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LOW-LIGHT ENHANCEMENT AND NOISE REMOVALFOR RAW IMAGES

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ABSTRACT: Low-light imaging on mobile devices has always been a challenge, as it often results inimages with low quality, noise, and poor color reproduction. In this paper, a new framework for low-light imaging is proposed, which performs joint illumination adjustment, color enhancement, and denoising. Unlike previous methods, this framework is designed to be practical and generalizable inreal-world settings. The framework consists of two branches: a coefficient estimation branch and a joint operation branch. The coefficient estimation branch predicts the coefficients for enhancement via bilateral learning, while the joint operation branch progressively performs joint enhancement anddenoising. This approach significantly reduces the efforts required to fine-tune the approach for practical usage. The experiments demonstrate the framework's potential in real-world low-light imaging applications, making it a promising solution to the challenge of low-light imaging on mobile devices. **Index Terms –** Low light image enhancement, Color enhancement, Convolution Neural Networks.

1. INTRODUCTION:

Images captured in low light conditions often have underexposed areas, high noise levels, and dull colors. This can make it difficult to obtain useful information from the images and can alsonegatively impact computer vision tasks such as object detection [1]. For one thing, the visual quality of images captured in low-light conditions is barely acceptable. Furthermore, it is very likely that it degrades the performance of algorithms that are primarily designed for high- visibility inputs [2].

Low light image enhancement is an essential task in computer vision, image processing, and various other fields where images are captured in low-light conditions. The traditional image enhancement techniques [3] noticed a similarity between haze images and inverted low-light images, and applied dehazing methods to deal with low-light images. In Retinex decomposition[4]–[8],and deep learning [9] [10], the dominant assumption is that the (color) image can be processed by decomposition method and then noise reduction can improve the visual quality of low light images to some extent. However, these methods have certain limitations and may not always provide satisfactory results. To address this, a VGG16 network that extracts the features of the low light image is preferred in the proposed method that showed improved performance when compared to several existing techniques. The qualitative and quantitative analysis of the proposed methos showed improved contrast and visibility in the output.

2. RELATED WORK

Many low-light enhancement methods ignore images with a lot of noise. As a result, they frequently increase the noise at the same time. To address this issue, the method called low- light image enhancement (LIME) [11] is introduced. The LIME method estimates the illumination of each pixel individually by finding the maximum value in the red, green, and blue channels. This initial illumination map is then refined by imposing a structure prior on it to create the final illumination map. With a well-constructed illumination map, the authors then enhance the image accordingly. By focusing on individual pixel illumination and imposing a structure prior, the method is able to achieve high-quality results while maintaining efficiency. LIME method imposes a structure prior on the illumination map to refine it, which may result in over-smoothing and loss of image details.

The method Joint enhancement and denoising method via sequential decomposition joint low-light enhancement and denoising [12] strategy is applied to sequentially estimate a piece-wise smoothed illumination and a noise-suppressed reflectance. This decomposition is done sequentially, with each step enforcing spatial smoothness on each component and skilfully using weight matrices to suppress the noise and improves contrast. The illumination layer is estimated first, which provides an estimate of the overall brightness of the image. This is then followed by the estimation of the reflectance layer, which captures the underlying texture and details of the image. This method then adjusts the illumination layer to generate the final enhanced low-light image, while simultaneously reducing the noise. One of the strengths of this method is that it is able to achieve a balance between enhancing the brightness of the image and preserving the details and texture. The spatial smoothness constraint imposed on each component ensures that the enhanced image is not overly processed, while the noise suppression techniques help to improve the overall quality of the image.

The LR3M -Robust low-light enhancement via low-rank regularized retinex model [13] methodseems to be a promising approach to enhancing low-light images and videos while suppressing noise. By injecting a low-rank prior into the Retinex decomposition process, the LR3M is able to effectively suppress noise in the reflectance map and obtain a noise-suppressed reflectance that is used to generate the final enhancement result. However, the LR3M method may have some potential disadvantages compared to other methods. For example, the LR3M method may be more computationally expensive than simpler approaches such as the LIME method, which estimates the illumination of each pixel individually and imposes a structure prior to create the final illumination map.

The framework of Progressive Joint Low-light Enhancement and Noise Removal for Raw Images for low-light imaging on mobile devices [14] that performs joint illumination adjustment, color enhancement, and denoising. Previous low-light imaging works have focused on single-task or camera-specific joint enhancement and restoration, limiting their practicality and generalizability in real-world settings. The framework includes a low-resolution coefficientestimation branch using MobileNetV2 for coefficient prediction and a full-resolution joint operation branch for joint enhancement and denoising. One advantage of this framework is that it does not need to recollect massive data when adapted to another camera model, significantly reducing the efforts required to fine-tune the approach for practical usage. When it comes to low light images, MobileNetV2 may have a disadvantage compared to VGG16 due to its smaller size and lower complexity.

3. PROPOSED SYSTEM

Low-light photography can be a challenging task due to the lack of available light, resulting in underexposed and noisy and often require post-processing to enhance the overall image quality.These algorithms aim to reduce the amount of noise present in the image while preserving theoverall details and sharpness of the image. While traditional noise reduction techniques such as wavelet denoising, spatial filtering, and statistical methods have been widely used for many years, they do have some limitations compared to machine learning-based methods.

Traditional techniques often require manual parameter tuning and assume a specific noise model, making them time-consuming and less suitable for complex or diverse images. adaptable to different image conditions, and selectively remove noise while preserving detailsfor visually pleasing results.

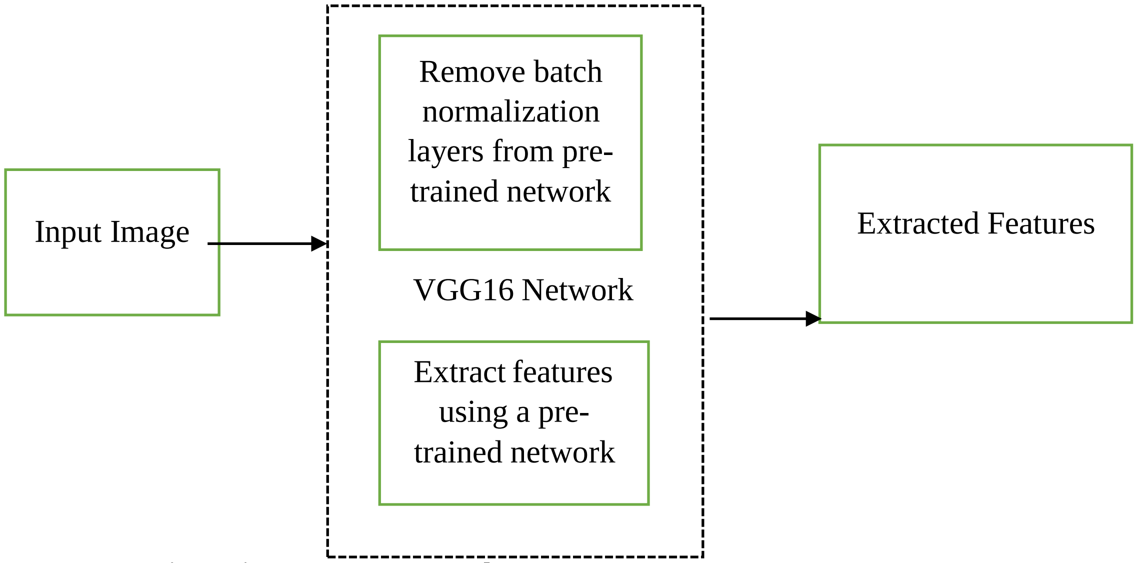

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Fig 1: Feature extraction using VGG16 Network

Feature extraction using VGG16:

VGG16, is a deep convolutional neural network architecture that can be used for feature extraction in image classification tasks. The network consists of 13 convolutional layers and 3 fully connected layers. The first 13 layers are used for feature extraction, while the last 3 layers are used for classification. The convolutional layers use small 3x3 filters with stride 1, and are followed by a rectified linear unit (Re LU) activation function and 2x2 max pooling with strideThe max pooling layer reduces the spatial dimensions of the feature maps, while the Re LU activation function introduces non-linearity into the model.

During feature extraction, an input image is passed through the network, and the output of the final convolutional layer is extracted as a feature vector to perform image classification. The advantage of using VGGNet for feature extraction is that the network has already been trained on a large dataset, such as ImageNet, and has learned a set of useful image features that can be transferred to other image classification tasks. This process, known as transfer learning, allowsfor more efficient training on smaller datasets and can lead to better performance on the targettask.

VGG-16 Network

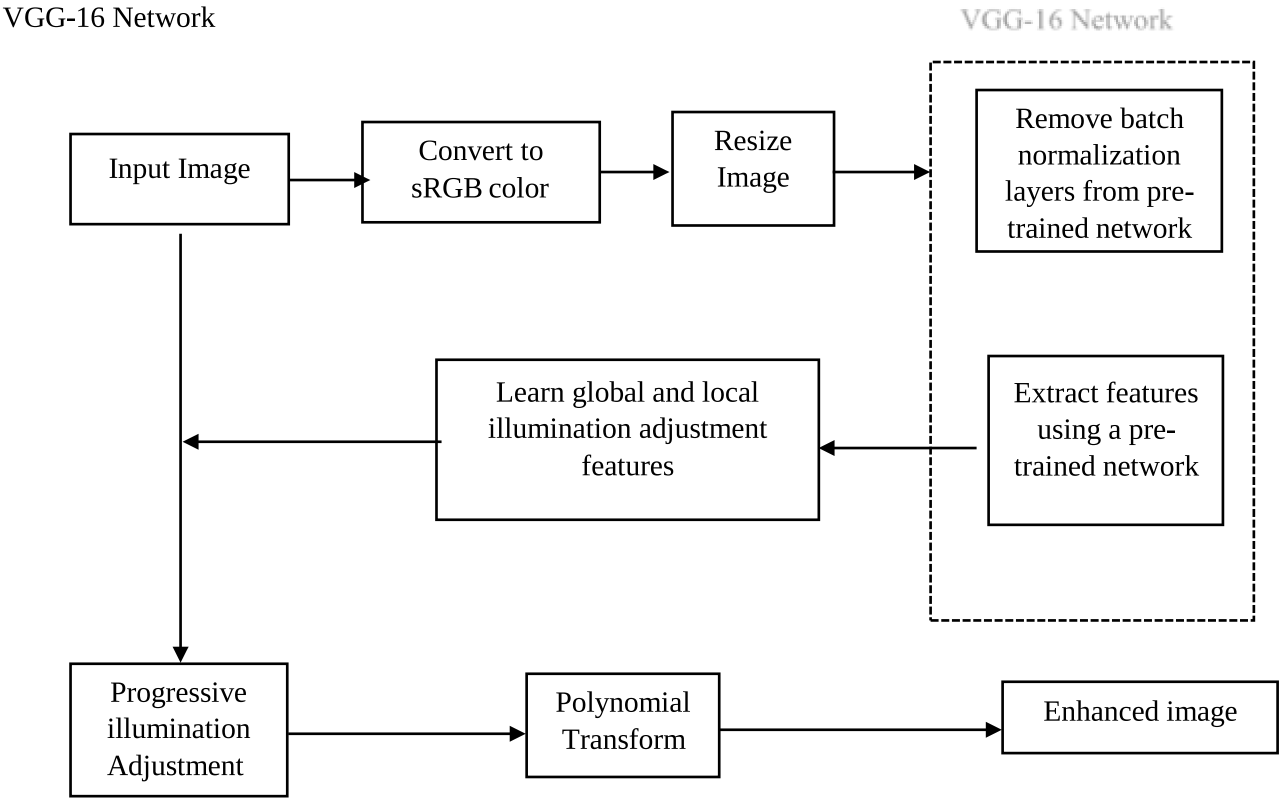

Fig 2 Frame work of Low light enhancement for noise removal for raw image

The image processing pipeline starts with loading the input image into memory from a file system or another source. Next, the image is converted to the sRGB color space, which is a widely used standard for displaying images on screens. The image is then resized to a desired size, which could be necessary for reducing the computational cost of subsequent steps or adapting the image to a specific output size. Here by employing VGG16 as the backbone feature extractor to remove Batch Normalization. In order to learn the features for global and local illumination adjustments, we have designed two separate paths: a global path and a local path. These paths are used to implicitly

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combine the two types of adjustments in the feature space. After combining the global and local features, a convolutional layer is used to map the fused features to the desired dimensions. The final output of the network is a set of bilateral grids denoted as B, which consists of N grids: B1, B2, ..., BN.

The value of N is determined by the number of total iterations. Each grid, Bn, has a size of 16x16x16. The next step is to obtain the full-resolution coefficient map Θn. This is achieved by applying the learned bilateral up sampling method to the grids. The bilateral up sampling method takes into account both the spatial and range domain information to achieve high- quality up sampling. It involves slicing the 3D grids along the depth dimension and applying a2D bilateral filter to each slice. The resulting filtered slices are then stacked along the depth dimension to obtain the full-resolution coefficient map Θn

$$\theta(x, y) = \sum_{i,j,k} r(x, i) r(y, j) r(z_{x,y}, k)\, B_n(i, j, k) \quad (1)$$

where τ i

The process is repeated for all N bilateral grids, resulting in a set of full-resolution coefficient maps. The use of iterative methods can also be beneficial in enhancing and denoising data by utilizing residual data. In this approach, a model is first created to approximate the data, and then residual data is generated by subtracting the model's prediction from the original data. This residual data is then used to improve the model iteratively until the desired level of enhancement and denoising is achieved. By using Polynomial transformation is a technique that can be used to adjust the color and contrast of an image. This technique works by transforming the pixel values of an image using a polynomial function. The degree of the polynomial function determines the level of nonlinearity in the transformation, and can be adjusted to achieve different levels of color and contrast adjustment. The resulting output has been improved through enhancements in noise reduction and color, resulting in an overall enhancement of the image.

4. SIMULATION RESULTS

Images captured under low illumination condition are considered for evaluating the proposed method. Simulations are carried out in MATLAB for the input images considered and the results obtained for the proposed method are compared with existing techniques. Both qualitative and quantitative analysis is performed for comparison.

QUALITATIVE ANALYSIS:

The simulation results obtained for the proposed are compared with existing techniques and areshown in figure 3. The LIME, JED, LR3M, MobileNET are the techniques considered for comparison. The qualitative comparison shows that the images obtained for the proposed method has clear details with improved contrast and brightness in the output.

Input **Output of LIME** **JED** **LR3M** **Mobilenet** VGG Image1

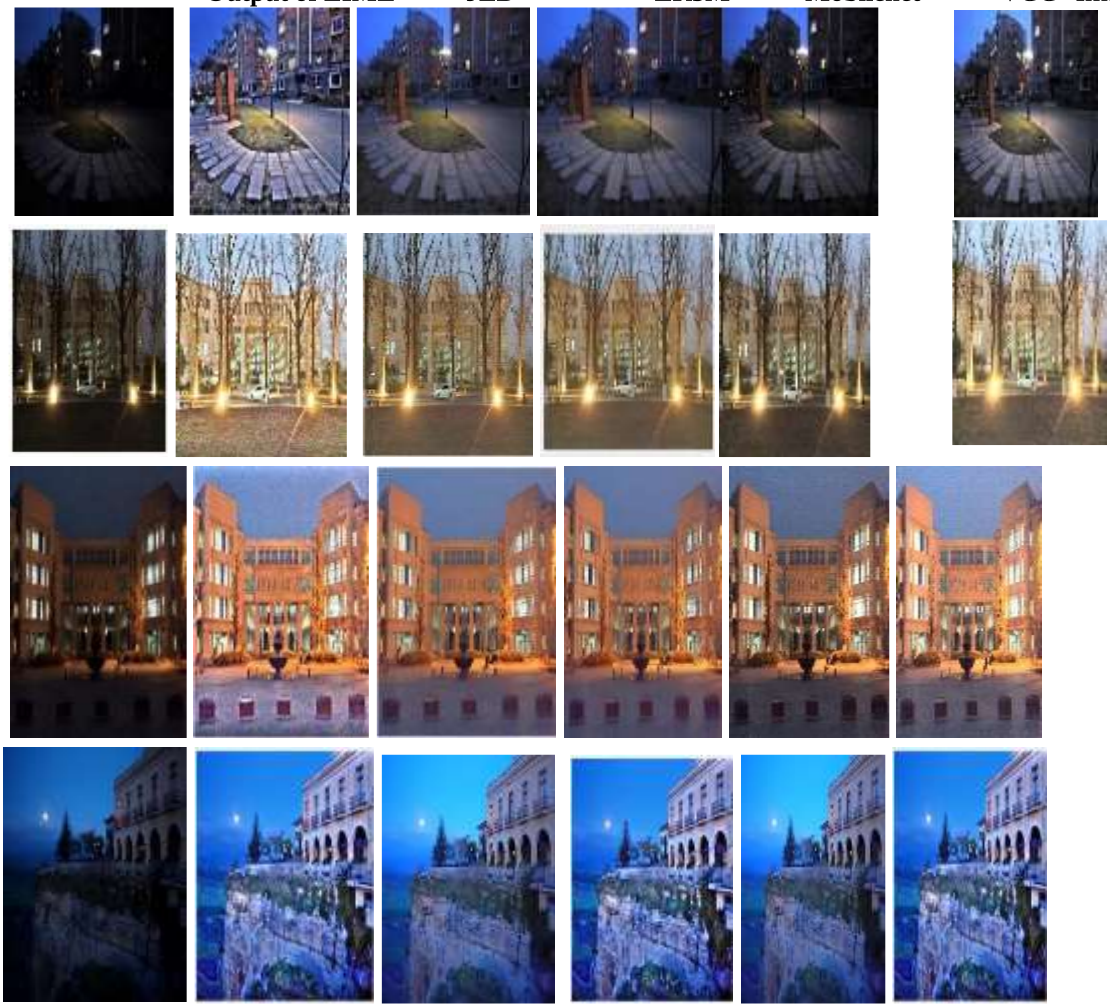

Image2

Image3

Image4

Fig 3 Comparative Analysis: LIME, JED, LR3M, MobileNet & Proposed VGG

Quantitative Analysis:

The quantitative comparison is performed by computing the following metrics discussed as: **NIQMC (Natural Image Quality Evaluator)** is a full-reference image quality assessmentmetric based on the statistical natural scene statistics (NSS) model.

Information Entropy((IE) measures the amount of information contained in the image.

Peak Signal-to-Noise Ratio (PSNR) is a widely used metric for measuring the quality of an image or video. It compares the original image or video with a processed (compressed, filtered,or degraded) version and calculates the ratio of the maximum possible power of the original image to the power of the difference image, which represents the distortion caused by the processing. The PSNR is expressed in decibels (dB) and is defined as:

$$\mathbf{PSNR} = 10 \times \log 10\left(\frac{MAX^2}{MSE}\right) \quad (2)$$

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where MAX is the maximum possible pixel value

MSE is the mean squared error between the original and processed images

GCF (Global Contrast Factor) is calculated as the ratio of the standard deviation of the image intensity values to the mean of the image intensity values. it is given by the formula:

$$\text{GCF} = \frac{std(img)}{mean2(img)} \quad (3)$$

Table 1: Quantitative Comparison

Method/Metric	PSNR	IE	NIQMC	GCF
LIME	4.87	5.97	**4.19**	0.32
LR3M	5.89	5.73	3.15	0.46
JED	5.79	5.80	3.09	0.44
MOBILENET	**12.93**	6.70	2.7	0.48

5. CONCLUSION

This paper proposes a learning-based framework for low-light image enhancement, which performs joint illumination enhancement, color enhancement, and model-specific denoising progressively. The proposed framework is designed with a two-branch structure that handles coefficient estimation, joint enhancement, and denoising in different domains, making it practical for real-world applications. The network can be retrained for a new camera model using only a few new image samples, reducing the human effort required to recollect massive amounts of paired data. The proposed approach is shown to outperform existing state-of-the- art methods in extensive experiments.

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