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Low Light Image Enhancement (LLIE): Nakshatra Drishti Deep learning Model

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Abstract
Images when captured under low light or insufficient illumination and limited exposure time or in darkness or under inevitable environmental or technical constraints are difficult to recognize and becomes challenging to derive valuable intelligence out of it. The quality of such images are badly degraded due to noise, buried scene content, inaccurate color and contrast information thereby posing significant difficulty in performing various analysis operation upon it like object detection , change detection, tracking, face recognition, disguise recognition. Figure 1 shows some examples of the degradations induced by images captured under low light condition.

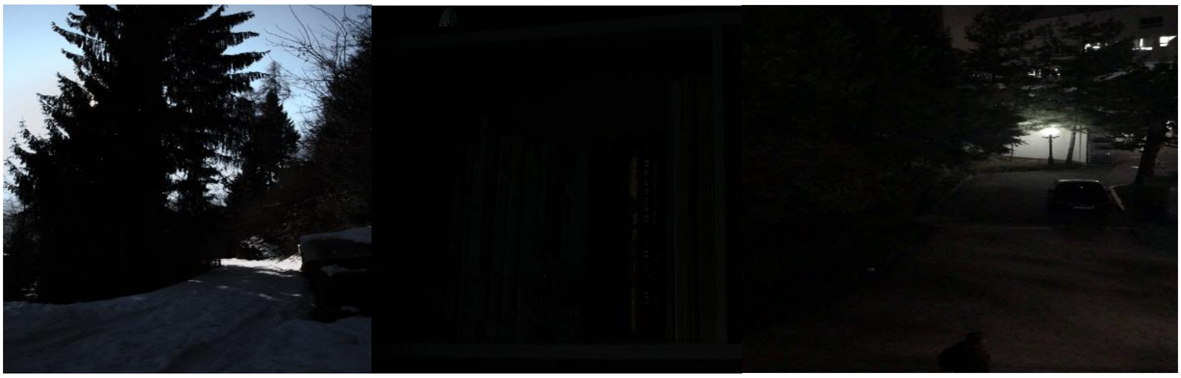

Figure 1. Examples of images taken under sub-optimal lighting conditions.

To resolve the problem this problem we propose a highly effective supervised learning based convolutional neural network model dubbed Nakshatra-Drishti Low-light image enhancement (LLIE) deep learning model that produces powerful results on enhancing low light image, video and real-time live camera feed all integrated under a single umbrella. Our deep learning model has been supervised and trained on paired dataset and has been extensively tested on various benchmarks and has demonstrated outstanding results. A set of carefully formulated loss functions to measure enhancement quality and optimizing the learning process of deep learning model has been adopted alongwith noise function to remove various types of noises that degrades the image quality under dark light condition. Our user-friendly web-based software application aims at improving the perception or interpretability of an image captured in an environment with poor illumination on which further Artificial intelligence analysis can be effectively performed that helps in better decision making and reducing OODA loop.

1. Introduction

Images captured in dark or under poor illumination environment conditions are degraded compromising aesthetic quality thereby effecting viewer's experience and interpretation. Therefore performing high-level computer vision operations and Artificial intelligence analysis on such degraded images or videos like object detection, change detection and face recognition become extremely challenging. Therefore low light image enhancement techniques has always been widely recognized field of future research and developments are taking place every year.

To enhance the low light images a large number of algorithms have been developed ranging from histogram equalization, retinex model based conventional methods [1],[2]. Since 2017, there have seen surge in deep learning based low light image enhancement model developments that have produces better accuracy, reliable results, robustness and speed over traditional methods therefore paving the way for more robust computer vision applications in challenging light conditions [3],[4],[5].

In this study we present a novel deep learning algorithm using Convolutional neural network for low light image enhancement. It works well with diverse lighting conditions including clouds/fogs environment conditions and images captured during night or under non-uniform lights. Our Nakshatra-Drishti model achieves visually pleasing images and videos improving color, naturalness, contrast and vital information. Our model excel in handling high-dimensional data such as images. Our Nakshatra-Drishti model learn hierarchical feature representations from the input data, identifying complex patterns that can be used to enhance image quality significantly. Our model has been trained on paired image pairs on lol dataset using supervised learning to understand the characteristics of low-light images and apply appropriate transformations to improve their quality. It has been tested on various dataset to include LOL, LIME, MEF, DICM and real world images captured by digital cameras and has effectively increased brightness, enhance contrast, and reduce noise, even in complex and highly variable low light scenarios [6],[7],[8],[9]. Our model is capable of processing images and videos in real-time (about 500 FPS for images of size 640x480x3 on CPU and takes only 40 minutes for training on GPU.

2. Related work

Traditional Approaches. Low-light image image enhancement has been an active field of research as part of an image processing domain. Various traditional methods have been under use such as the adaptive histogram equalization (AHE) [2], Retinex [1] and multiscale Retinex model [10]. To make a balance between details and naturalness, recently [11] proposed an low light image enhancement algorithm for non-uniform illumination images, by using a bi-log transformation method. Based on logarithmic transformation, [12] developed a weighted variational model to estimate both the reflectance and the illumination from an observed image with imposed regularization terms. In [13], another low-light image enhancement was developed by estimating illumination of each pixel by finding the maximum value in its RGB channels, thereafter illumination map was constructed by imposing a structure prior. In [14] a joint low-light image enhancement and denoising model was introduced using decomposition in a successive image sequence. In [15] a Retinex model was proposed, by considering a noise map and comparing it with conventional Retinex model for low light image enhancement.

Deep Learning Approaches.

Since 2017 the focus has been shifted to development of various deep learning models for low light image enhancement tasks. The low light image enhancement task using deep learning can be classified into into supervised learning, reinforcement learning, unsupervised learning, zero-shot learning, and semi-supervised learning according to different learning strategies. Out of these study shows that the supervised learning strategy for development of low light image enhancement model has been more successful and approximately being used 73% of times as shown in figure. Supervised learning solutions mostly use paired training, where low-light images and corresponding day light image pairs are used for training of model. In [3] a stacked auto-encoder (LL-Net) model was developed to learn joint denoising and low-light enhancement on the patch level. Retinex-Net in [4] provided an end-to-end framework to combine the Retinex theory with deep learning model. In HDR-Net [16] the idesas of deep learning network models were incorporated bilateral grid processing and local affine color transforms with pairwise supervision for model developement. In HDR domain, some multi-frame low-light enhancement techniques were developed, such as [17], [18], [19]. Lately, [20] proposed a learning method to see in the dark that achieves impressive results. This method operates directly on raw sensor data and it focuses more on avoiding the amplified artifacts by learning the pipeline of color transformations and denoising. CNN-based solutions were developed that rely on paired data for supervised training, therefore they are resource-intensive.

LLNet was trained on data simulated on random Gamma correction. Another deep learning method GANs [21], [22] have been developed for image synthesis, translation, image restoration and enhancement that uses paired training data. Several unsupervised GANs are proposed to learn inter-domain mappings using adversarial learning and are adopted for many other tasks. EnlightenGAN [23] model was proposed that refers to unpaired training but with a lightweight one-path GAN structure which is stable and easy to train. EnlightenGAN is an unsupervised GAN-based and pioneer method that learns to enhance low-light images using unpaired low/normal light data. The network was trained by taking into account elaborately designed discriminators and loss functions. However, unsupervised GAN-based solutions usually require careful selection of unpaired training data. Deep curve estimation network, Zero-DCE [24], was proposed that formulates the light enhancement as a task of image-specific curve estimation, which takes a low light image as input and produces high-order curves as its output. These curves are used for pixel-wise adjustment on the dynamic range of input to obtain an enhanced image. Thereafter, an accelerated and lightweight version of zero-DCE was also proposed, called Zero-DCE++ [25].

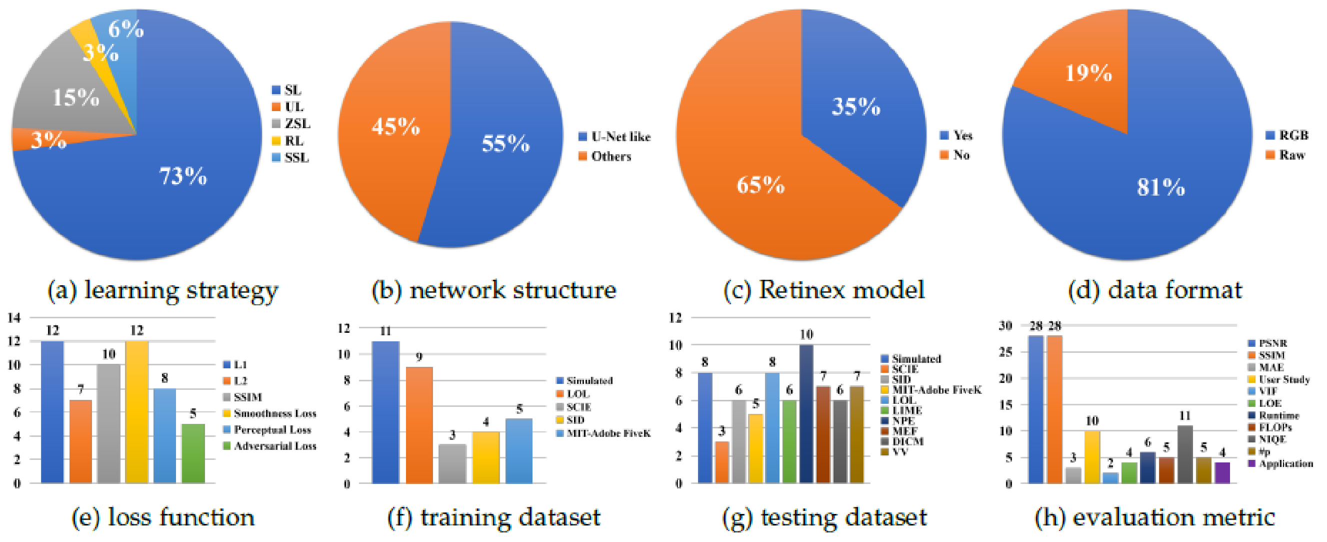

Figure 2. A statistic analysis of deep learning-based LLIE Techniques

3. Methodology

Mathematical Modelling Of Problem Statement

We first give a common formulation of the deep learning based LLIE problem. For a low-light image $I \epsilon\ Y^{W \times H \times 3}$ of width W and height H, the process can be modeled as:

$$¥ = F(I; \phi)$$

where $¥ \epsilon\ R^{W\times H\times 3}$ is the enhanced result and F represents the network with trainable parameters ϕ. The purpose of deep learning is to find optimal network parameters ø that minimizes the error.

$$ø = \text{argmin } L(¥,Y),$$

The loss function L(¥,Y) drives the optimization of deep learning network. The loss functions used in our Nakshatra-Drishti model are Exposure loss, Color constancy loss, Spatial constancy loss, illumination smoothness loss during training of deep learning model.

We present the framework of Nakshatra-Drishti model in figure 2.

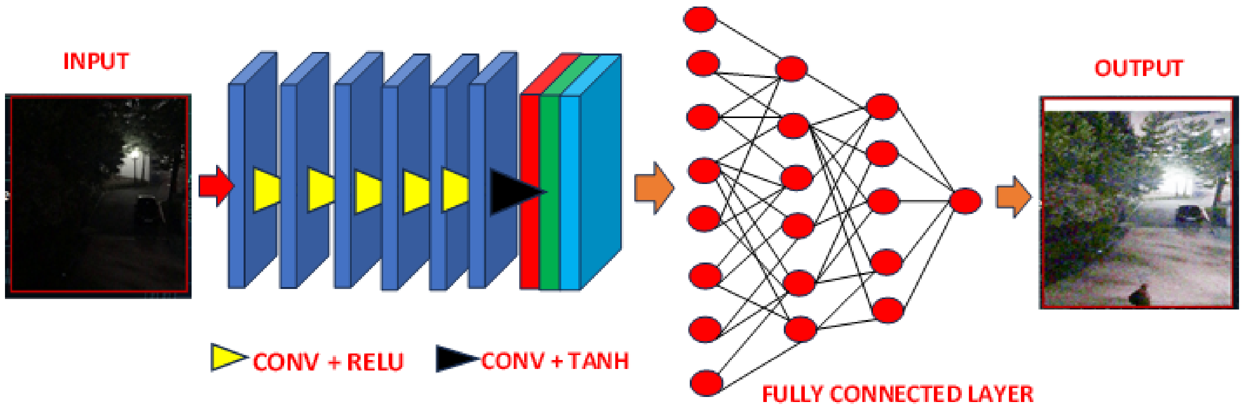

Figure 3 : Architecture-Nakshatra Drishti deep learning Model

Noise Filter

In our LLIE Model, the denoise filter serves as a crucial component to alleviate the adverse effects of various types of noise present in the captured images. Specifically, the denoise filter aims to mitigate Gaussian noise, which is commonly encountered in low-light conditions due to factors such as sensor limitations and electronic interference. By employing a median-based denoising technique, the filter effectively suppresses Gaussian noise while preserving image details and edges.

Furthermore, the denoise filter is instrumental in addressing other types of noise prevalent in low-light images, including temporal noise, color noise, and quantization noise. Temporal noise arises from fluctuations in pixel values over consecutive frames in video sequences, while color noise manifests as aberrations in color channels, resulting in unwanted color artifacts. Quantization noise, on the other hand, stems from the discretization of continuous intensity values during image digitization, leading to visible artifacts and loss of fidelity.

By incorporating a denoise filter equipped with robust noise reduction capabilities, our Nakshatra Drishti model achieves superior results by effectively suppressing various forms of noise while preserving essential image details and enhancing overall image quality. Thus, the denoise filter serves as a very significant tool in our model employed to enhance low-light images, enabling the production of visually appealing and artifact-free results suitable for a wide range of applications.

Neighbouring Frame Utilization.

Our Nakshatra-Drishti Model exploits neighboring frames for enhancing performance and accelerating processing speed during video and real-time live camera feed enhancement. By harnessing information from adjacent frames in video sequences, our algorithms leverages temporal coherence to better estimate scene characteristics and mitigate noise, resulting in enhanced image quality. Moreover, this approach enables efficient utilization of computational resources by reducing the need for extensive per-frame processing, thereby facilitating real-time or near-real-time applications such as surveillance, autonomous navigation, and medical imaging.

Optimizer Function.

Our Nakshatra-Drishti Model, utilizes Adam optimizer with a learning rate of 0.0001 for refining model parameters, minimizing loss, and ultimately improving accuracy. By employing Adam, an adaptive optimization algorithm, our model iteratively adjusts its parameters based on the gradients of the loss function, facilitating efficient convergence towards optimal solutions. This meticulous fine-tuning process ensures that the model effectively minimizes the loss associated with low light image enhancement while simultaneously enhancing its accuracy. The carefully chosen learning rate of 0.0001 enables the optimizer to strike a balance between exploration and exploitation, leading to significant improvements in the overall quality of the enhanced images, video and real-time camera feeds.

Network Structure

Our Nakshatra-Drishti Model employs network structure of U-Net type. U-Net architecture gives added advantage of effectively integrate multi-scale features and employ both low-level and high-level features. Such characteristics are essential for achieving optimized low-light enhancement.

Data Format

As RGB data format dominates most methods as it is commonly found as the final imagery form produced by smartphone cameras, other digital cameras and drone cameras therefore our Nakshatra-Drishti Model has been trained using RGB data input images. This also helps recover clear details and high contrast, obtain vivid color, reduce the effects of noises and artifacts, and improve the brightness of extremely low-light images.

Loss Function

For training of our model and evaluating the quality of enhanced images our Nakshatra-Drishti Model employs following loss function.

Exposure Loss. Exposure loss plays a crucial role in adjusting the brightness and exposure levels of enhanced images.By quantifying the difference between the exposure levels of the enhanced image and the ground truth, exposure loss guides our model to optimize image brightness. Minimizing exposure loss helps enhance visibility and details in low-light conditions by adjusting image exposure appropriately.

Color Constancy Loss. Color constancy loss focuses on preserving color consistency and accuracy in the enhanced images. It ensures that the colors in the enhanced image maintain fidelity to the original scene, regardless of variations in lighting conditions. By penalizing deviations from the true colors of objects, color constancy loss helps produce realistic and natural-looking images with accurate color representation.

Spatial Constancy Loss. Spatial constancy loss is instrumental in promoting spatial coherence and smoothness in enhanced images. It encourages our deep learning model to produce images with coherent structures and smooth transitions between pixels, reducing artifacts such as noise and blurriness. By penalizing abrupt changes or discontinuities in pixel values, spatial constancy loss contributes to sharper, clearer, and visually pleasing results.

Illumination Loss. Illumination loss is employed to enhance the overall brightness and illumination quality of low-light images. By quantifying the difference between the illumination levels of the enhanced image and the desired illumination target, illumination loss guides our model to adjust image brightness effectively. Minimizing illumination loss helps to mitigate the effects of poor lighting conditions, such as under exposure or uneven illumination, resulting in visually improved and more perceptually appealing images.

Smoothness Loss. Smoothness loss focuses on promoting spatial coherence and smoothness in the enhanced images. It encourages our model to generate images with smooth transitions between pixels, thereby reducing artifacts such as noise, jagged edges, or blurriness. By penalizing abrupt changes or discontinuities in pixel values, smoothness loss contributes to sharper, clearer, and visually pleasing results, enhancing the overall visual quality of the images.

4. Experiments

Implementation details. Our CNN-based Nakshatra-Drishti Model uses lol_dataset [26] paired images for network training incorporating both low-light and over-exposed images into our training set. A novel approach has been adopted for development of GUI based integrated image enhancement, video enhancement and live camera feed enhancement software application. A suitable web-based framework has been developed using Flask library in python to integrate all functionalities under single umbrella. Visual studio & Python has been used as for establishing software development environment. On executing the deep learning model training module, the execution of python codes starts and it fetches linked lol_dataset. NVIDIA 2080Ti GPU has been used for Model Trg having 512GB RAM which took approximately 40 minutes for training of our deep learning model. Epoch was set as 100 and Adam Optimizer with a learning rate 0.0001 was used for adjusting Model Parameter, Minimize Loss, Improve Accuracy. On 12th Generation Intel® Core™ i3 processor CPU, it takes approximately 5 hours training time for model training. The model is capable of real-time processing at approximately 500 frames per second for images of size 640×480×3 on GPU. The training cycle is depicted in figure.

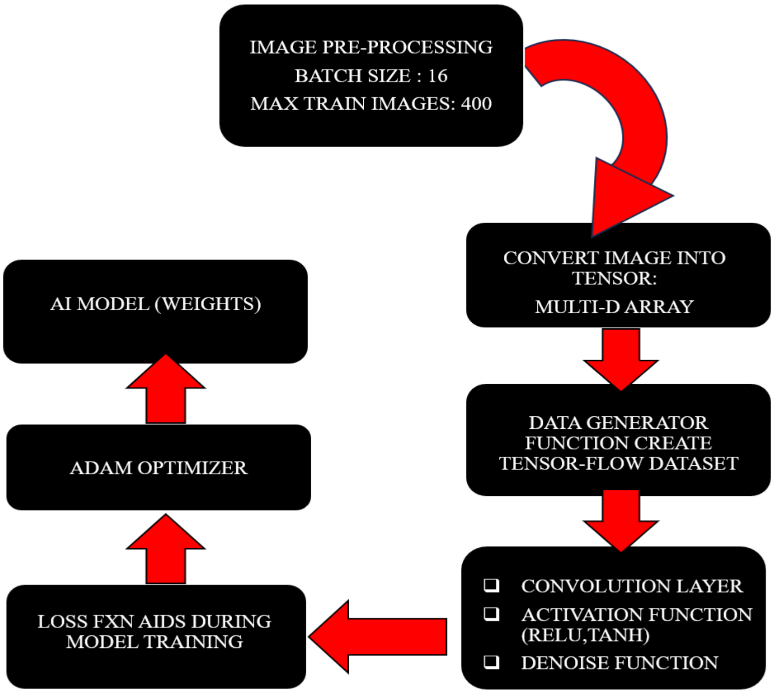

Figure 4: Work-flow

Dataset.

For training of our Nakshatra-Drishti Model, we have used lol_dataset [26] available open source. The dataset is composed of 500 low-light and normal-light image pairs and divided into 485 training pairs and 15 testing pairs. All the images have a resolution of 400×600 saved in RGB format. The model performance has been tested on two datasets i.e on BrighteningTrain dataset and lol_dataset. However as the performance of model was better on lol_dataset so this has been finally selected for saving trained model weights parameters which were then utilized on integrated web-interface in low light image, video and live feed enhancement modules. The lol_dataset is the first paired low-/normal-light image dataset taken in real scenes. The low-light images are collected by changing the exposure time and ISO. lol_dataset contains 500 pairs of low-/normal-light images of size 400×600 that includes real-world captured datasets, synthetic datasets and variety of paired training datasets for training low-light image enhancement networks.

LLIE Model Training.

Our LLIE model is primarily based upon CNN-based model that use self-captured paired data for network training.The dataset used as a part of the training data in lol_dataset[26]. We randomly split 500 low-light and normal-light image pairs into 485 training pairs and 15 testing pairs of different exposure. we have resized the training images to the size of 400×600. we have implemented my coding framework with tensorflow and keras library on an NVIDIA 2080Ti GPU. A batch size of 16 is applied. The filter weights of each layer are initialized with standard zero mean and 0.02 standard deviation Gaussian function. Bias is initialized as a constant. We have used ADAM optimizer with default parameters and fixed learning rate of 0.0001 for our network optimization. We have used Relu and Tanh as activation function. The execution of code and calculation of various parameters are depicted in screenshot in figure.

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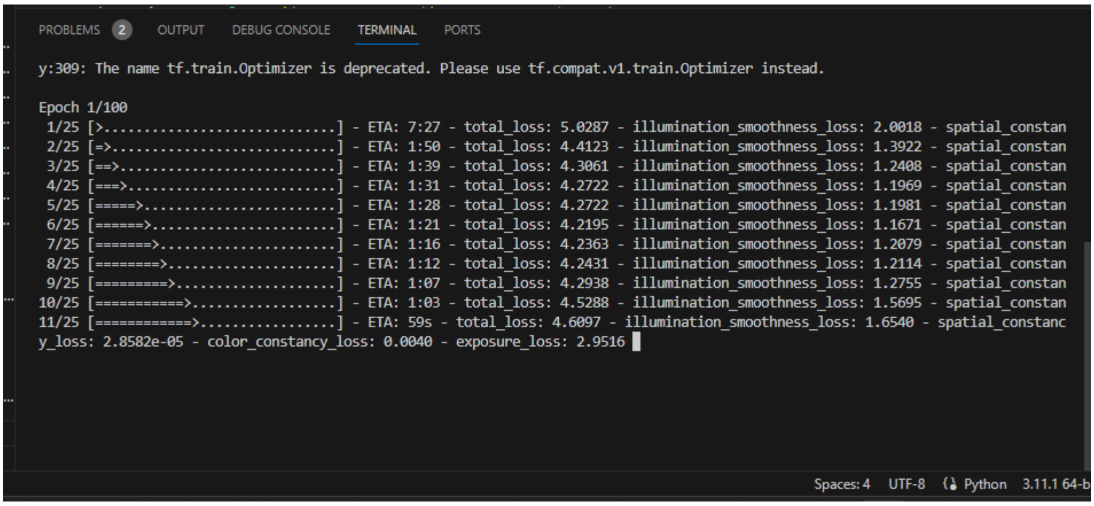
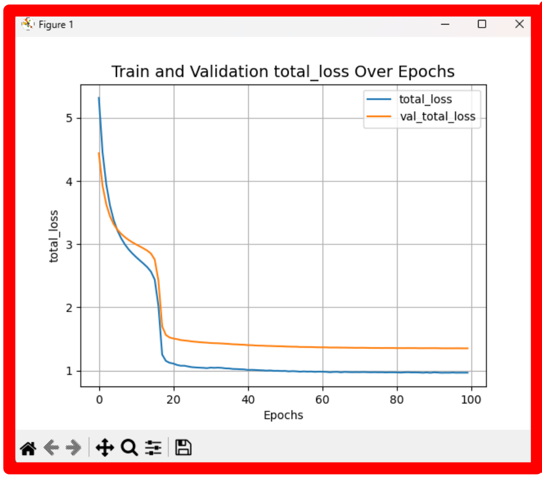
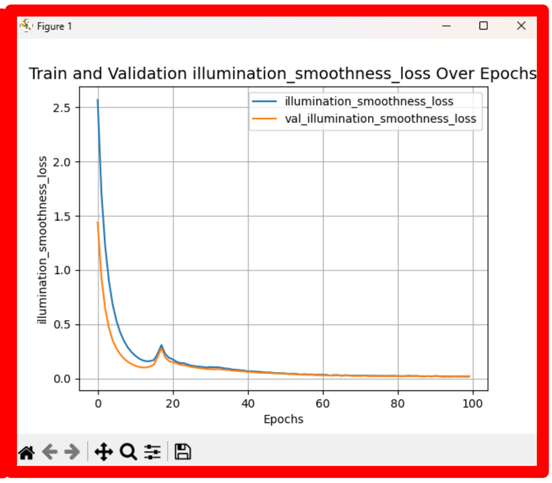


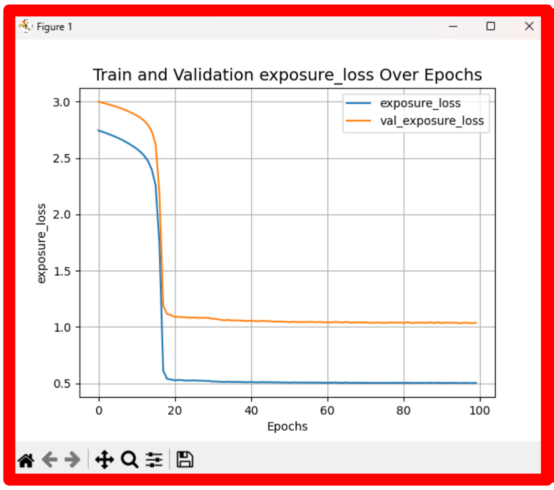
Figure 5 : Nakshatra Drishti Model training

Loss Function Graph.

The incorporation of exposure loss, color constancy loss, spatial constancy loss, illumination loss and smoothness loss functions further refined the model's capabilities, ensuring optimal image enhancement outcomes. The variation of various loss function with respect to epoch are as depicted in charts below:







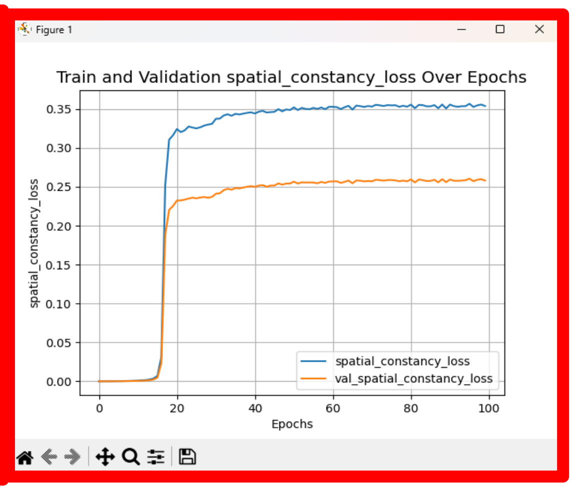


Figure 6 : Loss function chart

Web-Based GUI Interface Frontend

The web-based GUI interface frontend of our low light image enhancement model provides a user-friendly dashboard featuring modules for viewing images, videos, and live camera feeds. Through this interface, users can easily upload images, videos, and provide access to low light live camera feeds, all conveniently displayed and accessible from a single location which on single click of a button will get enhanced producing excellent results. The frontend utilizes flask based web interface to ensure seamless interaction, allowing users to navigate through different modules with ease while providing an intuitive and visually appealing experience.

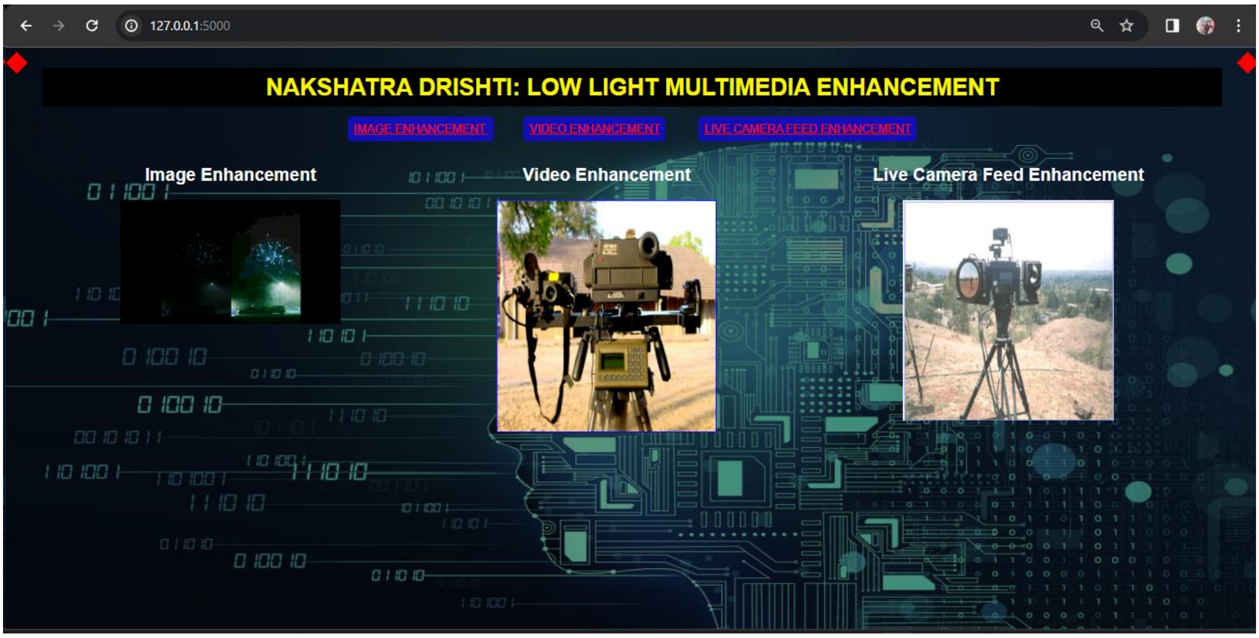


Figure 7 : GUI based Dashboard

Image Enhancement Module.

The low light image enhancement module is the core component of the our Nakshatra-Drishti model, designed to improve the visual quality of images captured in low-light conditions. Leveraging our trained Nakshatra-Drishti model, this module enhances brightness, contrast, and overall clarity while minimizing noise and artifacts commonly associated with low-light photography. By analyzing the input image and applying deep learning model weights learnt during training process this module ensures that details hidden in shadows or darkness are revealed, resulting in significantly improved image quality.

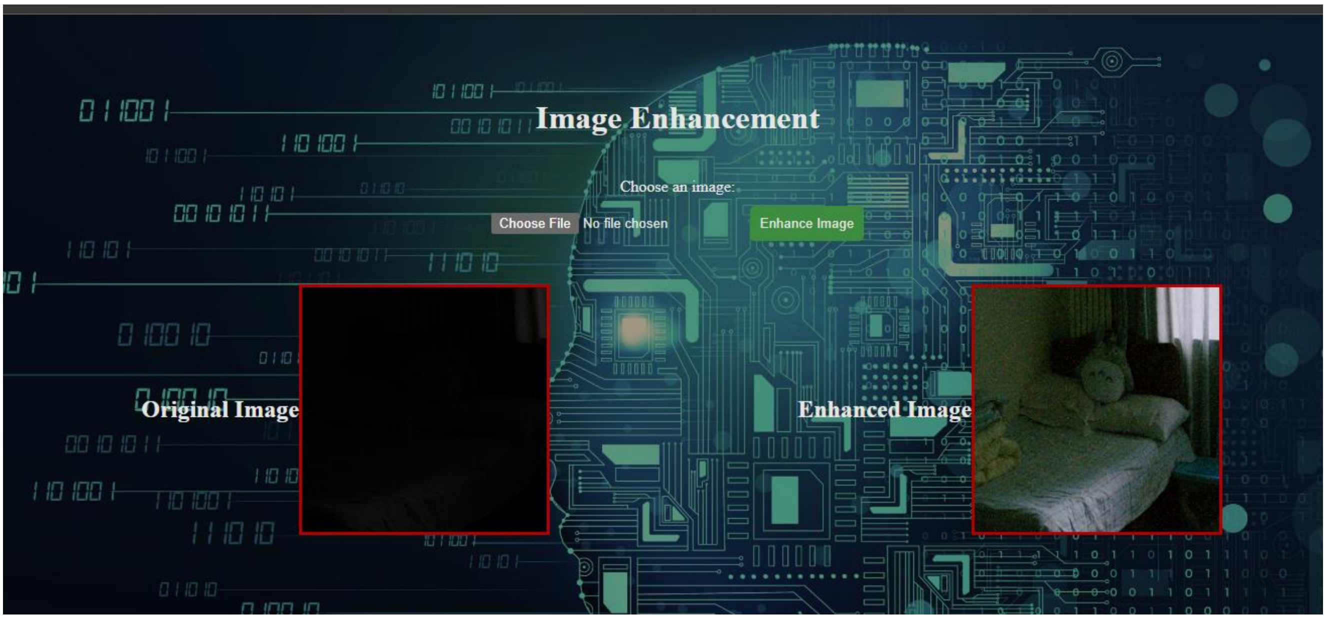


Figure 8: Dashboard of Low light image enhancement module

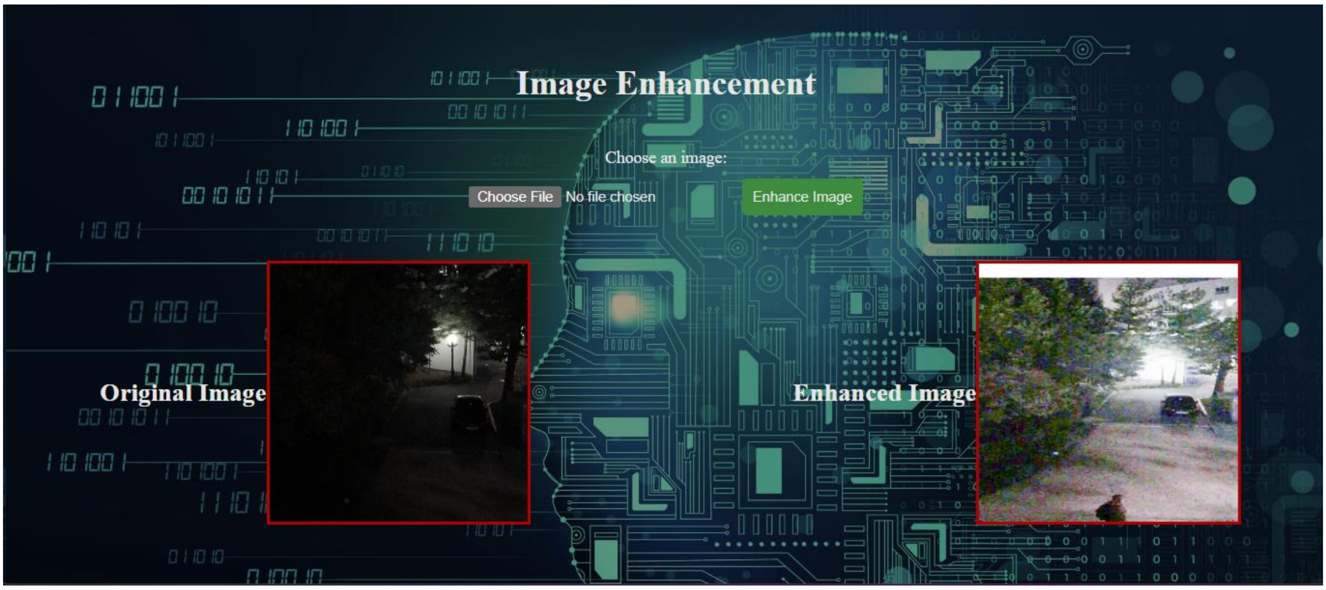


Figure 9: Experimental Result on Low light image input and output

Low Light Video Enhancement Module

The low light video enhancement module extends the capabilities of the image enhancement module to process videos captured in low-light environments. Utilizing our Nakshatra-Drishti model, this module enhances the visibility and clarity of video footage, ensuring that even moving scenes captured in challenging lighting conditions appear clear and well-defined. By applying enhancement techniques consistently across each frame of the video, this module delivers smooth and visually appealing results, allowing users to enjoy enhanced video playback without sacrificing quality or performance.

Figure 10: Dashboard of Low light video enhancement module

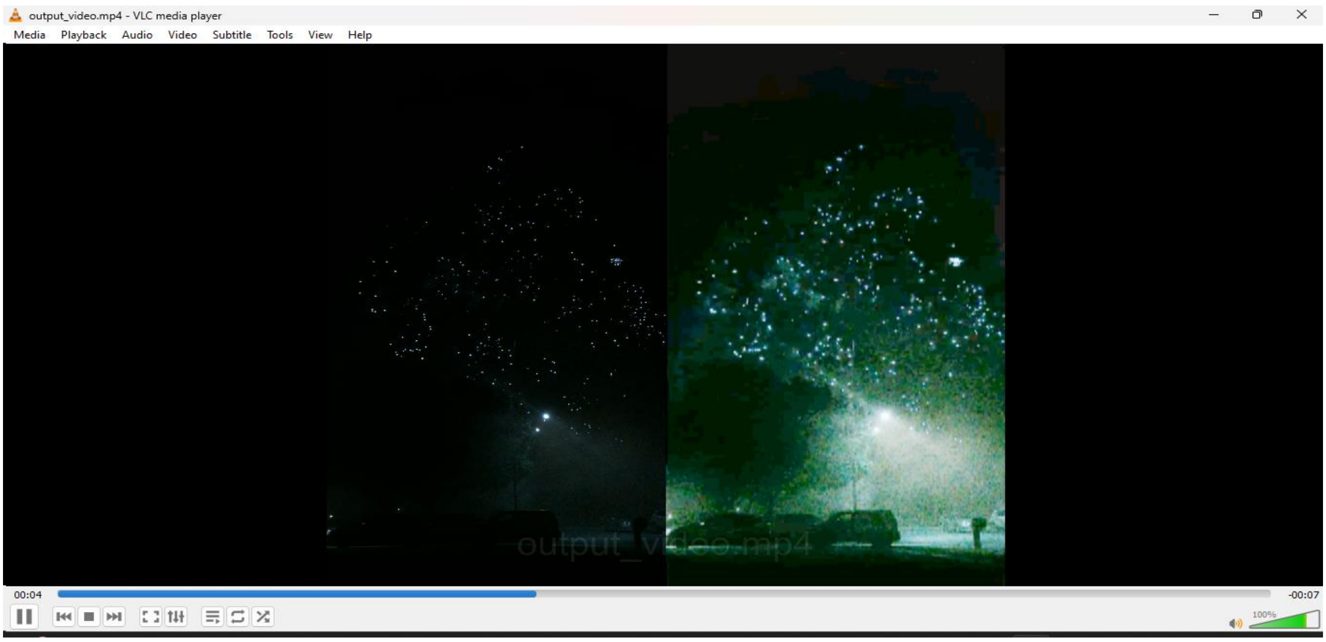


Figure 11: Experimental Result on Low light video input and output

Low Light Live Camera Feed Real Time Enhancement Module

The low light live camera feed enhancement module provides real-time enhancement capabilities for live camera feeds, enabling users to monitor and enhance scenes captured by cameras in low-light conditions. This module processes incoming video streams from connected cameras in real-time, applying enhancement algorithms to improve visibility and quality on the fly. By dynamically adjusting enhancement parameters based on changing lighting conditions, this module ensures that live camera feeds remain clear and detailed, empowering users with enhanced visibility for surveillance, monitoring, or other applications in low-light environments. Our Nakshatra-Drishti model have been tested on webcamera , C270 HD webcamera and IP camera under varied low light conditions and have displayed excellent results.

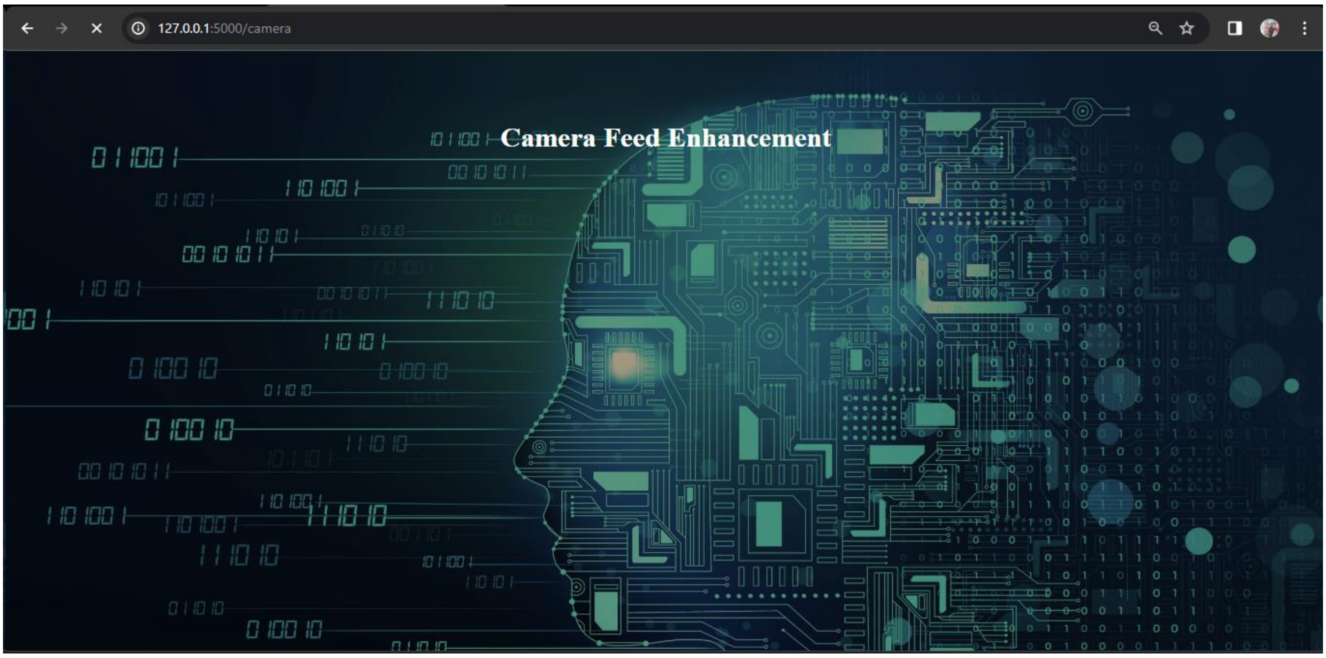


Figure 12: Dashboard of Low light live camera feed enhancement module

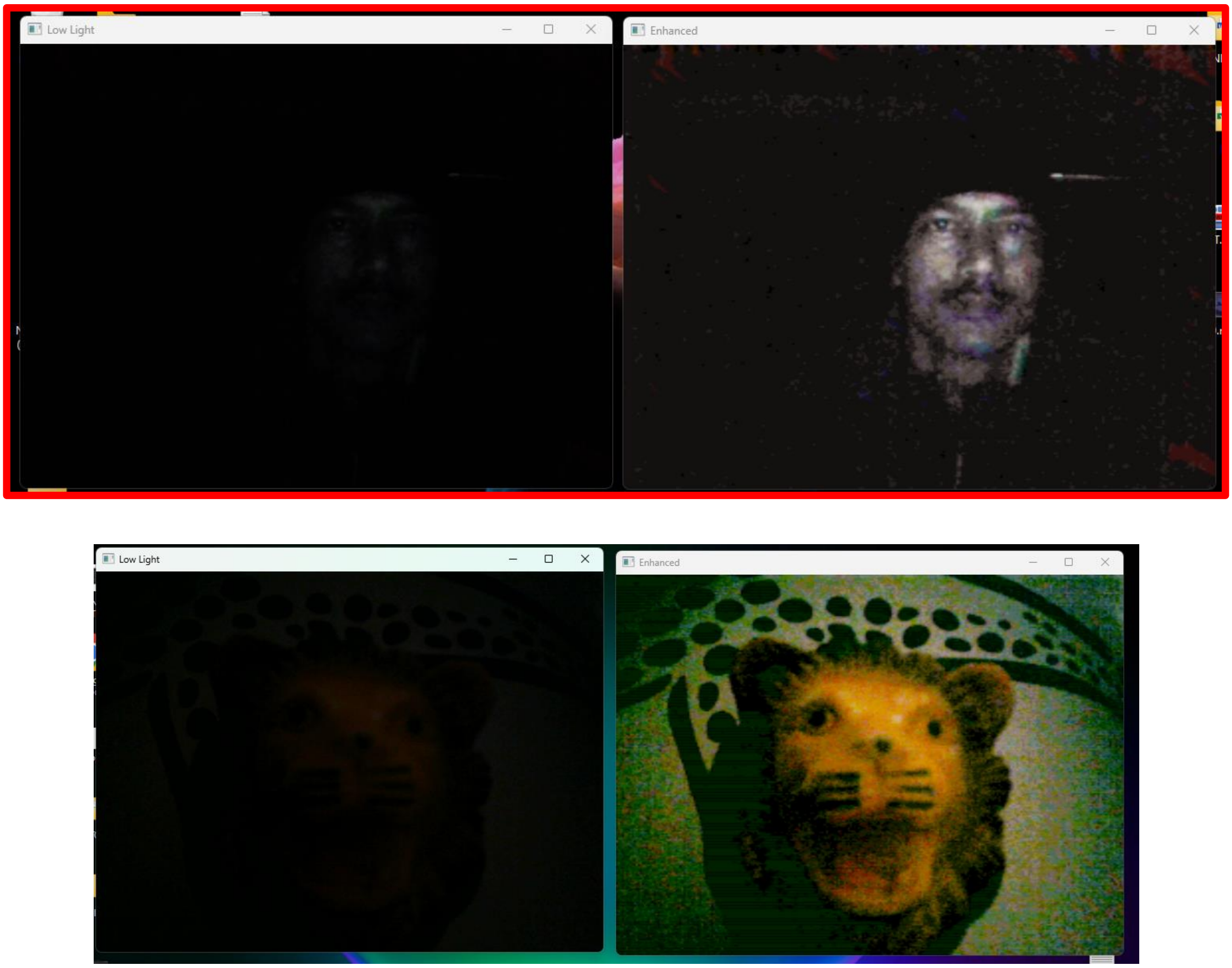


Figure 13: Experimental Result on Low light real-time camera feed input and output

System Requirements

The project has been developed using open source and platform independent programming languages and software framework. VSCodeUserSetup-x64-1.87.2, Python ver 3.10.4, Flask Web framework, HTML. The project can be executed with minor configuration changes on LINUX environment also.

Evaluation Metrics :

Besides human perception-based subjective evaluations, MSE and PSNR are able to evaluate image quality objectively. PSNR and MSE. PSNR and MSE are widely used IQA metrics. They are always non-negative, and values closer to infinite (PSNR) and zero (MSE) are better. The table below shows the experiment results on performance metric used for evaluating performance of my LLIE model on datasets and the details about performance metric are also enumerated below.

MSE

Mean Squared Error (MSE) is a widely used metric in image processing and computer vision to evaluate the quality of an image or the performance of an image processing algorithm. It measures the average squared difference between the original pixel values and the corresponding pixel values in a processed or reconstructed image.

Mathematically, MSE is calculated as follows:

$$\mathbf{MSE=1/}\ \boldsymbol{N} \sum(\boldsymbol{I}(\boldsymbol{i})-\boldsymbol{I}\mathbf{ref}(\boldsymbol{i}))^2$$

Where:

- N is the total number of pixels in the image
- $I(i)$ is the pixel value of the processed or reconstructed image at position
- Iref(i) is the corresponding pixel value in the original reference image

A lower MSE value indicates that the processed or reconstructed image is closer to the original reference image in terms of pixel values. Conversely, a higher MSE value suggests greater deviation from the original, indicating poorer image quality or performance.

MSE is particularly useful when comparing images or evaluating the performance of algorithms that involve image reconstruction, denoising, compression, or restoration. However, it's important to note that MSE does not always correlate well with human perception of image quality, especially in cases where small changes in pixel values may not be visually significant. Therefore, MSE has been used in conjunction with PSNR.

PSNR

Peak Signal-to-Noise Ratio (PSNR) is a widely used metric in image processing and video compression to quantify the quality of a reconstructed or processed image or video in comparison to its original version. PSNR is expressed in decibels (dB) and measures the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of the signal.

Mathematically, PSNR is calculated as follows.

$$\mathbf{PSNR=10\cdot log10\ (MAX^2/MSE)}$$

Where:

- MAX is the maximum possible pixel value of the image (for example, 255 for an 8-bit image).
- MSE (Mean Squared Error) represents the average squared difference between corresponding pixel

values of the original and processed images.

PSNR has been used with goal to minimize the distortion introduced during processing or transmission while maximizing the fidelity of the reconstructed image. A higher PSNR value indicates better image quality, as it signifies lower distortion or noise relative to the original image.

Learning	Deep learning Model	Lol_dataset		Brightening_Train	
		MSE	PSNR	MSE	PSNR
Supervised Learning	Nakshatra Drishti Deep learning Model	1.180	18.85	1.390	17.95

Table 1: Quantitative comparisons on LOL-test and Brightening Train datasets in terms of MSE ($\times 10^3$), PSNR (in dB)

Capability of Nakshatra-Drishti deep learning model.

The capability of the our deep learning model are to Carry out low light image, video and real-time live camera feed enhancement tasks. The GUI Based user friendly web interface provides all solution under single umbrella. The Graphical display of the performance parameters and metrics measured on the dashboard with epoch are obtained during training of model and evaluating results on testing data. The results can be dynamically stored in a database. Our Nakshatra-Drishti model provides flexibility with security/control room operator to train model as per their dataset and custom requirements.

5. Conclusion

Future scope

Nakshtra-Drishti deep learning model can be loaded in edge device and mounted on UAV for enhanced live feed to ground station even under dark / insufficient illumination/ Cloudy environment condition. Artificial intelligence analysis can be performed on the enhanced image for Face detection, Object detection, and classification, change detection and Terrorist in disguise recognition.

Open Issues

Distinguishing Semantic Regions. Existing methods tend to enhance a low-light image without considering the semantic information of its different regions. As an example lets consider the black hair of a women in a low-light image is enhanced to be off-white as the black hair is treated as the low-light regions. An ideal enhancement method is expected to only enhance the low-light regions induced by external environments factors. Therefore distinguishing such semantic regions is an open issue for future research.

Removing Unknown Noises and unknown artifacts.

when the types of noises are unknown, finding an approach to remove such noise becomes very challenging. There are different kinds of noise like Gaussian, Poisson noises, real noises. Removing unknown noises is still an area of future research and requires deliberations. Similarly low light images and videos when downloaded from various sources and transferred from one storage to another, then it undergoes series of degradation and may contain unknown artifacts. The mitigation of such unknown artifacts is very challenging and is another future area of study.

Summary

In this paper, we have addressed the low-light image, video and real-time camera feed enhancement problem with a novel and flexible supervised framework. Our Nakshatra-Drishti deep learning model has provided promising experimental results across various low light datasets shows that our approach outperforms other state-of-the-art techniques under various evaluation metrics and performance benchmarks. Our work integrates low light image, video and real-time camera inputs in one unified model and provides a user-friendly web-based GUI. Our future research will explore methods to distinguish semantic regions, remove unknown noises and artifacts for achieving optimal enhancement outcomes. Through concerted efforts in these directions, the development of more effective and robust low-light enhancement methodologies can be realized, ultimately enhancing image and video quality across diverse scenarios and applications.

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