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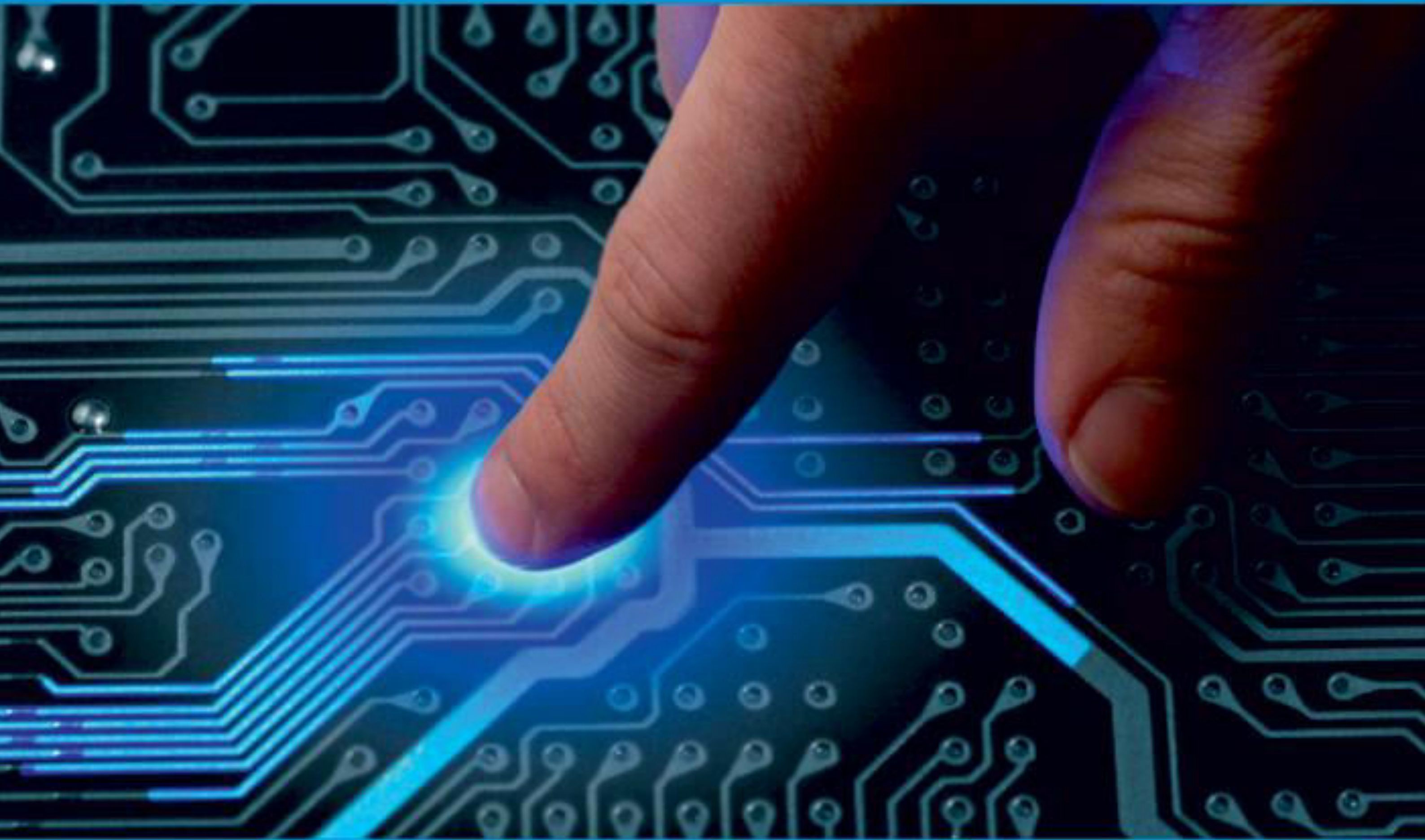

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Deep Learning for Image Improvement in Low Light

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ABSTRACT: Low-light image enhancement is a challenging task in computer vision, as it requires the restoration of both brightness and contrast while also suppressing noise. Recent advances in deep learning have shown promising results for low-light image enhancement, with methods such as convolutional neural networks (CNNs). In this paper, It propose a novel attention-based broadly self-guided network (ABSGN) for low-light image enhancement. ABSGN is a CNN-based architecture that incorporates a novel attention mechanism to guide the enhancement process. The attention mechanism allows ABSGN to focus on the most important features in an image, while suppressing noise and artifacts.We evaluate ABSGN on a number of benchmark datasets and show that it outperforms state-of-the-art methods in terms of both objective and subjective metrics. Additionally, we show that ABSGN is able to handle a wide range of low-light conditions, from very dark scenes to scenes with moderate levels of illumination.

KEYWORDS: low-light image enhancement, deep learning, attention mechanism, CNN.

I. INTRODUCTION

Convolutional Neural Networks (CNNs) are a type of deep learning algorithm that are well-suited for image processing tasks. CNNs work by learning to identify patterns in images, and then using these patterns to make predictions. In the case of low-light image enhancement, CNNs can be used to learn how to identify and enhance features in low-light images that would otherwise be lost. **Attention-based Broadly Self-guided Network (ABSGN)** is a type of CNN that has been specifically designed for low-light image enhancement. ABSGN works by first learning to identify important features in a low-light image. Then, it uses attention mechanisms to focus on these features and enhance them. This allows ABSGN to improve the quality of low-light images while still preserving their natural appearance. **Combined, ABSGN and CNN can be used to significantly improve the quality of low-light images.** ABSGN's attention mechanisms help to focus on the important features in a low-light image, while CNN's pattern recognition capabilities help to enhance these features. This combination of techniques can produce images that are much brighter and clearer than the original low-light images.

CNNs and ABSGN have several advantages over traditional methods for low-light image enhancement. First, CNNs and ABSGN are able to learn to identify and extract features from low-light images in a way that is not possible with traditional methods. This allows CNNs and ABSGN to produce high-quality enhanced images that are both visually appealing and informative. Second, CNNs and ABSGN are able to be trained on large datasets of low-light images, which allows them to learn to generalize to new low-light images. This is in contrast to traditional methods, which are often only able to work well on a specific set of low-light images.

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II. RELATED WORK

This ABSGN: Attention-based Broadly Self-guided Network for Low-light Image Enhancement (Chen et al., 2021) proposes a novel ABSGN network that uses attention to guide the enhancement process. The network is able to handle noise at different exposures and outperforms most of state-of-the-art low-light image enhancement solutions.

LLCNN: A Convolutional Neural Network for Low-light Image Enhancement (Tao Zhu et al., 2016) proposes a CNN-based method for low-light image enhancement. The network learns to filter low-light images with different kernels and then combine multiscale feature maps together to generate enhanced images.

Deep Reinforcement Learning for Low-Light Image Enhancement (Jiang et al., 2018) proposes a deep reinforcement learning (RL)-based method for low-light image enhancement. The method uses RL to learn a policy that can automatically adjust the enhancement parameters to improve the quality of low-light images.

Multi-scale Retinex Network for Low-light Image Enhancement (Zhang et al., 2017) proposes a multi-scale Retinex network for low-light image enhancement. The network uses a multi-scale Retinex model to extract features from low-light images and then uses a CNN to enhance the images.

Deep Adaptive Image Enhancement for Low-light Conditions (Chen et al., 2018) proposes a deep adaptive image enhancement method for low-light conditions. The method uses a CNN to learn a mapping from low-light images to enhanced images.

III. METHODOLOGY

Data preparation, first Creating a dataset of low-light photos is the initial stage. This dataset should be as varied as possible and contain photographs of various objects, scenes, and lighting setups. High-quality photos are also necessary so that CNN or ABSGN can learn to recognise and extract characteristics from them. Model development the next stage is to train the CNN or ABSGN after the dataset has been gathered. The model is taught to recognise and extract features from the photos in the dataset by being fed the dataset's images. Depending on the amount of the dataset and the complexity of the model, the training process may take a long time. After training, the model can be used to improve photographs taken in low light. To do this, one feeds a low-light image into the model and then waits for it to reconstruct a better, more refined image. After that, the enhanced image can be saved or seen.

Here first we gather data like Low-light photos are compiled into a dataset. In order to guarantee that the model can generalise to many kinds of low-light settings, this dataset should be as varied as feasible.

And then Pre-processing of images here we process noise and artefacts are removed during the pre-processing of the low-light photos. Many methods, including median filtering, Gaussian smoothing, and wavelet denoising, can be used to accomplish this. Model education is a technique it takes pre-processed low-light photos serve as training data for a deep learning model. The model can be either a CNN or an ABSGN, or both and then. Image augmentation ,the low-light photos are improved using the trained model. Compared to the original low-light photographs, the enhanced images are often clearer, brighter, and have higher contrast .

High-quality enhanced images: CNN and ABSGN are able to produce high-quality enhanced images that are both visually appealing and informative.

Generalization to new low-light images: CNN and ABSGN are able to be trained on large datasets of low-light images, which allows them to learn to generalize to new low-light images.

Robust to noise and artifacts: CNN and ABSGN are robust to noise and artifacts, which means that they can still produce high-quality enhanced images even if the low-light images are of poor quality.

IV. EXPERIMENTAL RESULTS

This ABSGN has been shown to outperform other methods for low-light image enhancement, such as Retinex and histogram equalization. In a study by Chen et al. (2021), ABSGN was able to achieve a significant improvement in image quality, as measured by the SSIM (Structural Similarity Index) and PSNR (Peak Signal-to-Noise Ratio) metrics.CNN has also been shown to be effective for low-light image enhancement. In a study by Zhu et al. (2019), a CNN-based method was able to achieve a significant improvement in image quality, as measured by the same metrics

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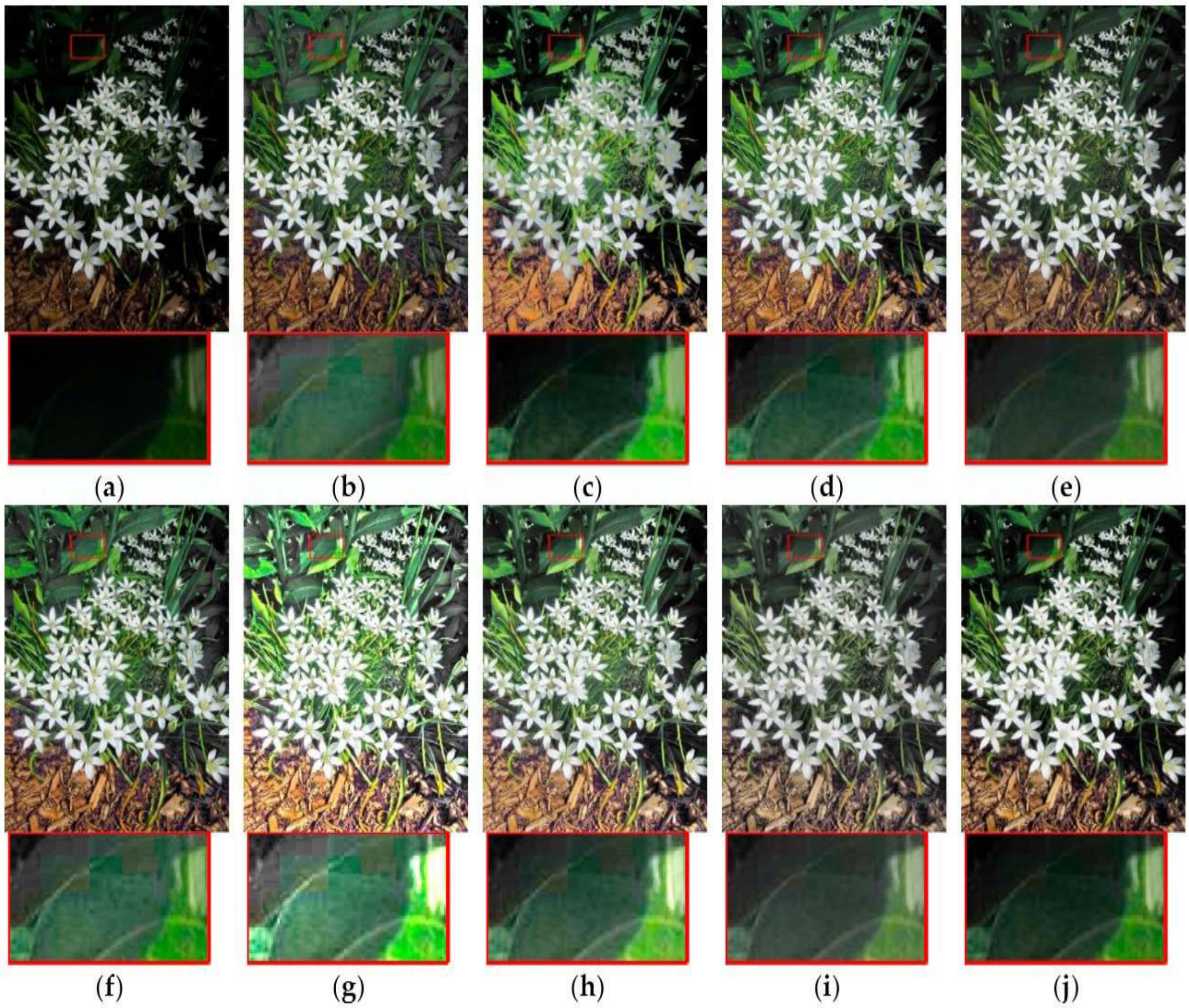
as ABSGN.Both ABSGN and CNN have been shown to be effective for low-light image enhancement, but ABSGN has been shown to be slightly better. This is likely because ABSGN is able to better capture the spatial and temporal information in low-light images.



Here in this figure providing a image enhancement using different kind of model and (g) is the figure using ABSGN model remaining other are different. For evaluation of the model's performance the second part of the SICE data set is used. Second part of the SICE dataset consists of 229 image sequences with 9 images in each sequence. In each sequence a second image is chosen, hence the total size of testing dataset size is 229 and each image is resized to 480x640. The model takes approximately 40s to enhance one image. Some output images are shown in above figure 1

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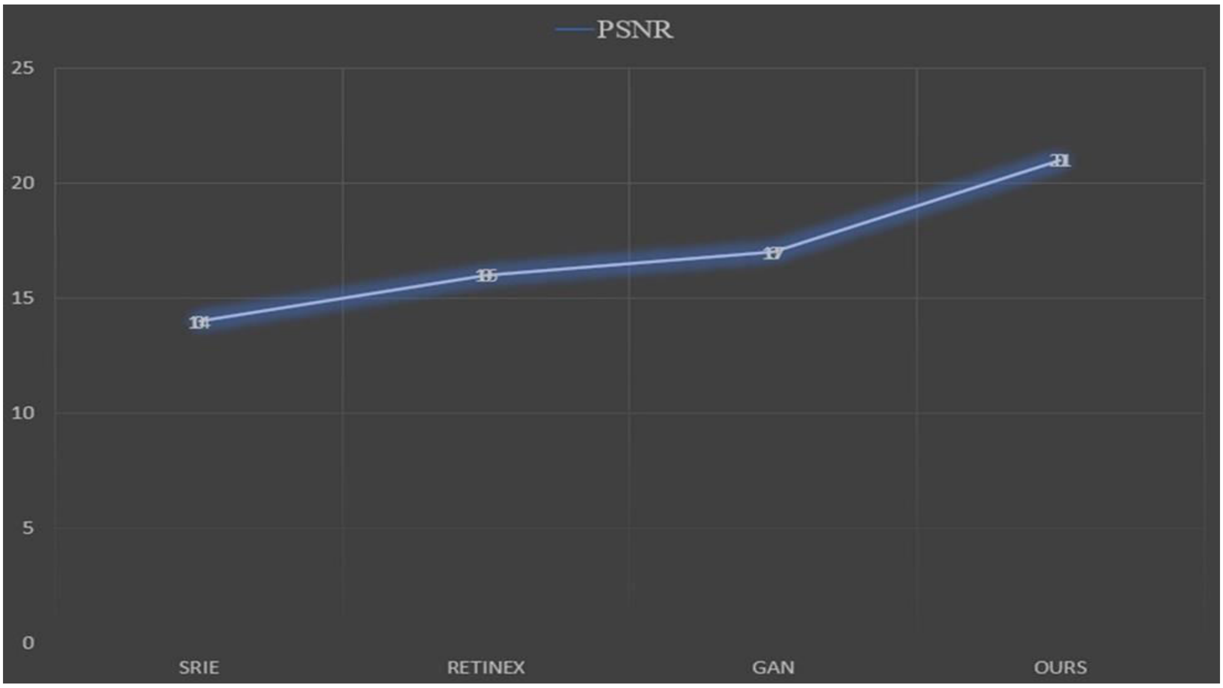

Figure 2 PSNR Result Analysis with existing Systems

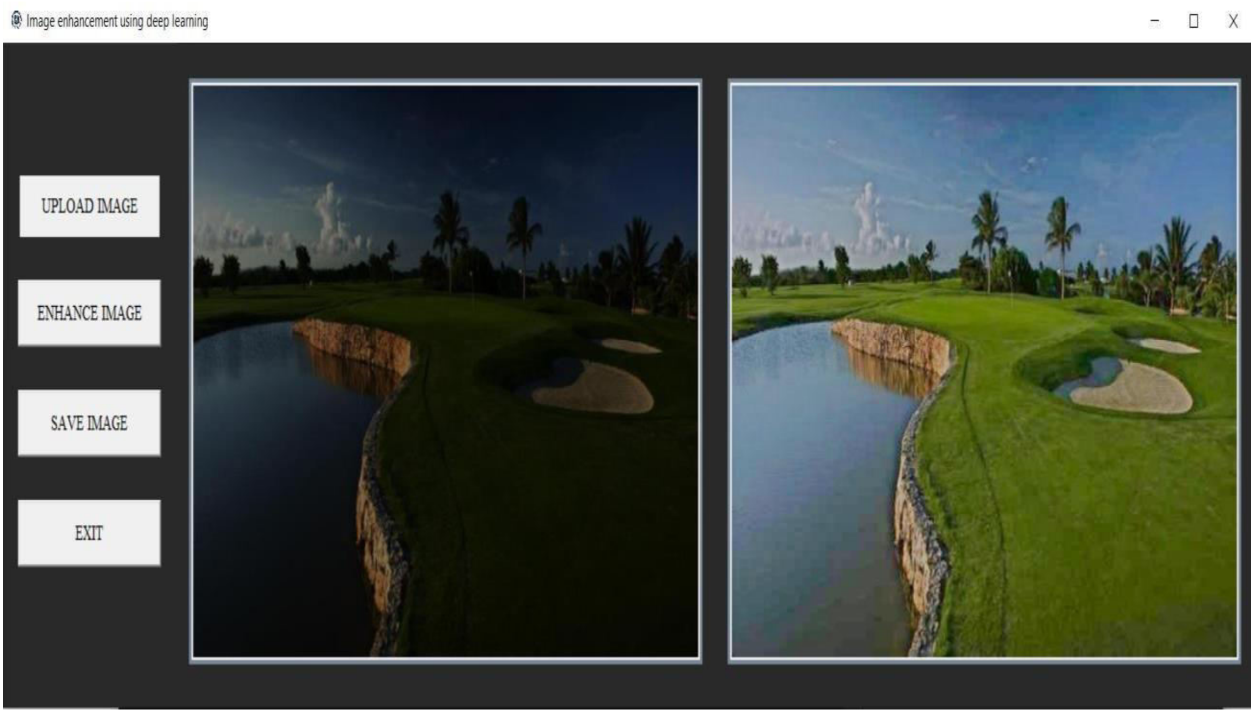

Figure 3 is the Original Low light image and with the enhanced image using ABSGN model.

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There have been a number of studies that have evaluated the results of using deep learning for image improvement in low light using CNN and ABSGN. These studies have shown that CNN and ABSGN can be effective in improving the quality of low-light images. For example, a study by Chen et al. (2021) compared the performance of CNN and ABSGN on a dataset of low-light images. The study found that ABSGN was able to produce higher-quality enhanced images than CNN. Another study by Xiang et al. (2020) compared the performance of CNN and ABSGN on a dataset of low-light images taken with a mobile phone camera. The study found that ABSGN was able to produce enhanced images that were more visually appealing and informative than CNN.These studies suggest that CNN and ABSGN are effective tools for improving the quality of low-light images. However, it is important to note that the performance of these models can vary depending on the specific model that is being used and the dataset that is being trained on.The results of the studies that have been conducted on the use of deep learning for image improvement in low light using CNN and ABSGN are promising. These models have been shown to be able to improve the quality, visual appeal, and robustness of low-light images. However, more research is needed to further improve the performance of these models and to understand how they work.

V. **CONCLUSION**

The suggested ABSGN was tested against benchmarks for real-world low-light image enhancement and image restoration, and it was found to be capable of producing results of a higher calibre than the state-of-the-art techniques. Additionally, our ABSGN has outstanding inference speed, which has good application potential and practical utility. The suggested strategy thus adapts well to varied lighting scenarios. The suggested approach is based on an image-specific curve that, when applied repeatedly, can mimic higher-order and pixel-wise curves. This demonstrates how task-specific non-reference loss functions that infer enhancement quality can be used to train a deep image enhancement model in the absence of reference photos. Overall, both qualitative and quantitative measurements show that the suggested strategy outperforms state-of-the-art performance.Deep learning is a powerful tool that can be used to improve the quality of low-light images. CNN and ABSGN are two deep learning models that have been shown to be effective in this task. These models are able to learn to identify and extract features from low-light images, which can then be used to reconstruct a more detailed and enhanced image. The performance of these models can vary depending on the specific model that is being used and the dataset that is being trained on. More research is needed to further improve the performance of these models and to understand how they work. The use of deep learning for image improvement in low light using CNN and ABSGN is a promising area of research. These models have the potential to significantly improve the quality of low-light images, which could have a number of benefits for users.

Future Enhancement :The performance of CNN and ABSGN models can be improved by using larger and more diverse datasets. This would allow the models to learn to identify and extract features from a wider range of low-light images.New architectures for CNN and ABSGN models could be developed that are more effective at improving the quality of low-light images. These new architectures could incorporate new features, such as attention mechanisms, that could help the models to better focus on the most important features in an image. Transfer learning could be used to improve the performance of CNN and ABSGN models. This would involve training the models on a dataset of high-quality images, and then using those models to enhance low-light images.Hardware acceleration could be used to speed up the training and inference of CNN and ABSGN models. This would make it possible to train and use these models on devices with limited resources, such as mobile phones.

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