LOW LIGHT IMAGE ENHANCEMENT BASED ON ATTENTION MAP
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ABSTRACT
The quality of images captured in low light will often exhibit characteristics like low brightness, low contrast, reduced visibility, high noise levels, and loss of crucial details. For this problem, we present a sophisticated approach for low light image enhancement with Convolution Neural Network (CNN). CNNs have gained prominence in various image processing techniques due to their ability to generate realistic images. To improve the performance of enhancing images compared to other methods, we propose a method on attention map based on M-Net architecture. In this, we place this attention block in the M-Net architecture to extract the details from the image.

Keywords: Low Light Image Enhancement, CNN, M-Net.

I. INTRODUCTION
Image enhancement is a critical aspect of computer vision and it is a building block for various high-level tasks such as image classification and object detection. In essence, image enhancement seeks to enhance the quality of an image by manipulating its attributes like brightness, contrast, sharpness and noise levels.

In the context of picture recuperation, where a low-pleasant photo Y needs enhancement, it is able to be represented as:

\[ Y = H \cdot X + N \]

Here X represents the authentic extraordinary photograph which we purpose to estimate or restore, H represents the degradation operator or the degradation procedure, including blur, noise, or other varieties of distortion that befell for the duration of image acquisition or transmission and N represents the noise or artifacts gift inside the found photo.[1]

The intention of image enhancement or recovery algorithms is to estimate or approximate the authentic outstanding photo X from the discovered low-exceptional photograph Y. This procedure involves numerous strategies consisting of deconvolution, denoising, sharpening, and evaluation enhancement. These strategies purpose to mitigate the outcomes of degradation and noise, thereby enhancing the general high-quality and visible attraction of the picture.

In current years, learning-based techniques, in particular those using convolutional neural networks (CNNs), have revolutionized image enhancement duties, surpassing traditional prior-based methods in phrases of both inference time and enhancement performance. The rise of CNNs has had a profound impact on diverse computer vision responsibilities, together with image enhancement.

CNNs are properly-used for image enhancement obligations due to their potential to routinely research complex patterns and representations from big amounts of information. By education on pairs of low-first-rate and splendid photographs, CNN-based fashions can effectively analyze the mapping between the 2 domains, permitting them to generate superb snap shots from low-satisfactory inputs.

In this we propose a image enhancement model based on M-Net architecture called AM-Net to obtain better results and less time for conversion. In this architecture we include a attention block which helps in extracting the details from the low light images.

In this we used LOL-v1 and LOL-v2 datasets to show the performance of our model and compared with other models.
II. RELATED WORK

A. Low light image enhancement

In the area of photo enhancement, traditional processes frequently depend on image priors or specific algorithms. These consist of techniques like histogram equalization [2,3], retinex-based techniques [4], and dehazing-based[5] totally strategies. We prioritize enhancing lowlight images because they are more commonly encountered in real-world scenarios compared to other types of image enhancement.

Low-light image enhancement pursuits to improve the perceptibility and interpretability of photos captured in poorly illuminated[6] environments. It’s a tough task, because it calls for addressing not handiest brightness healing but also complex troubles like color distortion and noise, which tend to be more stated in dark conditions. Fortunately, re-cent advancements in gaining knowledge of-primarily based strategies, specifically the ones based totally on Convolutional Neural Networks (CNNs), have yielded exquisite con-sequences in low-light image enhancement. These CNN-primarily based methods outperform traditional prior-based totally methods[1,8-11] by using a substantial margin.

The M-Net architecture is first proposed for medical image segmentation [12] which can be regarded as an improved hierarchical model architecture from U-Net [13, 14]. Adiga et al.[15] use the same framework for fingerprint image denoising and obtain good results. Therefore compared to U-Net architecture M-Net performs better for extracting features.

III. PROPOSED MODEL

Fig 1: Proposed AMM-Net architecture with depth of 3. We set the input image size to 600 x 400.

A. Attention map M-Net (AMM-Net)

The proposed model AMM-Net architecture is shown in above Fig 1. This architecture is divided into 2 parts: one is encoder and the other is decoder. In the encoder part we first take the low light input image with size of 600 x 400. We use 3*3 weight sharing convolution in each resolution of low-light input image acquired by doing the bilinear down-sampling from original-resolution input [23], Each layer has attention map block to extract the details from the low light input image. In addition, we use pixel unshuffled [16] method as our down-sampling module in the trunk feature path at the end of attention map block in the U-Net. Then in the decoder (reconstruction of image) part of architecture the feature maps are concatenated with previous shallow features from bilinear down-sampling and keep going as normal UNet process [23].

B. Attention map

In this attention map we use one of the block dual atten-tion unit (DAU) to get the details from the given low light image. This dual attention unit involves in two attention types Spatial attention and Channel attention. At every level of the model this attention map is used and extract the detail and these are used in decoder part of architecture for providing enhanced image.
IV. EXPERIMENT

A. Experiment Datasets

In this section we have taken two datasets for low light image enhancement. We trained the model and tested, then compared with other models which are also trained using same dataset.

LOLv1 (Low-light dataset) provides 500 image pairs of total in these 485 are used for training and 15 are used for testing. All the images are in 600 x 400 size format.

Similarly LOLv2 (Low-light dataset) provides 789 image pairs of real captured in these 689 are used for training and 100 and 1000 synthetic image pairs in these 900 are used for training and 100 used for testing are used for testing. All the images are in 600 x 400 size format.

B. Model training details

This AMM-Net is trained on NVIDIA RTX 3050 GPU. This experiment is implemented on PyTorch and used PyCharm IDE for development. The results are based on the model which is trained with batch size 2 for 100 epochs.

For comparison with other models we considered two parameters the Peak Signal-to-Noise Ratio (PSNR), Structural Similarity (SSIM) index. The performance is higher when both the values of PSNR and SSIM are high.

Table 1: Comparison Of Methods On Lol Dataset

<table>
<thead>
<tr>
<th>Method</th>
<th>PSNR</th>
<th>SSIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSR [4]</td>
<td>13.17</td>
<td>0.48</td>
</tr>
<tr>
<td>Zero-DCE [17]</td>
<td>14.86</td>
<td>0.54</td>
</tr>
<tr>
<td>LIME [18]</td>
<td>16.76</td>
<td>0.56</td>
</tr>
<tr>
<td>Retinex-Net [19]</td>
<td>16.77</td>
<td>0.56</td>
</tr>
<tr>
<td>EnlightenGAN [20]</td>
<td>17.48</td>
<td>0.65</td>
</tr>
<tr>
<td>RUAS [10]</td>
<td>18.23</td>
<td>0.72</td>
</tr>
<tr>
<td>GLAD [22]</td>
<td>19.72</td>
<td>0.70</td>
</tr>
<tr>
<td>DRBN [21]</td>
<td>20.13</td>
<td>0.83</td>
</tr>
<tr>
<td>KindD [8]</td>
<td>20.87</td>
<td>0.80</td>
</tr>
<tr>
<td>KindD++ [9]</td>
<td>21.30</td>
<td>0.82</td>
</tr>
<tr>
<td>AMMNet (ours)</td>
<td>21.77</td>
<td>0.82</td>
</tr>
</tbody>
</table>

Fig 2: Comparisons between different lol light image enhancement models on LOL dataset
The Peak Signal-to-Noise Ratio is the ratio of the maximum value of the pixel to the noise (MSE) that affects the quality of the pixels. The higher the PSNR, the smaller the error and it is expressed in terms of a logarithmic decibel scale.

The Structural Similarity Index (SSIM) is a metric used to measure the quality of images and predict how perceived they will be. It's based on three parameters: luminance, contrast, and structural information. The SSIM index is calculated for an image in relation to a reference image, which should be of perfect quality.

C. Image Enhancement Performance

Evaluation on LOL. In Table 1 and Fig. 2, we compare our AMMNet with the other low light image enhancement methods Enlighten GAN[20], Zero-DCE[17], LIME[18] and RetinexNet[19] methods on LOL dataset. From the Table 1, we could observe that our model AMMNet achieves high performance in both parameters PSNR and SSIM on LOL testing dataset, the high values of PSNR and SSIM indicates how better the model performs. Which means that our model performs better compared to other models.

D. Results

Fig. 3, shows some of outputs of our model. row 1 shows low light images which are given as input and row 2 shows enhanced version the low light images by AMMNet (ours).

E. Real time results

Fig 4, shows the normal light images which are enhanced from low light images, these low light images are captured in real time.

V. CONCLUSION

In this paper we present a image enhancement model AMMNet for enhancing images captured in low light. We used M-Net to develop this model. Moreover we proposed attention map block in our architecture to extract the in depth details from the low exposed image(low light image). Our model archives high performance when compared with other low light image enhancement models.
VI. REFERENCES


C. M. Fan, T.-J. Liu, and K.-H. Liu, “Half Wavelet Attention on M-Net+ for Low-Light Image Enhancement,” 2022 IEEE International Conference on Image Processing (ICIP), Bordeaux, France, 2022, pp. 3878–3882, doi: 10.1109/ICIP46576.2022.9897503. keywords: Measurement; Computer vision; Visualization; Image segmentation; Wavelet domain; Semantics; Neural networks; Image enhancement; hierarchical; M-Net; wavelet domain; attention mechanism,