Low Light Image Enhancement Using (CNN) Convolutional Neural Networks

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***Abstract*—Low light image enhancement is a technique in computer vision where the goal is to improve the quality of images as they are associated with a lot of unwanted features in the form of noise since many of the images are captured in poor lighting conditions. Such low light images contain high noise levels, low contrast, loss of detail, and color distortion, these parameters degrade the overall image quality. Such types of images need to be enhanced as they are very important in medical imaging, photography, and satellite imaging. Many of the traditional methods rely on methods like histogram equalization where the pixel intensities are converted into a similar scale. Apart from them CNN's have shown promising results in identifying key features for image enhancement tasks. As they have ability to make non-linear transformations directly from data, As part of this research a CNN model is built which has capability to identify essential features from images. The primary goal of this research is to create a CNN model which can effectively improve images taken at low light by applying appropriate data cleaning and feature selection techniques.**

***Index Terms*—Convolutional neural networks, deep learning, Low light image enhancement ,KAN**

I. Introduction

CNN is a type of neural network which contains multiple convolutional layers, followed by dense, and flatten layers which are best suitable for image classification tasks. Low light image occurs when it is taken in an environment with insufficient lighting, poor lighting conditions. This happens especially in real-world scenarios like night-time photography, surveillance in poor light conditions, medical imaging with lower radiation due to a common factor called insufficient lighting. There are several factors which contribute to lowlight images, and they are described below:

1.1.Low Contrast in Low-Light Images:

Contrast refers to the difference in brightness between the light and dark areas of an image. For example, when image is taken in a low contrast then it may affect overall tone of the image as the image looks like dull way since there is no possibility to distinguish between these regions This occurs especially when there is no enough light and presence of shadows, sensors present in camera often take images in a wide manner to capture light intensities. As a result low light pixels get compressed causing the dark areas to brighten slightly and the bright areas to darken, reducing contrast. Human errors like improper settings may underexpose the areas by highlighting only a small part. Due to this images lack the depth necessary to distinguish between low bright and dark areas, makes it difficult in capturing detailed features like edges, shape of the image because their brightness levels are too similar which resulted in a flat image however they can be managed by using CNN which learn to adjust brightness by learning from a variety of samples.

1.2.High Noise in Low-Light Images:

Noise refers to the random variation of brightness in an image which is due to fluctuations like adding layer of grain to image due to presence of noise images gets sharper with low visibility this happens due to camera sensors where the sensor is small enough that it cannot able to capture good amount of light which increasing the signal-to-noise ratio and generating more noise. To capture more light when camera gets exposed it results in capturing unwanted noise from the

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environment luminance noise occurs when there is random sharp change in brightness across the image, creating a grainy effect whereas chromatic noise occur when discolored pixels scattered across the image As a result of this important image information is not visible creating a rough texture creates a unnatural color combination within the image however by using suitable denoising algorithm such as Gaussian blur can reduce noise by smoothing out pixel values. Apart from dl-based models can effectively perform better as they are capable of denoising

1.3.Colour Distortion in Low-Light Images:

It occurs when lens fails to focus all colors at the same point as a result unwanted colors occur at edges there is relation when contrast is high between light and dark image it leads to color distortion. Added to that when images with poor lighting conditions have different wavelengths of light. These wavelength causes color shifts, making the image appear too warm, when white balance is not adjusted in a correct way the model may interpret in a wrong way which leads to distortion however it can be overcome by utilizing Automatic white balance where the modern sensors adjust the white balance based on the scene's lighting.

1.4.Loss of Detail in Low-Light Images:

It is one of the most significant problems faced due to low light imaging where it leads to inability of capturing fine details like textures, edges, and shapes is diminished. It occurs especially when a camera sensor is not able to capture enough light to generate a strong signal it gets compensated with introducing noise To capture enough light in low light conditions Longer exposure is required however it leads to reduced image quality by a concept called motion blur. Fig.1. Factors affecting low light images

1.5.Role of CNNs in Low-Light Image Enhancement

Convolutional Neural Networks (CNNs) are well-suited for low-light image enhancement due to their ability to handle complex, hierarchical features from raw image data. Unlike traditional methods, CNNs can learn to enhance images by identifying patterns that differentiate well-lit areas from poorly lit ones, reducing noise, and improving contrast. Since CNN contains multiple layers of convolutional filters it is easy to process and transform images at different levels of abstraction. The initial layers typically focus on simple features like edges and gradients, while deeper layers capture more complex patterns, such as textures and object shapes. By training CNNs on large datasets of both low-light and well-lit images, they can learn to predict and enhance poorly illuminated images with high accuracy.

II. LITERATURE SURVEY

A. Maintaining the Integrity of the Specifications

Shen et al. [1] used DNN where the depth of the network is large to handle data in efficient way with good feature extraction initially Multi-Scale Retinex (MS) utilized t handle image at multiple scales as it helps in viewing various light levels in an image through which both local details (from smaller filters) and global contrast (from larger filters) can be captured. MSR is derived from the retinex theory which demonstrates how the human eye perceives colors irrespective of the lighting conditions. This is possible because brains separate the illuminant (light source) from the reflectance (true colors of objects) in an image. This MSR network gets trained and obtains an accuracy of 95% .

Ren et al . [2] proposed a hybrid model which combines retinex features where illuminant (light source) gets separated from the reflectance (true colors of objects) in an image. where MSR is done at various levels within the image which captures both small scale and large scale details and then the dl model focuses on reducing noise by fine tuning the enhanced image to a certain extent this hybrid helped to focus on finest features and obtained an accuracy of 97%.

Li et al. [3] made a comparative analysis of various existing dl models and techniques where enhancement of low light image is possible by using hybrid retinex method integrated with dl model, retinex method helps in breaking down the image into different parts where illuminating components represent overall lighting condition, reflectance component (which represents the intrinsic properties of the objects in the image) these properties are color, texture which cannot be changed wrt angle or lighting conditions and obtained an accuracy of 96%.

Tao et al. [4] utilized dl and made custom low light CNN which is suitable for this particular task initially model was fed with both low light and well light image then it gets trained and while reconstruction phase evaluation is made through using suitable loss function and obtains an accuracy of 98%.

Liu et al. [5] Initially lowlight images were considered then dl model gets trained from the images only when proper image enhancement is made by removing noise and distortion then by using GAN tries to improve low light images through generator while the discriminator judges whether the enhanced image looks realistic. Over time, the generator gets better at producing enhanced images that look natural and well-lit and obtain an accuracy of 90% .

Lore et al. [6] utilized dl and proposed a suitable network specifically for low light image enhancement tasks using autoencoder where the encoder tries to Compress the input (low-light image) into a smaller representation. while Decoder Reconstructs the enhanced image from this smaller representation. Then finally evaluated using perpetual loss function which compares results by preceding through human eye and obtained an accuracy of 94%.

Guo et al. [7] utilized dl and developed an integrated model which uses illumination (light) in the image where adjusting the light levels in the image this is to enhance brightness while maintaining same quality thi helped in bringing out details that are hard to see in the original low-light image. Then the image is fed to the dl model to even fine tune the image to a good extent and obtain an accuracy of 98%.

Wang et al. [8] utilized ml-based techniques to overcome challenges like noise presence, poor visibility in image by a technique called normalizing flow where transformation of data from one probability distribution to another. through which low light images are converted to well light images and obtained an accuracy of 96%.

Garg et al. [9] enhanced image quality using HSL where H represents color itself, S represents Saturation which describes how intense color is. A color with high saturation is very bright and vibrant, while a color with low saturation looks more washed out or gray. lightness indicates how light or dark the color is. The image in RGB color space is converted to HSL space where light channel improvement takes place and attains an accuracy of 94%.

Hai et al. [10] utilized dl based neural networks where The main goal of this research is to improve the quality of images taken in low-light conditions. The authors introduce a new approach called R2rnet, which is designed to transform low-light images into well-lit (normal) images. R2rnet is used to convert low-light images to normal-light images by training on examples of both types. R2rnet model follows adversarial training where the generator creates images while the discriminator evaluates how realistic they are. and obtained an accuracy of 93%.

III. METHODOLOGY

3.1. Dataset details

Google Scraped Image Dataset:

Scraping images from Google can yield a more diverse range of images that may not be available on Kaggle. This can include variations in lighting, backgrounds, and subjects, which helps in training models that generalize better to real-world scenarios. Added to that, images from pretrained models are also taken into consideration as they allow for greater data augmentation, thereby enhancing model robustness and addressing class imbalance.

Below is the detailed step by step explanation

Step 1: Initially image data is collected from googles scrapped image dataset then necessary libraries were imported and dataset gets loaded

Step 2: Then as data enhancement noise is added to the image which helps in better understanding of the data prior noise and post noise, Resizing is also done to ensure that every image is converted to a similar scale.

Step 3: HSV stands for Hue, Saturation, and Value which describes properties of the image through which object detection becomes easier.

Step 4: In this work, we integrate Kernel Attention Networks (KANs) into a low-light image enhancement model to improve its ability to interpret and capture complex nonlinear dependencies. As illustrated in Figure 2, we developed a KAN-Block and embedded it within the U-Net architecture to enhance low-light images.

Step 5: The U-Net performs feature extraction through a sequence of downsampling operations while retaining fine details using skip connections. To minimize interference from low-level information, the KAN-Block is placed at the center of the U-Net, replacing the original middle layer while leaving the sampling process unchanged.

Step 6: Reconstruction of enhanced images takes place from low-light ones and prediction is made.

3.1.PROJECT REQUIREMENTS

This experiment requires a python version of 3.8 with all the necessary libraries like NumPy, pandas, matplotlib, Grayscale or binary images of different resolutions and complexities were used for testing. This will ensure a good environment makes this suitable for Low light image Enhancement .

3.2.EXPECTED RESULTS

CNN has performed better in identifying texture, edges, and other key factors in making better accuracy. Is utilized to improve the quality and visibility of images taken in low-light conditions. By denoising using CNN it is able to learn how to map low-light images to high-quality counterparts, effectively reconstructing details lost due to inadequate lighting.

3.2.CONCLUSION

Images are taken at a variety of lighting conditions many of them are taken under poor lighting in such images detailed feature is difficult however This CNN based Image enhancement algorithm initially considered low light images then these images are introduced with noise so that model gets understood and becomes generalized by identifying patterns by using salt & peer results in rough texture of the image The Proposed algorithm have performed better in identifying noisy images then initially PIL reconstruction is where it helped in improving the quality of images captured under challenging lighting conditions

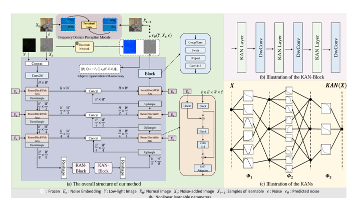

Fig. 1. Fig.1. Proposed model architecture .

Figure Description:

The figure shows the architecture of our proposed low-light image enhancement method using Kolmogorov-Arnold Networks (KAN). (a) The overall structure begins by concatenating the low-light image and noise embedding, followed by convolution and ResNet blocks with attention, progressively downsampling. The features are then reshaped and passed through KAN blocks for nonlinear feature extraction before being upsampled to reconstruct the enhanced image. An adaptive regularization term with uncertainty is applied to improve robustness. (b) The KAN-Block illustration highlights the use of alternating KAN layers and depthwise convolution (DwConv) for refining features.

(c) The KAN architecture captures complex relationships between input features through learnable nonlinear parameters, enhancing the overall image quality. This approach effectively combines CNN-based feature extraction with the powerful representation capabilities of KANs.

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