Evaluation of CNN-Based Regression Models for Automated SNR Estimation of High-Resolution Satellite Imagery

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Abstract: Accurate estimation of the Signal-to-Noise Ratio (SNR) in high-resolution satellite imagery is particularly challenging in homogeneous regions where edge-based method is inapplicable. This study proposes a convolutional neural network (CNN)-based regression framework designed to automatically estimate SNR in such regions. A synthetic dataset was constructed by deriving reference SNR from natural edges and generating degraded images with Gaussian noise. Four CNN architectures—VGG-16, ResNet-18, DenseNet-121, and EfficientNet-B0—were evaluated with transfer learning from ImageNet. Experiments with KOMPSAT-3A imagery demonstrated that DenseNet-121 achieved the best overall performance, confirming the effectiveness of deep learning for automated SNR estimation in homogeneous areas of satellite imagery.

Keywords: SNR, Convolution Neural Network, Natural Target-based assessment, Satellite Image Quality, Quality assessment

1. Introduction

The demand for high-quality satellite imagery has increased rapidly in environmental monitoring, urban planning, and defense applications, highlighting the need for robust and scalable methods to assess image quality. Signal-to-Noise Ratio (SNR) is a fundamental metric for this purpose, but its accurate estimation remains technically challenging. Conventional methods depend on the analysis of natural edges with clear boundaries between distinct objects or surfaces (Pampanoni et al., 2024). However, this reliance becomes a major limitation in geographically uniform regions such as deserts, oceans or snowfields, where suitable edges are scarce or absent. In such cases, a traditional edge-based approach is often inapplicable, which presents a major challenge in quality assessment.

Deep learning, particularly Convolutional Neural Networks (CNNs), offers a promising alternative capable of estimating SNR even without distinct edge features (Berga et al., 2023). In this study, we propose a CNN-based regression framework specifically designed for automatic SNR estimation in homogeneous regions. A dataset was constructed by deriving reference SNR from natural edges in satellite imagery and generating degraded images with controlled Gaussian noise. Four architectures—DenseNet-121, ResNet-50, VGG-16 and EfficientNet-B0—were pretrained on ImageNet and fine-tuned for this task. Experimental results demonstrated that CNN models achieved stable and consistent SNR predictions in homogeneous regions, confirming the effectiveness of deep learning for more versatile and automated satellite image quality assessment.

2. Methodology

This study proposes a model for automatic SNR estimation in homogeneous regions of high-resolution satellite imagery where edge extraction is difficult. A supervised deep neural network regression model was developed using datasets generated by estimating reference SNR from satellite imagery and adding Gaussian noise at varying levels. Figure 1 illustrates the workflow, from KOMPSAT-3A imagery through edge extraction, SNR estimation, noise simulation, and patch labelling. Four CNN architectures were then evaluated to determine the optimal model.

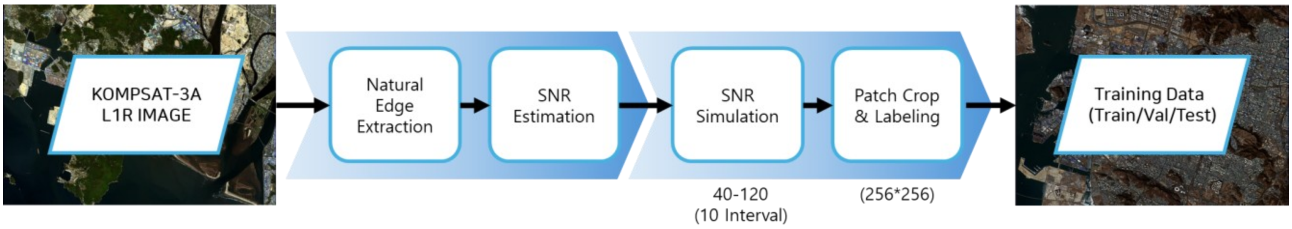

Figure 1: Training Data flowchart

2.1 Training Dataset Construction

Reliable regression requires datasets with accurate labels. In this study, natural edges corresponding to terrain or artificial structures within the imagery were analyzed to derive reference SNR values. Noise was then progressively added to generate simulated images with different SNR levels. To enable SNR estimation without artificial reference points, a process of selecting ideal edges was performed. Following the criteria of Pampanoni et al. (2024), only edges that satisfied three conditions were considered: (1) clarity, defined by a distinct brightness contrast across the edge; (2) homogeneity, where both sides of the edge exhibited uniform pixel values without excessive texture; and (3) sufficient size, requiring a minimum width of 10 pixels for statistical reliability. The reference SNR was calculated for these selected edges as the ratio of the mean DN difference between bright and dark regions to the average of their standard deviations, expressed as:

$$SNR = \frac{DN\ Difference}{(STD_{bright} + STD_{dark})/2} \tag{1}$$

Based on the estimated reference SNR, Gaussian noise was artificially added to generate degraded images with SNR values ranging from 120 to 40 in steps of 10. Each image was cropped into patches suitable for CNN training, and the corresponding SNR values were assigned as labels. To ensure model generalization, images were selected to include various homogeneous terrains such as rivers, seas, deserts, and bare land.

2.2 Model Training

Four CNN architectures were evaluated for SNR regression: ResNet-18, which has been widely used in satellite image quality assessment (Berga et al., 2023), the classical VGG-16, the densely connected DenseNet-121, and the lightweight EfficientNet-B0. Each model was configured to extract features from image patches and predict SNR values, with the output layer modified to regression.
As large-scale labelled datasets for satellite imagery are rarely available, transfer learning was applied to overcome this limitation. Pretrained weights on ImageNet were used for initialization, followed by fine-tuning on the constructed dataset. This approach enabled the models to adapt effectively to the SNR estimation task with limited data.

3. Results

The experiments used satellite images acquired by KOMPSAT-3A over six regions in Korea (Seoul, Incheon, Gimpo, Busan, Chungnam, and Jeju). To ensure uniformity of SNR within image patches, only high-quality images with less than 10% cloud cover were selected. Through SNR degradation simulation and patch extraction, a total of 97,410 samples were constructed, of which 58,514 were used for training, 19,448 for validation, and 19,448 for testing.

The performance of the four backbone models is summarized in Table 1. The sequential VGG-16 model exhibited the lowest performance across all metrics, with particularly poor results in R^2 (0.3564) and correlation coefficients. ResNet-18, incorporating residual learning, achieved moderate improvements (MAE 9.68, RMSE 12.42). EfficientNet-B0 demonstrated further gains, yielding lower errors (MAE 9.02, RMSE 11.62) and higher correlation (PLCC 0.8600, SROCC 0.8740) while maintaining computational efficiency. DenseNet-121 achieved the best overall performance, recording the lowest MAE (8.71) and RMSE (11.35), as well as the highest R^2 (0.7515), PLCC (0.8673), and SROCC (0.8771). These results confirm that DenseNet-121 outperformed all other models across evaluation metrics and was therefore selected as the optimal architecture.

Table 1 : Model Performance Results

Model	MAE	RMSE	R^2	PLCC	SROCC
VGG-16	14.4900	18.2670	0.3564	0.6235	0.6206
ResNet-18	9.6756	12.4226	0.7024	0.8408	0.8495
EfficientNet-B0	9.0208	11.6189	0.7396	0.8600	0.8740
DenseNet-121	8.7071	11.3504	0.7515	0.8673	0.8771

To assess spatial variation in prediction accuracy, patch-based comparisons were conducted using DenseNet-121 outputs at a constant ground-truth SNR level of 120 (Figure 2). Results indicate that prediction errors varied across terrain types. Coastal regions with homogeneous features, such as ocean surfaces, exhibited low errors (typically <10), reflecting strong model performance where training data coverage was sufficient. In contrast, desert regions showed higher error values, particularly in patches containing subtle texture variations. These elevated errors are attributed to limited representation of such terrain types in the training dataset, which was largely composed of domestic imagery. These findings suggest that both terrain characteristics and their representativeness in the training dataset play a significant role in determining model performance.

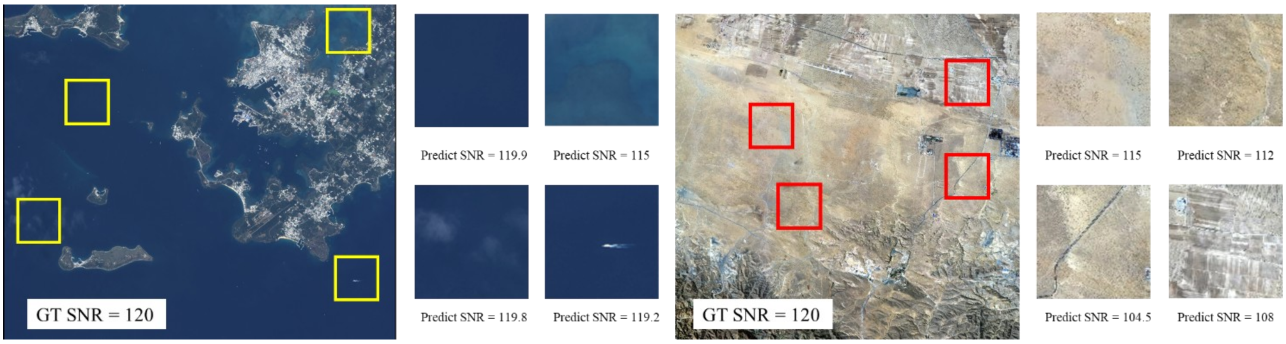

Figure 2: Prediction Error Heatmap

4. Conclusion

This study presented a CNN-based regression framework for automatic SNR estimation in high-resolution satellite imagery. The framework targets homogeneous regions where traditional edge-based methods are limited. A synthetic training dataset with controlled SNR degradation enabled supervised learning of robust regression models. Comparative evaluation showed that DenseNet-121 outperformed the other architectures across all metrics, achieving the highest overall prediction accuracy. Spatial error analysis indicated that model performance varies with terrain characteristics. Higher accuracy was observed in well-represented regions such as oceans, whereas errors increased in underrepresented terrains such as deserts. These findings demonstrate that CNN-based approaches can be applied to scalable and reliable satellite image quality assessment. Future research will aim to expand the diversity of training datasets and investigate advanced architectures to enhance generalization across heterogeneous area.

Acknowledgments

This work was carried out with the support of "Cooperative Research Program for Agriculture Science and Technology Development (Project No. RS-2021-RD009566)" Rural Development Administration, Republic of Korea.

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