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A COMPARATIVE STUDY ON CNN-BASED LOW-LIGHT IMAGE ENHANCEMENT

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ABSTRACT

Low- light image improvement is a grueling task that has attracted considerable attention. filmland taken in low- light conditions frequently have bad visual quality. To address the problem, we regard the low- light improvement as a residual literacy problem that's to estimate the residual between low- and normal- light images. In this paper, we propose a new Deep Lightening Network (DLN) that benefits from the recent development of Convolutional Neural Networks (CNNs). The proposed DLN consists of several Lightening Back protuberance (LBP) blocks. The LBPs perform lightening and darkening processes iteratively to learn the residual for normal- light estimations. To effectively use the original and global features, we also propose a point Aggregation (FA) block that adaptively fuses the results of different LBPs. We estimate the proposed system on different datasets. Numerical results show that our proposed DLN approach outperforms other styles under both objective and private criteria.

I. INTRODUCTION

Taking Prints is one of the most popular and accessible ways to record memorable moments of our life. Images taken in low- light conditions are generally veritably dim. This makes it delicate to fete the scene or object. still, frequently it is ineluctable to take prints in low light conditions. To gain high-visibility images in low light conditions, we can borrow three results.

1. To use flash, It's a direct way to break the problem. still, it is not allowed in some public areas, similar as galleries, playhouses, and exhibition halls.
2. To increase the ISO (perceptivity of the detector) This system could increase the visibility of dark areas, but advanced ISO will also bring further noise to the image, and the normal- light area will fluently face the overexposure problem.
3. To take a print with longer exposure time landing an image with longer exposures allows further light that enlightens the dark area. nonetheless, long- time exposure may blur the image if there's camera shake or gormandize- moving objects.

A large number of conventional approaches have been proposed to alleviate the declination caused by low- light conditions. Histogram Equalization (HE) counts the frequence of the pixel values. By rearranging the pixels to observe a invariant distribution, it improves the dynamic range(i.e., better visibility) of the low- light image. Retinex- grounded styles regard one image as a combination of illumination and reflectance, where the reflectance is an essential trait of the scene that's incommutable in different lighting conditions, and the illumination maps store the differences between the low- and normal- light images. The Retinex- grounded styles en- hance the illumination chart of the low- light image to estimate the corresponding normal- light image.

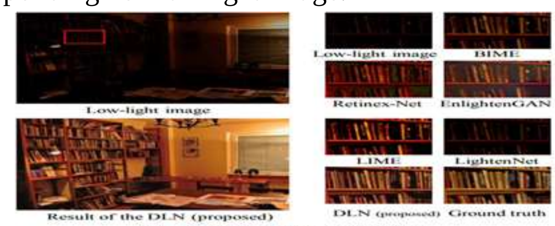

Figure 1. Effect of our proposed method

Other Styles borrow dehazing proposition that decomposes the low- light image into ambient light, refraction, and scene information. Refining the refraction chart can also enhance the visibility of low- light images.

Convolutional Neural Networks (CNNs) have achieved emotional results in numerous tasks, similar as image bracket, semantic segmentation, super-resolution, and object discovery. Compruned with conventional approaches, CNNs have better point representation that benefits from the large dataset and important computational capability. For CNNs, the information partner tracted from the shallow layers has detailed original information (like edge, texture), while deep layers have large open fields that can gain further global features (like complex texture and shape). CNNs tend to have further convolutional layers and complex structures to gain more important literacy capacities.

The low- light improvement can be regarded as an image restoration task. Image Super Resolution (SR) is one of the analogous motifs, which reconstructs a high- resolution (HR) image from a low- resolution (LR) image of different scales. Some SR networks borrow an end- to- end structure that minimizes the mean squared error between the repaired SR and HR images. Other approaches add Back Projection structures that iteratively over- and down- test the LR images. It improves the effectiveness of the network that's extensively used in the field. For illustration, Deep Back- Projection Network (DBPN) approach has several BP stages that iteratively canvass - struct the SR image. Back protuberance and Residual Network (BPRN) refine the DBPN structure by edging in the advantages of Residual Network structure. Hierarchical Back- Projection Network (HBPN) investigates the benefits of Hour- Glass and weighting structures to enhance the BPRN.

Recent literature shows that CNN technology also benefits low- light image improvement. Some approaches (like Retinex- Net, LightenNet) are grounded on the Retinex proposition that contains two CNNs one network decomposes the low- light image into illumination and reflectance, where reflectance is an essential trait of the scene which is incommutable in different light conditions. The other network works as an enhancer to upgrade the illumination chart of the low- light image. still, the delineations of ground-verity illumination and reflectance are not clear, which makes the corruption delicate. Another problem is that these CNN- grounded approaches make use of shallow CNN structures that have many trainable parameters, which leads to a considerable limitation on the performance. For illustration, Retinex- Net has only seven convolutional layers in the corruption network, and LightenNet has four convolutional layers only. It's egregious that deep literacy for low-light improvement is still in its immaturity stage.

Some other approaches use Generative inimical Networks (GANs) that regard low- light improvement as a sphere transfer literacy task by chancing the mapping between low- and normal-light disciplines (e.g., Enlighten GAN). Each GAN has a creator and a discriminator, where the creator estimates normal- light images from the low- light bones, while the discriminator constrains the visual quality of the estimations and tries to distinguish the estimations from real normal- light images. still, the generators may collapse to a setting where it al- ways labors the same settings that are delicate for the discriminator to distinguish. In addition, the two models need to be trained contemporaneously, but they have fully contrary targets that make it delicate to gain the asked affair.

MOTIVATION

Photography is one of the most intuitive and important ways humans record recollections and gests. still, a patient challenge in photography is landing high- quality images under low- light conditions. Whether it's night cityscapes, inner gatherings, or natural settings without artificial lighting, low- light photography frequently results in images that are dim, noisy, and lacking in critical details. similar demoralized images not only reduce the aesthetic quality but also vitiate the capability to recoup meaningful information from the captured moments.

Traditional styles to alleviate low- light issues, similar as using flash, adding ISO perceptivity, or dragging exposure times, have notable downsides. Flash operation can be protrusive and is confined in numerous public places like galleries and galleries. Raising ISO introduces significant noise, reducing the clarity and natural look of the print. Extending exposure times, while effective at gathering further light, pitfalls stir blur from camera shakes or moving subjects. therefore, there is a critical need for computational results that enhance low- light images with- out compromising on quality or introducing new vestiges.

Conventional image enhancement techniques, such as Histogram Equalization (HE) and Retinex based approaches, have been applied with moderate success. They attempt to adjust pixel distributions or decompose images into illumination and reflectance components. However, these methods often struggle with balancing brightness enhancement and noise suppression.

Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), offer transformative potential for low-light enhancement. CNNs have revolutionized fields like classification, segmentation, and super-resolution by learning complex representations from large datasets. Nevertheless, most CNN approaches for low-light enhancement have relied on shallow architectures with limited capacity, leading to suboptimal performance. Additionally, while Generative Adversarial Networks (GANs) have shown promise, training them remains difficult due to instability and issues like mode collapse.

PROBLEM STATEMENT

The problem statement is that low-light images often have poor quality, with significant noise, poor contrast, and a lack of detail, making them unsuitable for practical applications. Traditional methods like histogram equalization and gamma correction fail to effectively reduce noise and retain image details, leading to artifacts and distorted visuals. There is a demand for more advanced and automated solutions, such as deep learning techniques, to enhance low-light images while preserving important features like sharpness and texture.

SCOPE AND OBJECTIVE

The primary objective of this project is to develop a novel deep learning- based framework, called the Deep Lightening Network (DLN), for enhancing low- light images effectively and efficiently. The goal is to address the deficiencies in existing traditional and deep learning approaches by building a model that delivers superior image enhancement, preserves natural textures, and is adaptable to different low-light conditions.

First, the project aims to model the low-light enhancement problem as a residual learning task. Rather than predicting the final enhanced image directly, DLN estimates the residual between the low-light and normal-light images. This formulation simplifies the learning process, al- lowing the model to focus on learning the missing details, illumination gaps, and contrast adjustments, which leads to faster convergence and better performance.

Second, the project proposes an end-to-end trainable network architecture composed of several Lightening Back-Projection (LBP) blocks. Each block iteratively refines the enhancement by lightning and darkening the feature maps, similar to the principles seen in back-projection- based super-resolution models. By using iterative refinement, the network progressively im- proves the quality of the output image, making it possible to deal with complex lighting variations and subtle texture preservation.

Third, an innovative interactive enhancement control factor is integrated into the DLN. This factor allows users to dynamically adjust the strength of the enhancement according to their preferences or specific application needs. Such flexibility makes the method applicable across a wide range of scenarios—from minor brightness corrections to significant illumination improvement offering greater usability and control compared to traditional fixed-output methods.

Furthermore, the DLN introduces a Feature Aggregation (FA) block to combine global and local features extracted during the lightening stages. Aggregating multi-scale features ensures that fine details and overall scene structures are both considered during enhancement. This aggregation enables the network to generate images that are not only brighter but also sharp and natural-looking.

II. LITERATURE SURVEY

Early approaches, such as Histogram Equalization (HE) and Gamma Correction, aimed to enhance visibility by redistributing pixel intensities. Retinex theory-based methods decomposed images into reflectance and illumination, enhancing illumination maps to approximate normal-light images [6][7].

With the rise of deep learning, CNNs have been employed for low-light enhancement. Retinex-Net [8] introduced a CNN-based Retinex decomposition model, while LightenNet [9] attempted direct end-to-end illumination correction. Generative Adversarial Networks (GANs), such as EnlightenGAN [10], modeled enhancement as a domain transfer problem but suffered from instability and mode collapse during training.

Back-Projection Networks (DBPN) [11] and Residual Networks (ResNet) [12] have demonstrated success in image restoration tasks. Inspired by these architectures, the DLN introduces LBP blocks for iterative enhancement and FA blocks for feature recalibration

III. MODULE DISCRIPTION

Gathering Data:

Data Gathering is the first step of the machine learning life cycle. The goal of this step is to identify and obtain all data-related problems. In this step, we need to identify the different data sources, as data can be collected from Kaggle . It is one of the most important steps of the life cycle. The quantity and quality of the collected data will determine the efficiency of the output. The more will be the data, the more accurate will be the prediction.

This step includes the below tasks:

- Identify various data sources
- Collect data
- Integrate the data obtained from different sources

By performing the above task, we get a coherent set of data, also called as a dataset. It will be used in further steps.

Data Preparation:

After collecting the data, we need to prepare it for further steps. Data preparation is a step where we put our data into a suitable place and prepare it to use in our machine learning training.

In this step, first, we put all data together, and then randomize the ordering of data. This step can be further divided into two processes:

➢ Data exploration:

It is used to understand the nature of data that we have to work with. We need to understand the characteristics, format, and quality of data.

A better understanding of data leads to an effective outcome. In this, we find Correlations, general trends, and outliers.

➢ Data pre-processing:

Now the next step is preprocessing of data for its analysis.

Data Wrangling

Data wrangling is the process of cleaning and converting raw data into a useable format. It is the process of cleaning the data, selecting the variable to use, and transforming the data in a proper format to make it more suitable for analysis in the next step. It is one of the most important steps of the complete process. Cleaning of data is required to address the quality issues.

- Missing Values
- Duplicate data
- Invalid data
- Noise

So, we use various filtering techniques to clean the data.It is mandatory to detect and remove the above issues because it can negatively affect the quality of the outcome.

Data Analysis

Now the cleaned and prepared data is passed on to the analysis step. This step involves:

- Selection of analytical techniques
- Building models

The aim of this step is to build a machine learning model to analyze the data using various analytical techniques and review the outcome. It starts with the determination of the type of the problems, where we select the machine learning techniques such as Classification, Regression, Cluster analysis; Association, etc. then build the model using prepared data, and evaluate the model.

Hence, in this step, we take the data and use machine learning algorithms to build the model.

Train Model

Now the next step is to train the model, in this step we train our model to improve its performance for better outcome of the problem.

We use datasets to train the model using various machine learning algorithms. Training a model is required so that it can understand the various patterns, rules, and, features.

Test Model

Once our machine learning model has been trained on a given dataset, then we test the model. In this step, we check for the accuracy of our model by providing a test dataset to it.Testing the model determines the percentage accuracy of the model as per the requirement of project or problem.

Deployment

The last step of machine learning life cycle is deployment, where we deploy the model in the real-world system.If the above-prepared model is producing an accurate result as per our requirement with acceptable speed, then we deploy the model in the real system. But before deploying the project, we will check whether it is improving its performance using available data or not

IV. SYSTEM DESIGN

SYSTEM ARCHITECTURE

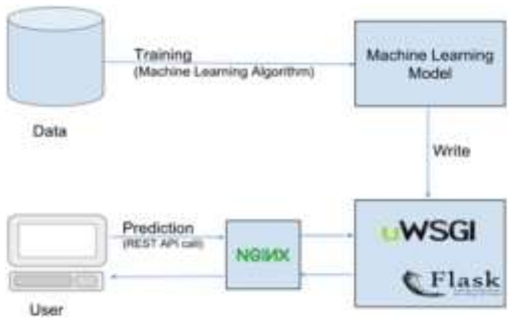

Fig : System Architecture

V. OUTPUT SCREENS

ACTIVATION OF PROJECT

FIG : ACTIVATION OF PROJECT

HOME PAGE

FIG : HOME PAGE

SELECTING IMAGE

FIG: SELECTING IMAGE

SELECTED IMAGE APPEARS

FIG : SELECTED IMAGE APPEARS

OUTPUT IMAGE IS GENERATED

FIG: OUTPUT IMAGE GENERATE

FIG: OUTPUT IMAGE

VI. CONCLUSION

In this paper, we have introduced our proposed Deep Lightening Network (DLN) for low-light image enhancement. Unlike the previous methods that either learn the mapping between the low- and normal-light images directly, or adopt GAN-based method for perception reconstruction, we propose a novel Lightening Back-Projection (LBP) block which learns the differences between the low- and normal light images iteratively. To strengthen the representation power of the input of the lightening process, we fuse the feature maps with different receptive fields through the Feature

Aggregation (FA) block, which is an extension of the squeeze-and-extension structure that investigates both the spatial and channel-wise dependencies among different feature maps. Benefited from the residual estimation of LBP and the rich features of the FA, the proposed DLN gives a better reconstruction of the normal- light condition. Besides, the network works in an end-to-end way, which makes it easy to implement. We have used both objective and subjective evaluations to compare the performance of the proposed DLN with other methods. Extensive results show that our proposed method outperforms other recent state-of-the- art approaches (conventional, CNN-based, and GAN-based methods) in quantitative and qualitative aspects.

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