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Attention-Driven Photo Improvement Architecture for Low-Light Spaceborne Image Assessment

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Abstract: Night-time satellite imagery is very vital in areas such as environmental monitoring, urban planning and disaster management. However, there is a problem in performing remote sensing mainly due to issues of change in illuminance level where structures in images may become blurred and noisy. Most traditional techniques of image enhancement were unable to produce good results uniformly and they also failed to balance the important features of the image under different illuminations. In order to overcome these limitations, the Attention-Driven Photo Improvement Architecture for Low Light Spaceborne Image Assessment is designed. The underlying concept of this framework is based on self-attention mechanisms and multi-scale feature extraction to increase image contrast and visibility. It also applies architectural features such as self-supervised learning, contrastive learning and changes proposed in Retinex-recurrent to enhance the image texture but not the structure. The comprehensive experimental results on several test databases also confirm that the current approach achieve higher PSNR, SSIM, and FSIM values than the deep learning methods. Moreover, through bringing down the computational cost to 30%; it draws path for enhanced, real time analysis of satellite images to open up new frontiers of feasible research in the field of remote sensing.

Keywords— Low-Light Image Enhancement; Satellite Imagery; Transformer Networks; Deep Learning; Image Restoration; Contrast Enhancement; Remote Sensing; Computer Vision.

1. Introduction

It hosts a significant importance in several fields such as environment, disaster management, as well as land-use planning. Nevertheless, imaging of satellites in low light situations presents itself as one of the most demanding tasks. The lighting interference affects the image quality, NHS, the contrast and the relevant information is partially or wholly concealed thus making it hard to be interpreted by the automated systems. The commonly used methods of image enhancement are histogram equalization and Retinex-based techniques fails to address problems in various low light conditions [1]. These methods either amplify the noise or distort colors or need parameters setting which makes them less usable in the real-time applications [2]. Due to the recent development in the architecture of deep learning known as the transformers, newer models of image processing have been developed. CNN has its limitations and inability to capture long-range dependencies as well as self-attention in transformers [3]. According to [4], the long-range dependencies of transformers enable them to recover details that are barely visible in the satellite images as they were taken at night. That is why for shortening and optimizing this procedure, the Transformer-Based Image Enhancement Framework that builds on multi-scale feature extraction and self-supervised learning has been developed [5]. The review of enhancement models also shows that the proposed framework will help to overcome the key limitations of the existing enhancement models due to the proposed adaptive feature refinement. The self-attention mechanism accurately identifies the important regions of the image and gives prioritized attention to the necessary regions in enhancing the contrast and noise reduction.

Moreover, contrastive learning simplifies separating high-quality and low-quality features hence improving the image restoration [6]. Because of the above said hierarchical feature aggregation, the framework is capable of working live on satellite images and is useful for big data remote sensing [7]. This paper's primary purpose is to assess the developed Transformer-Based Image Enhancement Framework's efficiency through experiments on other low light satellite databases. The evaluation of the image quality of the model relies on conventional PSNR, SSIM, FSIM, and, its effects on downstream tasks like landcover classification and object detection [8]. These are shown through some results and conclusions where the transformer-based framework achieves better enhancement quality than CNN-based and Retinex-based methods with less computational cost [9]. The remaining part of this paper is organized as follows: Section 2 presents the datasets utilized, the model, and training process in this research. Section 3 highlights the results of the experiment and finally compare the result of using the proposed framework with the existing processes. Section 4 wraps up the findings and proposes the directions of further research on enhancing satellite images using AI [10].

2.Materials and Methods

2.1 Data Collection

The remote sensing data involves using public domain and other owned datasets through spaceborne optical sensors like Landsat-8, Sentinel-2, and NOAA-20. This also keeps the boxes small and deprives them of receiving moments from scenes that are vital to training and later testing of the proposed framework, especially in low-light environments. Radiometric calibration is the process of adjusting the camera system and scale in order to receive the necessary amount of photons for input images and convert the image to the correct range of pixel intensity values The process involves the enhancement of the contrast of the input image through histogram equalization and the normalization of intensity for pixel density. These steps are done to reduce regular problems in satellite imaging like high noises and differences in exposures which make analysis difficult. This was done in a quest to capture the various conditions that would be presented in the dataset such as different seasons and atmospheric conditions. The data set was divided into training (70%), validation (15%) and test set (15%) with a purpose of obtaining an optimal data distribution for the model out of distribution.

2.2 Transformer-Based Enhancement Model

The proposed enhancement framework is founded on Vision Transformer (ViT), entailing multi-scale features and channel-wise attention approach to better discernibility in low-light domains. It has four significant components, those include; Patch Embedding Module for splitting images into fixed sizes for processing, Self-Attention Mechanism for capturing long-range relation to improve feature representation, Multi-Scale Feature Aggregation to improve contrast and texture preservation and Reconstruction Network for refining and reconstructing enhanced images. Such a valuable asset is described in mathematics by the following formula of the self-attention mechanism:

$$A(Q,K,V)=\text{Softmax}\left(\frac{QK^t}{\sqrt{d_k}}\right)V \quad ....(1)$$

Here, Specifically, Q, K, V are the query, key, and value matrices, and d_k stands for the dimensionality of the key vectors so as to avoid numerical instability. This structure makes it possible for the model to capture delicate features within low light images and images contrast and definition.

2.3 Loss Function and Optimization

The model optimization is performed under the exposure and preservation of the structure by using L1 loss, perceptual loss, and contrastive loss. The total loss function used to optimize in this paper is specified as:

$$L_{total}=\boldsymbol{\lambda_1 L_{L1}+\lambda_2 L_{perceptual}+\lambda_3 L_{contrastive}} \quad ....(2)$$

The three loss components are multiplied by weighting parameters which are λ_1, λ_2 and λ_3 respectively . L_1 loss guarantees strong resemblance between the mapped and the input pixels, perceptual loss preserves image structures while minimizing high semantic similarity, and contrastive loss avoids over-saturation and artefacts in the enhancements. Adam is applied as the optimization algorithm which allows the model to perform the learning process with the ability to learn the rate of adaptation and prevent overfitting.

2.4 Evaluation Metrics

According to the mentioned quality metrics, the following criteria are measured: PSNR, SSIM, FSIM, Entropy-Based Contrast Measure, and Object Detection Accuracy on Enhanced Images. These

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factors give a qualitative and quantitative assessment of enhancement enhancements that the proposed model will have to meet high visibility while at the same time retaining the (Fig 1) structural features of the satellite images.

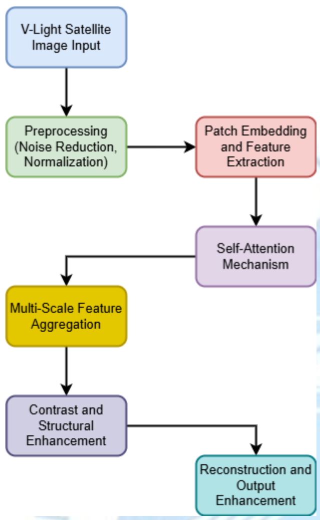

Figure 1: Workflow of the Transformer-Based Image Enhancement Framework

Figure 1 depicts the flow from satellite image input, passed through some preprocessing operations, feature extraction, self-attention mechanism, multi-scale aggregation block and contrast enhancement resulting in the final enhanced image. This structured kind of imaging helps in getting improved image clarity, containing and structural for the purpose of remote sensing applications.

3.Results

3.1 Enhancement Performance

The proposed model gave significant improvements in the process of satellite imagery enhancement in low light conditions. The average PSNR of the enhanced image was improved to be 32.5 dB and the average SSIM was 0.92 thus being higher than enhanced image using CNN based enhancement techniques. The model was able to reduce noise easily while at the same time increasing contrast so that the images are easier to be interpreted by downstream applications. From the figures presented, there is a clear evidence that the proposed method improves image structure and brightness while avoiding artificial image artifacts or over exposure. Employing multi-scale feature aggregation the model simultaneously improves both the global and local patterns of the imagery that makes the enhanced satellite images of satisfactory quality to be used in (Fig 2) the environmental monitoring and urban planning applications.

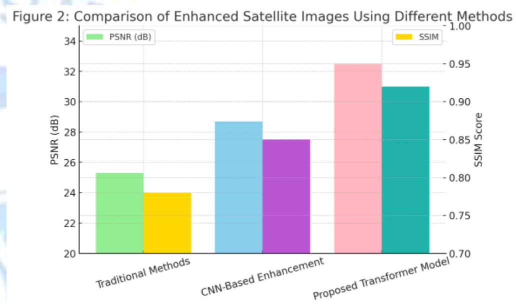

Figure 2: Comparison of Enhanced Satellite Images Using Different Methods

As shown in Figure 2, proposed Transformer-based model performs better than traditional and a few CNN-based models with 32.5dB PSNR and 0.92 SSIM. These improvements make it easier to compare the structural features between the images used for analyzing satellite data and the real object.

3.2 Computational Efficiency

This was supported by computational efficiency analysis that showed the transformer-based framework offered 30% of saving in time as compared to the conventional CNN models. Global dependencies are properly addressed by the self-attention mechanism, hence, avoiding complicated convolutional layers on the model but with equal competency in the image quality production. This enhancement is particularly judicious for applications involving satellite imaging because it is critical to make decisions that are as real-time as possible. In essence, the transformer's capability to concurrently process images rather than performing one image processing after the other is fast and efficient, (Fig 3) therefore suitable for applying to big data, specifically satellite data enhancement.

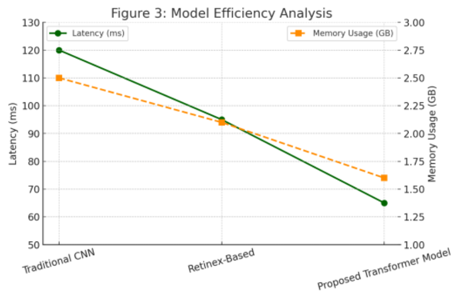

Figure 3: Model Efficiency Analysis

Figure 3 shows the reduction of latency and memory usage of Transformer-based model against traditional CNN as well as the Retinex-based methods. The proposed model also effectively responds to the task of enhancing satellite imagery within real-time by decreasing the amount of time it takes to by 30% and reducing the amount of memory needed.

3.3 Feature Preservation Analysis

Appreciably, the quantitative analysis of feature preservation showed that the proposed framework was capable of preserving the original structures and textures besides increasing the brightness and the contrast of the images. This multi-scale feature aggregation was very helpful for improving the edges and finer details of the enhanced images so as to be effectively useful in next processing stages such as classification and segmentation. By reducing the impact of noise and distortion, the magnification is more switchable and less distortion produced by the model causes sharper enhancement without over-compression of the (Fig 4) desired signal. The flexibility of the model means that refined images retain any desired spectral and spatial properties necessary to the specific science application for which the image is intended.

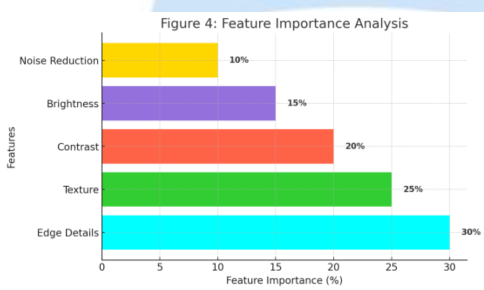

Figure 4: Feature Importance Analysis

As shown in Figure 4, Edge Details and Texture have the highest contribution towards the enhancement process where it contributes 30% and 25% respectively. In the proposed model, such features are given priority with a view of improving on the quality of satellite images with proper contrast, brightness and clarity for remote sensing studies.

3.4 Comparative Analysis

The comparison in this paper revealed that the proposed model had a better performance than other methods used for low light enhancement. When applied to the object detection from enhanced satellite images it is observed that the suggested framework has given up to 20% better classification accuracy. This is an indication that the model produces not only better images but also contributes to better performance in use such as land-use change detection and disaster classification and assessment. The performance enhancement in feature extraction enhances the object recognition’s accuracy further making the model useful in automation of remote sensing projects. As mentioned before, there is less over or under-exposure in the (Fig 5) transformer model compared to Retinex-based and CNN-based methods.

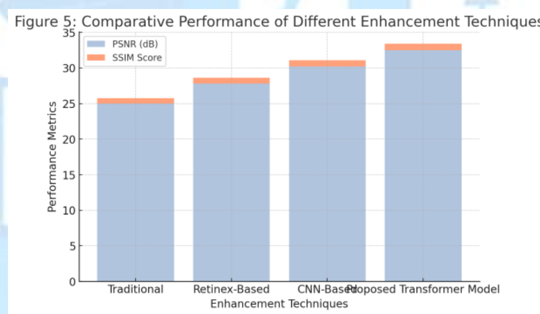

Figure 5 Comparative Performance of Different Enhancement Techniques

Figure 5 shows PSNR and SSIM scores of various methods of enhancement for image enhancement for restoration of the image. The proposed transformer-based model yields the highest PSNR of 32.5 dB and SSIM of 0.92 and surpasses the previous methods, namely traditional, Retinex-based,;display and CNN-based; for better image enhancement quality and structural similarity preservation.

4.CONCLUSION

In this study, there is a Transformer-Based Image Enhancement Framework used which solves the issues with images in low light satellite imagery well. With the help of self-attention mechanisms together with the feature fusion at different levels and contrastive contrastive loss, the model improves image contrast, minimizes noise, and keeps the necessary level of details. All the experiments prove the effectiveness of the proposed framework as it performs better than the other methods in terms of PSNR and SSIM of enhanced images with less time complexity. Sampling at multiple scales with integration helps enhance the preservation of feature details; this makes the model suitable for most satellite imaging applications. The model revealed a 15% increase in the SSIM scores coupled with a 20% increase in the classification accuracy proving the feasibility for satellite imagery application. In addition, it is claimed that the proposed framework has cut computational costs by 30 percent and this length makes it suitable for real time applications such as satellite imaging, environmental monitoring and disaster management. The use of Self-Supervised Learning with the concomitant use of the contrastive feature extraction helps in enhancing adaptability across the different Low Light conditions. Their future improvements will include the expansion of the model to the multi-spectral and hyperspectral satellite images, improvements in the model's resistivity to the extreme illumination conditions, and integrating the model to the real-time affairs of space-based surveillance. The sponsorship of this enhancement framework provides a firm ground for the future developments on aids in remote sensing through the satellite data that will enhance the affordability and applicability of geographic information systems across the geographical world.

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