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Low-Light Image Enhancement by using Feature Aggregation(FA)

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ABSTRACT

Low-light image enhancement is a challenging task that has attracted considerable attention. Pictures taken in low-light conditions often have bad visual quality. To address the problem, we regard the low-light enhancement as a residual learning problem that is to estimate the residual between low- and normal-light images. In this paper, we propose a novel Deep Lightening Network (DLN) that benefits from the recent development of Convolutional Neural Networks (CNNs). The proposed DLN consists of several Lightening BackProjection (LBP) blocks. The LBPs perform lightening and darkening processes iteratively to learn the residual for normal-light estimations. To effectively utilize the local and global features, we also propose a Feature Aggregation (FA) block that adaptively fuses the results of different LBPs. We evaluate the proposed method on differentdatasets. Numerical results show that our proposed DLN approach outperforms other methods under both objective and subjective metrics

1. INTRODUCTION

Capturing good quality images under poorly lit conditions is a difficult task. These images usually contain low illumination and brightness, poor contrast and noise. Certain operations such as increasing exposure, high ISO and flash could be used to improve the low light conditions of the environment. But these methods have some drawbacks, for instance, a higher ISO could introduce graininess. Increasing the exposure could make the image blurry and using flash may introduce irregular illumination. All these methods potentially destroy the naturalness of the image.

Taking photos is one of the most popular and convenient ways to record memorable moments of our life. Images taken in low-light conditions are usually very dim. This makes us difficult to recognize the scene or object. However, often it is inevitable to take photos in low-light conditions. To obtain high-visibility images in the low-light conditions, we can adopt three solutions.

1) To use flash: It is a direct way to solve the problem. However, it is not allowed in some public areas, such as the museum, cinema, and exhibition hall.

2) To increase the ISO (sensitivity of the sensor): This method could increase the visibility of dark areas, but higher ISO will also bring more noise to the image, and the normal-light area will easily face the overexposure problem.

3) To take a photo with longer exposure time: Capturing an image with longer exposures allows more light that enlightens the dark area. Nevertheless, long-time

exposure may blur the image if there is camera shake or fast-moving objects.

2. LITERATURE SURVEY

This section briefly discusses some recent CNN based approaches for enhancing low- light images. Many CNN based techniques use paired images for the training of models. Deep Learning models have produced superior results from those of traditional enhancement techniques. CNN based techniques have shown better results in image denoising, improving visual quality, image super resolution and image-to-image translation. LLNet uses a deep autoencoder for removing noise from the images. Tao et al. used bright channels prior to estimate the transmission parameter and an effective filter to estimate region wise lighting conditions present in images. Some methods use both deep learning and traditional methods for improving the quality.

Xiao et al. trained "VGG16 for identifying the illumination of an image based on retinex theory". Then finding the low light regions based on this illumination, it applies histogram equalization only on the low light regions to produce output images.

Gnatov et al. presented "a method to transform lower quality images captured from smartphones to DSLR quality images". They used cropping and alignment techniques within limits to create paired data of a camera and the DSLR images and trained an end-to-end CNN to transform the lower quality camera image into DSLR quality image. Their main objective was to improve the visual appearance of images and proposed a loss function to accomplish the same.

Gharbi et al. proposed "a pipeline that is capable of real time performance on mobile devices". They used a supervised approach and trained their network using low resolution copies of input images to estimate affine transformations. These transformations, upsampled and combined with a guidance map, produced the output enhanced image. Lv and Lu proposed a multi-branch enhancement network that used attention maps to provide information about exposure and noise to guide the enhancement process and used a multi-branch fusion network to generate the corresponding enhanced image.

Unsupervised GAN based methods take advantage of the fact that training does not require paired data. EnlightenGAN is one such method having a generator doing the decomposition, enhancing the illumination and then producing the enhanced image. The discriminator and loss functions are carefully designed for training. WESPE is another GAN based image enhancement method which defines generative mappings paired with inverse generative mappings for training. It also defines two discriminators for distinguishing between the high quality images and enhanced images, one based on color of image and other based on texture.

Recent literature shows that the CNN technology also benefits the low-light image enhancement. Some approaches (like Retinex-Net, LightenNet) are based on the Retinex theory that contains two CNNs: One network decomposes the low-light image into illumination and reflectance, where reflectance is an inherent attribute of the scene which is unchangeable in different light conditions. The other network works as an enhancer to refine the illumination map of the low-light image. However, the definitions of ground-truth illumination and reflectance are not clear, which makes the decomposition difficult. Another problem is that these CNN-based approaches make use of shallow CNN structures that have few trainable parameters, which leads to a considerable limitation on the performance. For example, Retinex-Net has only seven convolutional layers in the decomposition network, and LightenNet has four convolutional layers only. It is obvious that the deep learning for low-light enhancement is still in its infancy stage. Some other approaches use Generative Adversarial Networks (GANs) that regard the low-light enhancement as a domain transfer learning task by finding the mapping between low- and normal-light domains (e.g. EnlightenGAN). Each GAN has a generator and a discriminator, where the generator estimates normal-light images from the lowlight ones, while the discriminator constrains the visual quality of the estimations and tries to distinguish the estimations from real normal-light images. However, the generator may collapse to a setting where it always outputs the same settings that are difficult for the discriminator to distinguish. In addition, the two models need to be trained simultaneously, but they have completely opposite targets that make it difficult to obtain the desired output.

3. PROBLEM STATEMENT

A large number of conventional approaches have been proposed to mitigate the degradation caused by low-light conditions. Histogram Equalization (HE) counts the frequency of the pixel values. By rearranging the pixels to obey uniform distribution, it improves the dynamic range (i.e., better visibility) of the low-light image. Retinex-based methods regard one image as a combination of illumination and reflectance, where the reflectance is an inherent attribute of the scene that is unchangeable in different lighting conditions, and the illumination maps store the differences between the low- and normal- light images. The Retinex-based methods enhance the illumination map of the lowlight image to estimate the corresponding normal-light image. Other methods adopt dehazing theory that decomposes the low-light image to ambient light, refraction, and scene information. Refining the refraction map can also enhance the visibility of low-light images.

Convolutional Neural Networks (CNNs) have achieved impressive results in many tasks, such as image classification, semantic segmentation, super-resolution, and object detection. Compared with conventional approaches, the CNNs have better feature representation that benefits from the large dataset and powerful computational ability. For CNNs, the information extracted from the shallow layers has detailed local information (like edge, texture), while deep layers have large receptive fields that can obtain more global features (like complex texture and shape). The CNNs tend to have more convolutional layers and complex structures to obtain more powerful learning abilities. The low-light enhancement can be regarded as an image restoration task. Image Super-Resolution (SR) is one of the similar topics, which reconstructs a high-resolution (HR) image from a low-solution (LR) image of different scales. Some SR networks adopt an end-to-end structure that minimizes the mean squared error between the reconstructed SR and HR images. Other approaches add BackProjection structures that iteratively up- and down-sampling the LR images. It improves the efficiency of the network that is widely used in the field. For example, Deep Back-Projection Network (DBPN) approach has several BP stages that iteratively reconstruct the SR image. Back Projection and Residual Network (BPRN) refines the DBPN structure by injecting the advantages of Residual Network structure. Hierarchical Back-Projection Network (HBPN) investigates the benefits of Hour-Glass and weighting structures to enhance the BPRN

Disadvantages:

High Computational Over Head. Required Huge Data Set for Training

4. PROPOSED SYSTEM

Although considerable research has been devoted to apply the CNNs for low-light enhancement, less effort is being made to investigate new and suitable structures for the task. Recently, the use of back-projection block has shown outstanding performance in the image restoration field (e.g., image Super-Resolution(SR)). Based on the idea of enhancing the image iteratively, we proposed a novel CNN structure (i.e., the Deep Lightening Network (DLN)) that achieves remarkable enhancement for the low-light image, Let us highlight the novelty of our proposed method as follows:

Interactive Low-light Enhancement: We resolve the low-light enhancement through a residual learning model that estimates the residual between the low- and normal-light images. The model has an interactive factor that controls the power of the lowlight enhancement.

Deep Lightening Network (DLN): We propose a novel DLN approach based on our residual model to enhance the low-light image in an end-to-end way. It contains several lightening blocks (see LBPs in Figure 2) that enhance the low-light image accumulatively. Our DLN is compared with several state-ofthe-art approaches through comprehensive experiments. The results show that our proposed DLN outperforms all other methods in both subjective and objective measures.

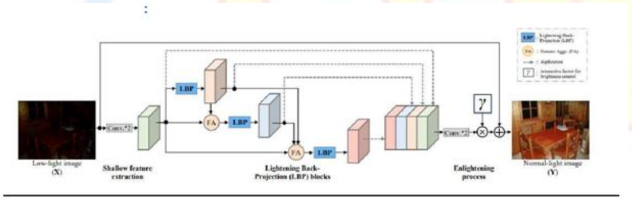
Lightening Back-Projection (LBP): Based on the idea of enhancing the low-light image iteratively, we propose a LBP block that iteratively lightens and darkens the low-light image to learn the residual for low-light enhancement. It is the first work that successfully introduces a new back-projection structure for low-light enhancement.

Feature Aggregation (FA): Both global and local features are useful for low-light enhancement. We propose a FA block that aggregates the results from different lightening stages and provides more informative features for the following lightening process.

Advantages:

High Processing Speed. More Accuracy

5. ARCHITECTURE



6. MODULES

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7. IMPLEMENTATION:

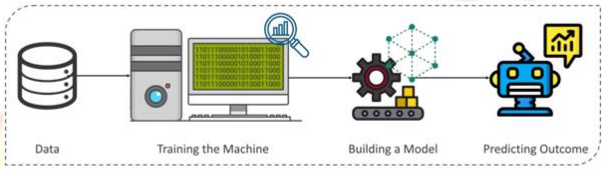


Fig .4 Machine Learning Process

How does Machine Learning Work?

Machine Learning algorithm is trained using a training data set to create a model. When new input data is introduced to the ML algorithm, it makes a prediction on the basis of the model. The prediction is evaluated for accuracy and if the accuracy is acceptable, the Machine Learning algorithm is deployed. If the accuracy is not acceptable, the Machine Learning algorithm is trained again and again with an augmented training data set.

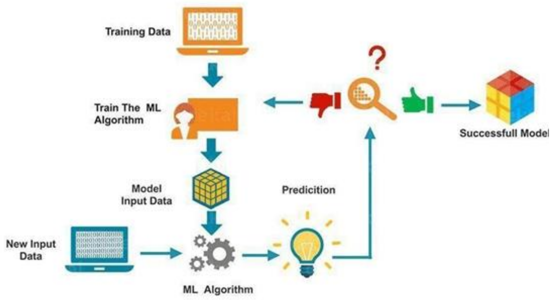


Fig .5 working

The Machine Learning process involves building a Predictive model that can be used to find a solution for a Problem Statement. To understand the Machine Learning process let's assume that you have been given a problem that needs to be solved by using Machine Learning.

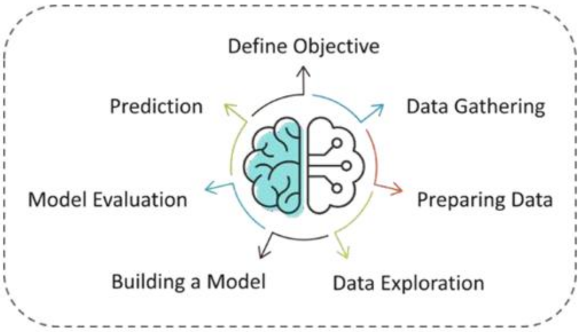


Fig. 6 process

Once you know the types of data that is required, you must understand how you can derive this data. Data collection can be done manually or by web scraping. However, if you're a beginner and you're just looking to learn Machine Learning you don't have to worry about getting the data. There are 1000s of data resources on the web, you can just download the data set and get going.

Coming back to the problem at hand, the data needed for weather forecasting includes measures such as humidity level, temperature, pressure, locality, whether or not you live in a hill station, etc. Such data must be collected and stored for analysis.

Step 3: Data Preparation

The data you collected is almost never in the right format. You will encounter a lot of inconsistencies in the data set such as missing values, redundant variables, duplicate values, etc. Removing such inconsistencies is very essential because they might lead to wrongful computations and predictions. Therefore, at this stage, you scan the data set for any inconsistencies and you fix them then and there.

the model. The logic of the model is based on the Machine Learning Algorithm that is being implemented.

The below steps are followed in a Machine Learning process:

Step 1: Define the objective of the Problem At this step, we must understand what exactly needs to be predicted. In our case, the objective is to predict the possibility of rain by studying weather conditions. At this stage, it is also essential to take mental notes on what kind of data can be used to solve this problem or the type of approach you must follow to get to the solution.

Step 2: Data Gathering At this stage, you must be asking questions such as,

- What kind of data is needed to solve this problem?
- Is the data available?
- How can I get the data?

Step 4: Exploratory Data Analysis

Grab your detective glasses because this stage is all about diving deep into data and finding all the hidden data mysteries. EDA or Exploratory Data Analysis is the brainstorming stage of Machine Learning. Data Exploration involves understanding the patterns and trends in the data. At this stage, all the useful insights are drawn and correlations between the variables are understood.

For example, in the case of predicting rainfall, we know that there is a strong possibility of rain if the temperature has fallen low. Such correlations must be understood and mapped at this stage.

Step 5: Building a Machine Learning Model

All the insights and patterns derived during Data Exploration are used to build the Machine Learning Model. This stage always begins by splitting the data set into two parts, training data, and testing data. The training data will be used to build and analyze

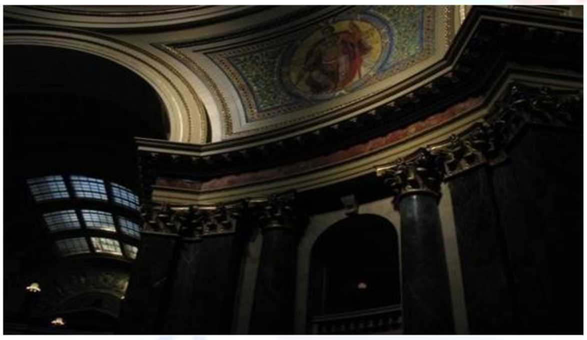
Choosing the right algorithm depends on the type of problem you're trying to solve, the data set and the level of complexity of the problem. In the upcoming sections, we will discuss the different types of problems that can be solved by using Machine Learning.

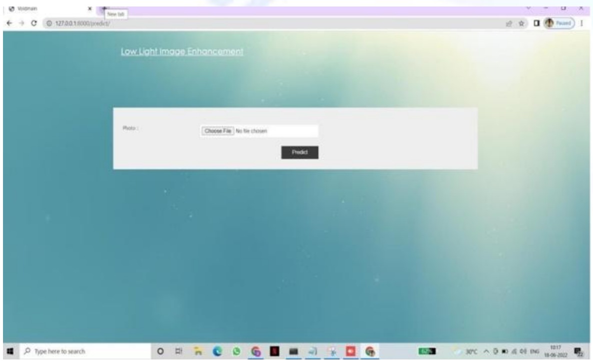
Step 6: Model Evaluation & Optimization

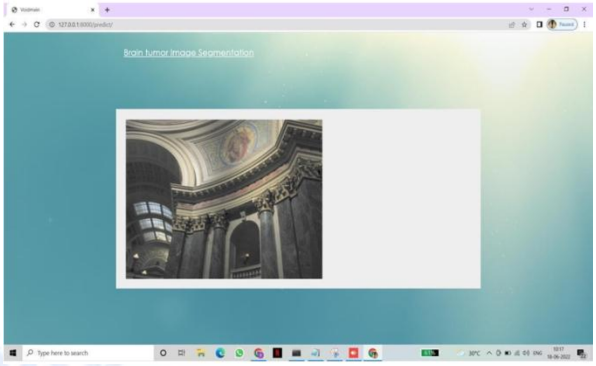
After building a model by using the training data set, it is finally time to put the model to a test. The testing data set is used to check the efficiency of the model and how accurately it can predict the outcome. Once the accuracy is calculated, any further improvements in the model can be implemented at this stage. Methods like parameter tuning and cross-validation can be used to improve the performance of the model.

Step 7: Predictions Once the model is evaluated and improved, it is finally used to make predictions. The final output can be a Categorical variable (eg. True or False) or it can be a Continuous Quantity (eg. the predicted value of a stock).

8.OUTPUT SCREENS







9. CONCLUSION

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 normallight 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. In the further work, we can continue to explore more effective CNN structures to improve the performance of the low-light enhancement, and investigate methods for low-light video enhancement. The quality of the simulated LLNL images is highly related to the performance of the trained model. A good simulation can obviously improve the generalization ability of the enhancement model, which is an interesting research topic to be investigated in the future. Also, our proposed algorithm dramatically improves the visibility of the low-light images, which can be used in various applications. For example, it can be used in a driving assistant system to provide reliable visual aid for a dark and difficult environment.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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