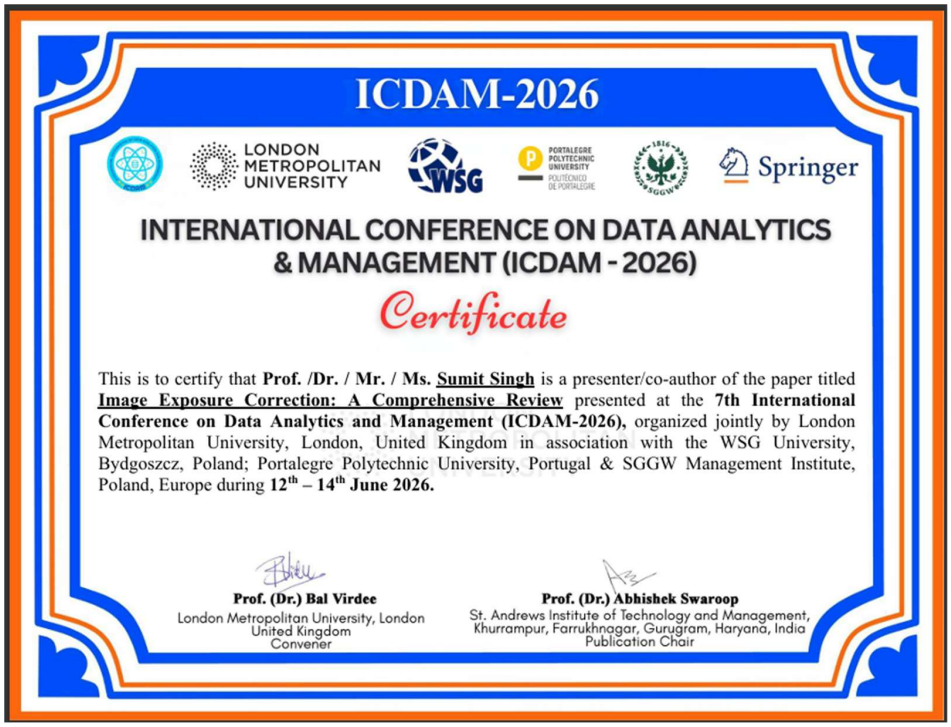
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Prof. (Dr.) Bal Virdee
London Metropolitan University, London
United Kingdom
Convener

Prof. (Dr.) Abhishek Swaroop
St. Andrews Institute of Technology and Management,
Khurrampur, Farrukhnagar, Gurugram, Haryana, India
Publication Chair

Paper 3 Details

Conference Name: 2026 International Conference on Intelligent Computing, Control & Communication (https://www.iciccc.in/cfp.html)

Title of Paper: EGA-Enhanced Zero-DCE for Low-Light Image Enhancement

Proof of Communication: Communicated

Submission Summary

Conference Name	2026 International Conference on Intelligent Computing, Control & Communication
Track Name	Track 2: Artificial Intelligence and Expert Systems
Paper ID	1069
Paper Title	EGA-Enhanced Zero-DCE for Low-Light Image Enhancement
Abstract	Low-Light Image Enhancement (LLIE) has significant importance in Computer Vision because of the role it plays in increasing the visibility of the images and their applications. The existing algorithms tend to have issues such as noise amplification and lack of adaptability in non-uniformly illuminated scenes. However, with deep learning techniques, better quality image enhancements can be achieved but with higher levels of computational complexities. Zero Reference Deep Curve Estimation (Zero-DCE) is one technique that allows efficient zero-reference enhancements in LLIE. However, Zero-DCE mainly focuses on global illumination adjustments and lacks any spatial adaptability in its enhancement procedure. In order to counteract this issue, we propose a enhancement framework based on the combination of illumination guided attention mechanisms into Zero-DCE. The enhancement framework includes Convolutional Block Attention Modules (CBAM) for feature refinement and an EGA module to adjust the features according to the darkness mask in severely underexposed areas of images. Experimental results indicate that the suggested EGA-Enhanced Zero-DCE technique outperforms the base Zero-DCE framework by improving the PSNR metric from 10.57 dB to 17.42 dB and SSIM metric from 0.233 to 0.482.
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Authors	**Sumit Singh** (Delhi Technological University) <sumit2023.cse@gmail.com> Sanjay Patidar (Delhi Technological University) <sanjaypatidar@dtu.ac.in>
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Name of Conference/Journal: 9th INTERNATIONAL CONFERENCE ON INNOVATIVE COMPUTING AND COMMUNICATION
Conference Dates with venue (if applicable): 06/02/2026 - 07/02/2026 (SHAHEED SUKHDEV COLLEGE OF BUSINESS STUDIES, UNIVERSITY OF DELHI, NEW DELHI)
Have you registered for the conference (Yes/No)?: Yes
Status of paper (Accepted/Published/Communicated): Accepted
Date of paper communication: 29 Sep 2025
Date of paper acceptance: 09th Oct 2025
Date of paper publication: NA

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Author names (in sequence as per research paper): Sumit Singh; Sanjay Patidar
Name of Conference/Journal: 7th International Conference on Data Analytics & Management (ICDAM-2026)
Conference Dates with venue (if applicable): 12/06/2026 – 14/06/2026 (London Metropolitan University, London, UK)
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Date of paper acceptance: 30 Apr 2026
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Conference Dates with venue (if applicable): 08/10/2026 – 09/10/2026 (Galgotias College of Engineering and Technology, Greater Noida, Uttar Pradesh)
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ACADEMIC DETAILS

Degree/Qualification	University	Year	CGPA/%
Master of Technology (Data Science)	Delhi Technological University, New Delhi	2024-26	9.34
Bachelor of Technology (CSE)	Graphic Era (Deemed to be University), Dehradun	2019-23	9.41
Senior Secondary Education	Blue Bells Model School, Gurgaon	2018-19	89.2%
Secondary Education	Blue Bells Model School, Gurgaon	2016-17	10

EXPERIENCE

- **Applied Scientist Intern**, Amazon (Gurugram) *Feb 2026 - Present*
  - Built reusable data preparation pipelines to transform raw data into feature-rich inputs for time series forecasting, enabling efficient experimentation across multiple model architectures.
  - Evaluated **7+ forecasting models** across **10+ datasets** to validate an event-based gating mechanism, achieving an average **~6% improvement in MAE** and enhancing event-driven seasonality modeling.
  - Developed a two-step forecasting architecture on top of Chronos, delivering a **6 pp improvement in WAPE** and a **12 pp improvement in Bias**.
  - Built and deployed an **agentic dashboard on AWS** for the Business Intelligence team, reducing manual data analysis and weekly reporting effort by **2–3 hours per week**.
- **Research Intern**, Samsung R&D Institute India (Bangalore) *Jul 2025 - Jan 2026*
  - Designed and implemented an end-to-end pipeline for training, evaluation, and inference of a lightweight Vision-Language Model (VLM) for visual question answering and captioning, achieving comparable performance with a **~76% reduction in model size**.
  - Generated large-scale synthetic datasets using outputs from multiple models (VLMs and LLMs) to support downstream model fine-tuning and improve adaptability across diverse use cases.
- **AIML Engineer**, Dreamalle Solution Private Limited (Remote) *Sep 2024 - Dec 2024*
  - Developed AI/ML-powered chatbots and virtual assistants using LLM APIs like ChatGPT, handling over 100+ daily user interactions while ensuring reliability and scalability.
  - Built, fine-tuned, and deployed multiple ML models including BERT and XGBoost, and created POCs for seamless integration, improving accuracy by 7% and efficiency by 20%.
- **Graduate Engineer Trainee**, Sunlife Global Solution Private Limited(Gurugram) *Aug 2023 - Aug 2024*
  - Developed multiple PoCs to extend Salesforce functionality and integrate Jira with Microsoft Teams, delivering scalable, cross-team solutions adopted across departments.
  - Designed JavaScript-based Lightning Web Components and a full-stack insurance PoC using Spring Boot and React, enhancing UI/UX and improving system usability by 15%.

PROJECTS

- **ZeroDCE Based Low Light Image Enhancement**, DTU *July 2025*
  - Developed a custom Zero-DCE model for low-light image enhancement with integrated loss functions, achieving a **2.5 dB PSNR improvement** and a **10% SSIM gain** in cross-dataset generalization.
  - Enhanced the architecture by integrating CBAM attention and enabling dual-branch predictions, improving **detection accuracy by 8% on the ExDark dataset**.
- **RAG Based Assessment Recommendation System**, DTU GitHub | *Apr 2025*
  - Built an AI-powered Assessment Recommendation System that extracts job descriptions from text or URLs and recommends the most relevant assessments available on SHL Assessment catalogue.
  - Deployed using FastAPI and Streamlit, integrating with third-party LLM APIs i.e. Google Gemini.
- **Negotiation Bot**, Dreamalle Solution Private Limited GitHub | *Oct 2024*
  - Enhanced user interaction by leveraging LLM-driven conversational capabilities to deliver personalized negotiation experiences, leading to improved customer satisfaction.
  - Used sentiment analysis to tailor strategies, boosting seller profit by converting prospects into buyers.
- **Liveness Detection System**, Smart India Hackathon, DTU *Sep 2024*
  - Achieved >90% accuracy in spoof face detection while reducing model size by 12× and improving processing speed 6×, enabling scalable, real-time image handling under 100 ms.
  - Project recognized during Smart India Hackathon (2024) evaluations for its scalability and applicability in secure authentication systems.

SKILLS

- **Languages**: Python, C++, C, Java, JavaScript, Apex, HTML, CSS, MySQL
- **Domains**: Computer Vision, Natural Language Processing (NLP), Backend Development (Python, Java), Databases (MySQL, PostgreSQL), Machine Learning, Deep Learning, Generative AI
- **Libraries/Frameworks**: Spring Boot, PySpark, TensorFlow, Scikit-Learn, Streamlit, FastAPI
- **Tools**: VS Code, Jupyter Notebook, AWS, GitHub, Power BI, Tableau, Excel

PUBLICATIONS

- **ZeroDCE-CBAM Lightweight Spatial-Channel Aware Illumination Enhancement for Images** in **9th International Conference On Innovative Computing & Communication (ICICC-2026)** .
- **Image Exposure Correction: A Comprehensive Review** , accepted at the **7th International Conference On Data Analytics & Management (ICDAM-2026)**.

KEY ACHIEVEMENTS **Certificates**

- Awarded the Best Paper recognition at ICDAM for the published research.
- Awarded the Best Paper recognition at ICICC for the published research.
- Mentored a student team shortlisted for Smart India Hackathon (SIH) 2025–26 in AI/ML solution design, guiding them through technical and implementation challenges.
- Qualified GATE in 2025 (AIR 2270) and 2024 (AIR 3506), demonstrating strong analytical and technical capabilities.
- Selected from over 1,500 applicants to participate in Graphs Camp, a three-day intensive program led by Codeforces Master Manas Kumar Verma, covering 11+ advanced graph algorithms.
- Qualified the BrAInwave Hackathon 2024–25 (Qualifier Round) at DTU, exhibiting rapid analytical thinking in high-pressure scenarios.
- Qualified the Smart India Hackathon 2024–25 (Qualifier Round) at DTU, reinforcing proficiency in AI/ML applications.
- Secured 2nd place in the ML Cryptic Hunt Competition 2024–25, conducted by DTU, highlighting collaborative efficiency in competitive environments.
- Published a paper titled *"Disease Prediction Using Random Forest Classifier"* at the 3rd ICPCSN, 2023, demonstrating applied machine learning research capabilities.
- Grand Finalist (AIR 10) in Latent View *The Number Thing*, 2022 (Data Analytics Hackathon), highlighting strong analytical and data interpretation skills.

AUTHOR PROFILE



Sumit Singh is currently pursuing a Master of Technology in Data Science at Delhi Technological University (DTU), New Delhi. He previously completed his Bachelor of Technology in Computer Science from Graphic Era Deemed to be University, Dehradun. His research interests include Machine Learning, Deep Learning, Computer Vision, Time Series Forecasting and Generative Artificial Intelligence.

He has worked on various research and industrial projects such as Image Processing, Vision Language Models, Time Series Forecasting through Events, and Computer Vision Applications. At present, he is working on researching how models can perform better for improving image quality in low lighting conditions. He was a Teaching Assistant at Delhi Technological University and has been part of various multidisciplinary projects with AI chatbots and intelligent systems.

Sumit has authored research papers in international conferences like Springer ICICC 2026 (Awarded as Best Paper) and Springer ICDAM 2026. Sumit worked as a part of Samsung Research Institute, India during his internship tenure and is presently working as an Applied Scientist Intern in Amazon, India. Some of the major technological skills he possesses include Python, Machine Learning, Deep Learning, Data Analytics, Large Language Models, and Web Development. Sumit has participated in various hackathons and competitions across the country, winning many awards and recognitions.