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Compressive Sensing for Image Reconstruction: A Deep Neural Network Approach

Geetha. P [1], Saju Raj. T[2], G. Malathi[3], Akhil Nair. R[4], S. Uma[5]

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Abstract: This research explores the application of Compressive Sensing (CS) for image reconstruction, introducing a novel approach based on Deep Neural Networks (DNN). Compressive Sensing is a technique employed to recover sparse signals or images from a small number of measurements, providing an efficient alternative to traditional image acquisition methods. In this paper, the capability of Deep Neural Networks to enhance the reconstruction process within the Compressive Sensing framework is proposed. The approach involves training a deep neural network, the intricate mapping between the matching high-resolution images and compressed measurements may be learned. Taking advantage of the innate patterns and structures found in pictures, the DNN aims to reconstruct the original content from highly under sampled measurements, demonstrating the potential of neural networks in addressing the challenges posed by sparse signal recovery. The paper provides an in-depth analysis of the proposed Compressive Sensing with Deep Neural Network (CS-DNN) approach, evaluating its performance against existing methods through comprehensive experiments. The result shows the effectiveness and versatility of the proposed technique, highlighting its potential to outperform traditional CS methods in terms of both image quality and computational efficiency. This research contributes to advancing the field of image reconstruction by integrating the power of Deep Neural Networks into the Compressive Sensing paradigm, opening new avenues for efficient and robust sparse signal recovery in various applications.

Keywords: *Deep learning, Compressive sensing, image reconstruction, Neural Networks*

1. Introduction

In the ever-evolving landscape of image processing and signal recovery, the quest for more efficient and effective methodologies has driven researchers to explore novel approaches. This research delves into the realm of Compressive Sensing (CS), a technique designed to reconstruct sparse signals or images from a reduced set of measurements [1, 2]. Traditional image acquisition methods often face challenges in terms of efficiency and computational demands [3]. Compressive Sensing offers a promising alternative by exploiting the inherent sparsity of signals, enabling the reconstruction of high-resolution images from a relatively small number of measurements [4]. This paper introduces a groundbreaking approach to Compressive Sensing by incorporating the capabilities of Deep Neural Networks (DNN). DL, especially in the form of neural networks, has demonstrated remarkable success in various domains, from natural language processing to computer vision. Leveraging this success, the proposed Compressive Sensing with Deep Neural Network (CS-DNN) approach seeks to enhance the image reconstruction process within the CS framework.

Compressive Sensing, also known as compressed sensing or CS, has emerged as a powerful paradigm in signal processing. The fundamental idea behind CS is to recover sparse signals or images using significantly fewer measurements than traditional methods would require. This concept has found applications in various fields, including medical imaging, remote sensing, and communication systems. The conventional approach to image acquisition involves capturing a large number of measurements to faithfully represent the image's details. However, this can be computationally intensive and may not be feasible in resource-constrained environments. CS addresses this challenge by exploiting the sparsity of signals, allowing for the reconstruction of high-quality images from a reduced set of measurements. The

[1]*Assistant Professor (SG), Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, (SIMATS), Thandalam, Chennai, India*
Email: geetha.saju@gmail.com
[2]*Assistant Professor (SG), Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, India*
Email: drsajurajt@veltech.edu.in
[3]*Professor & Head, M.Tech CSE,*
School of Computer Science & Engineering,
Vellore Institute of Technology, Chennai
Email: malathi.g@vit.ac.in
ORCID: 0000-0002-0303-7402
[4]*Assistant Professor, CSE Department,*
Velammal Engineering College,
Email: akhilnair@velammal.edu.in
[5]*Associate Professor, Department of Information Technology, Panimalar Engineering College.*
Email: umaokj@gmail.com
ORCID: 0000-0002-5161-1149

application of CS has the potential to revolutionize the efficiency of imaging systems.

Deep Neural Networks have become a cornerstone in modern machine learning and artificial intelligence [5]. Their ability to learn intricate patterns and representations from data has propelled them to the forefront of numerous applications. In the context of image processing, neural networks excel at tasks such as image classification, segmentation, and generation [6]. The integration of DNNs with CS introduces a new dimension to signal recovery, where the network learns the complex mapping between compressed measurements and the corresponding high-resolution images. The proposed CS-DNN approach represents a fusion of two powerful techniques: Compressive Sensing and Deep Neural Networks. In this paradigm, a Deep Neural Network is trained to understand the intricate relationships between compressed measurements and high-resolution images. The learning process involves capturing the inherent structures and patterns within images, enabling the network to reconstruct the original content even from highly undersampled measurements.

By combining the strengths of CS and DNNs, the CS-DNN approach aims to overcome the challenges associated with sparse signal recovery. The integration of neural networks introduces a level of adaptability and generalization that traditional CS methods may lack. This approach holds promise for applications where efficient and robust image reconstruction is crucial, such as in medical imaging or scenarios with limited data acquisition capabilities. The paper conducts a thorough analysis of the proposed CS-DNN approach through comprehensive experiments. The new methodology's performance is closely assessed and contrasted against existing methods in the field. Key metrics, such as image quality and computational efficiency, are considered to assess the overall effectiveness and versatility of the CS-DNN approach.

This research significantly contributes to the advancement of image reconstruction methodologies. By seamlessly integrating the power of Deep Neural Networks into the Compressive Sensing paradigm, the CS-DNN approach opens new avenues for efficient and robust sparse signal recovery. The ability to reconstruct high-quality images from limited measurements has far-reaching implications, impacting fields ranging from medical imaging, where minimizing radiation exposure is critical, to surveillance and communication systems operating under resource constraints. The results of the experiments showcase the potential of the CS-DNN approach to outperform traditional CS methods. The enhanced image quality and computational efficiency observed in the reconstructions demonstrate the efficacy of leveraging deep learning within the Compressive Sensing framework. This not only substantiates the theoretical foundations of the CS-DNN approach but also positions it as a viable and superior alternative for sparse signal recovery.

2. Literature Review

[7] Suggests using network training to train a sample matrix rather than a manually created one. They call their "deep learning-based reconstruction process" seamless integration with this tactic. The original reconstructed image, which was produced by a combination layer with reshaping and concatenation operations, and a convolutional layer, is enhanced by the deep reconstruction sub-network. Reconstructing non-linear signals is made possible by this advancement. The authors draw a link between their deep learning architecture and “compressed sampling reconstruction and the traditional block compressed sensing smooth projected Landweber algorithm”.

In [8], a pioneering method for deep learning, compressed sensing MR image reconstruction is presented. Clinicians' dependence on patient-based datasets is greatly decreased by this novel method, which does away with the requirement for pre-training or a specific training dataset. The technique, which is based on the Deep Image Prior (DIP) framework, uses a high-resolution reference magnetic resonance image as the convolutional neural network's input with the goal of introducing a structural prior during the learning phase. The efficiency and effectiveness of network learning are improved by this reference-driven approach.

[9] presented the multi-scale dilated convolutional neural network, a cutting-edge framework for measurement and reconstruction in compressed sensing (CS). The measurement phase uses completely convolutional structures that are simultaneously trained with the reconstruction network using the input image, enabling them to immediately obtain all measurements using a trained measurement network. As a result, the block effect is successfully avoided and block segmentation is not necessary. The Multi-Scale Feature Extraction (MFE) architecture, which they propose for the reconstruction phase, is intended to emulate the capacity of the human visual system to extract multi-scale characteristics from a single feature map. This improves the framework's ability to extract picture features, which in turn raises the quality of image reconstruction as a whole. According to their findings, the suggested method outperforms the most advanced techniques in terms of SSIM and PSNR.

Imaging systems face challenges related to lengthy data processing and prolonged image capture periods [10] presents ATResCS, an adaptive compressed sensing reconstruction approach based on residual learning for terahertz spectral pictures, in order to address these problems. The number of data samples is efficiently compressed by this approach, which lowers the amount of imaging data required and increases imaging speed overall.

The validation process employs terahertz spectral image data from a THz-TDS system to verify the efficacy of the algorithm. Peak signal-to-noise ratio (PSNR) and structural similarity are two areas where ATResCS outperforms traditional methods, leading to significant reconstruction time savings and real-time reconstruction capabilities.

[11] Observes the discrepancy in priorities between human observers, who emphasize the image's visual quality and machine users, who are more interested in hidden measures like identification accuracy than in an image's subjective beauty. Drawing inspiration from this insight, they introduce a machine recognition-centric approach to image compressed sensing (CS) using a technique known as adversarial learning. To include recognition accuracy as an extra optimization goal in the CS reconstruction network, several adversarial models are investigated. By means of end-to-end training, the CS reconstruction network learns an image recognition pattern on its own, producing recovered images that have extra recognition metrics, making them more machine-user-friendly.

[12] Examines -wavelet compressed sensing (CS) reconstruction by leveraging modern tools. Incorporating concepts Combining classical insights from wavelet representations and CS theory with algorithm unrolling and sophisticated optimization techniques, which are frequently used by deep learning algorithms on large datasets, the study shows that -wavelet CS can be precisely adjusted to nearly match the performance level of deep learning reconstruction for accelerated MRI. Compared to approximately 500,000 parameters in deep learning, the optimized -wavelet CS approach uses just 128. employs convex reconstruction during inference, and achieves results within less than 1% deviation from a deep learning approach extensively used in various studies, based on quantitative quality metrics.

In paper [13], an innovative deep-learning approach is developed for image reconstruction using a collection of MRI scans. The process involves both MRI acquisition and subsampling to decrease the image size for enhanced analysis. A convolution layer is employed to replicate the compressed sampling process, allowing the model to learn the sampling matrix without the need for intricate designs. Furthermore, another convolution layer is employed to perform the initial reconstruction. With low MSE and maximal PSNR, the proposed FSO-based CSNet performed better than alternative approaches.

3. Methodology

Every row in the sampling matrix $\notin$ can be thought of as a filter in the context of compressed sensing. In the case of a m x n sampling matrix, a convolutional layer can be used to simulate the sampling procedure. In practical terms, if presented with an image I measuring w x h, the compressive measurements, denoted as Y, can be generated by executing a convolutional operation over the image.

Every row in the sampling matrix $\emptyset$ can be thought of as a filter in compressed sensing. One can use a convolutional layer to simulate the sampling process for a given sampling matrix of dimensions m X n. Put another way, if we have an image I of size wxh, we can use a convolution technique to acquire the compressive measurements, Y.

$$Y = A_k(I) \tag{1}$$

Where, A(.) denotes the convolution process with kernel of size k x k where the aspect of the dimensions for each block is

$$n_k = \frac{m}{n} N_K \tag{2}$$

Therefore, the block size to be compressively sensed is determined by the size of the kernel and the stride, ensuring non-overlapping blocks. In this context, the compression ratio can be formulated as:

$$\frac{n_k}{N_K} \tag{3}$$

In precise, n can be written as $n = \emptyset_c$ with c sparse. Following constraints are imposed for generating a sparse sampling matrix.

3.1 Sparsity Restraints

Each row in the sampling matrix $\emptyset$ corresponds to a single channel and is an unrolled iteration of the weight matrix. The weights connected to different channels are stacked horizontally, forming a sampling matrix with dimensions $n_k \times N_K$. Here, N_K signifies the overall count of elements in a block measuring K × K, while n_k represents the total number of measurements or output channels. The degree of sparsity is determined by the ratio of the total number of non-zero elements in this matrix to the total number of elements within the matrix. The sparsity constraint is defined as follows in order to obtain the appropriate sample matrix with a predefined sparsity degree (μ):

$$S(\mu_{k,i}) = 0 \tag{4}$$

3.2 Normalization Constraint

To regulate the measurement range within to get a unit norm, all of the weights connected to the kth kernel in the sensing matrix are normalized. To do this, the convolutional layer's parameters in the sample network must be normalized channel-by-channel. ensuring that the total norm for each channel equals 1. Mathematically, this process can be formulated as:

$$N(S_{k,j}) = \frac{S_{k,j}}{1 \Big/ \sum_{i=1}^{n_k} S^2{}_{k,i}} \qquad j = 1,2, \dots, N_K \tag{5}$$

3.3 Image Recognition Sub-network

In order to obtain discriminative non-linear features from compressed measurements for image identification, an image recognition sub-network is utilised. The compressed measurements are first rearranged into spatial order using a convolutional layer in the image-recognition sub-network (K × K × nk). This restructuring enables the subsequent feeding of measurements into any standard deep neural network designed for typical images. The objective is to assess the classifier's performance across various deep learning outlines under diverse compression situations. As stated in the equation below, sparse categorical cross-entropy is the loss function used to train each network.

$$F_{Loss} = -\frac{\sum_{c\epsilon C} logt(s\epsilon c)}{N} \quad (6)$$

Figure 1 shows the proposed network architecture.

Data Preprocessing:

It aims to furnish a comprehensive explanation of the preprocessing steps applied to the data, preparing and transforming them into the input for the auto-encoder.

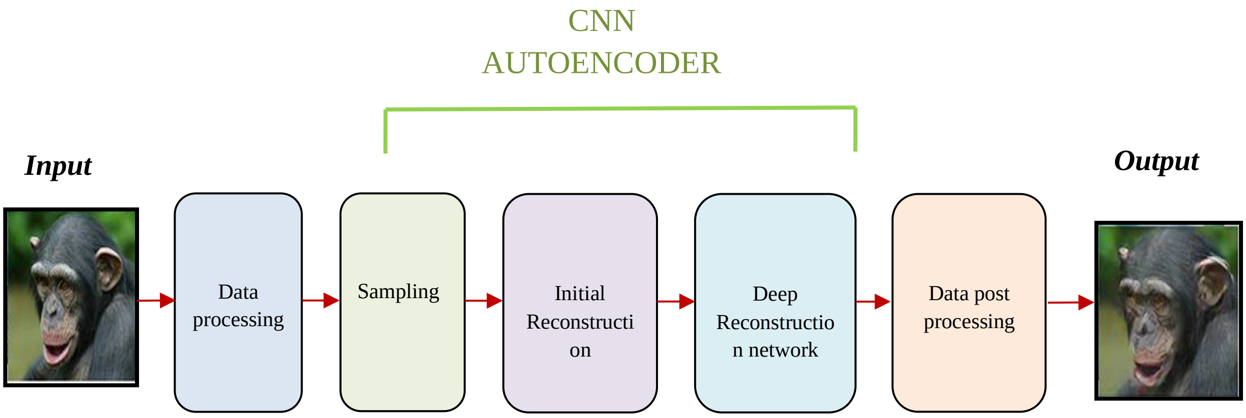

Fig. 1. Proposed Network Structure

CNN Autoencoder:

Deep Reconstruction Network:

This section will expound on the three primary layers: Sampling, Initial Reconstruction, and Deep Reconstruction Network, as illustrated in Figure 1. The network is designed with hierarchical layers, facilitating input reconstruction for various Compressed Sensing (CS) Ratios. Each layer capitalizes on the initial reconstruction from the preceding layer to augment performance.

Sampling: Initiating with the Sampling block, it resembles a Keras layer, specifically utilizing a conventional convolutional layer to replicate the sampling function. The strides parameter is set equal to the filter's size, and the kernel_size and kernel_initializer parameters are adjusted to 32 to maintain dimensionality.

Initial Reconstruction: The initial phase involves obtaining a CS reconstruction, processed through the Deep Reconstruction Network (DRN). Comprising three layers—two convolutional and one combination layer—this network transforms the sub-sampled image into n feature maps, followed by conversion into higher-level abstraction feature maps. Each layer enhances performance by leveraging the initial reconstruction from the prior layer.

The pivotal component of this work is the Deep Reconstruction Network, despite its seemingly straightforward structure. The DRN comprises a sequence of cascading Convolutional layers and is employed to execute six operations: "feature extraction, shrinking, non-linear mapping, expanding, feature aggregation, and skip connection".

Data Post processing:

This section will discuss the post-processing that is done on the data after the network. This procedure closely resembles the concatenation of patches within a CNN to construct the complete image. In reality, the image discussed in earlier sections is not the entire image but rather a patch. The input to the CNN consists of a batch of such patches, each processed individually before being reassembled. Consequently, in an almost recursive manner, the patches must be concatenated at the conclusion of the CNN to obtain the reconstructed image.

4. Results and Discussion

Compressive Sensing (CS) is a technique designed to efficiently obtain compressed output universally, minimizing time, memory, and computational resource utilization, and facilitating simplified data transmission. In this study, experiments were conducted across various Compressive Sensing ratios (CS ratios) with repeated trials for different block sizes. The employed CS ratios include 0.1, 0.2, 0.3, 0.4, and 0.5, each corresponding to a layer in the stack. The sensing matrix implemented in the initial Conv2D layer of Keras. The considered block sizes are (16, 16), (32, 32), and (48, 48), representing the entire image. These experiments explore the impact of varying

CS ratios, sensing matrices, and block sizes on the effectiveness of Compressive Sensing in image reconstruction.

After obtaining the initial reconstruction, the goal is to refine it for superior image quality. This involves the implementation of a Deep Reconstruction Network (DRN), designed in an hourglass shape following contemporary best practices. The unique hourglass configuration, featuring "bigger" first and last layers compared to the intermediate layers, enhances the network's ability to capture intricate features. This structural choice facilitates the refinement process, contributing to the achievement of high-quality image reconstruction. The DRN proves crucial in iteratively enhancing the reconstruction and ensuring optimal visual outcomes, aligning with advanced techniques in image processing.

The training period for a Convolutional Deep Neural Network is frequently time-consuming, requiring careful design to optimize efficiency. The essential Keras commands for implementing the training phase are limited, specifically: “Model”, “Model.compile”, and “Model.fit”. The initial command, "Model," is used to instantiate the Model class.

Training Phase

```
{
    Model = model (inputs=I, outputs= O)
    Model.compile (loss= ‘mean-squared_error’, optimizer= ‘my_adam_1’)
    Model.fit (train_36, epochs=20, batch_size=6, validation_data=(val_36), rearrange=true)
    Model.compile (loss= ‘mean_squared_error’, optimizer= my_adam_1)
    Model.fit (train_36, epochs=20, batch_size=10, validation_data= (val_36), rearrange=true)
    Model.compile (loss= ‘mean_squared_error’, optimizer=my_adam_1)
    Model.fit (train_36, epochs=15, batch_size=10, validation_data= (val_36), rearrange=true)
}
```

After constructing the model, it must be compiled, necessitating the definition of both the optimizer to be used and the loss function. "Mean Squared Error" is the loss function that was selected in this instance.

$$MSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n} \tag{7}$$

The selected optimizer is the Adam (Adaptive Moment Estimation) Optimizer, a Stochastic Gradient Descent variant created with the gradient's moments in mind.

To assess the performance of a Deep Learning algorithm, especially in the context of image processing, three common metrics are utilized in current research. The primary metric, accuracy, is widely employed for Neural Networks, though in this case, it corresponds to a simple MSE and is not the most crucial. The second metric, Peak Signal-to-Noise Ratio, holds significant importance for evaluating the quality of a compressed or reconstructed image concerning the ground-truth. In this specific context, this stands out as the most crucial metric. The third and final metric is the execution time, a valuable measure as time is a critical resource, especially in Deep Learning for image processing, where substantial time investments are necessary. The considered time factors encompass both the Training point time and the reconstruction time, with the latter being the more pivotal.

For single image, the peak signal to noise ratio is depicted as:

$$PSNR = 10\ log_{10}\left(\frac{MAX^2\{I\}}{\sqrt{MSE}}\right) \tag{8}$$

Where,

I - is the original image

$MAX^2\{I\}$ - Maximum value among pixels

And the MSE is the error assessed between original image (I) and the reconstructed image (R). MSE in images evaluated as:

$$MSE = \frac{1}{M.N}\sum_{p=0}^{M-1}\sum_{q=0}^{N-1}\left|\left|I(p,q) - R(p,q)\right|\right|^2 \tag{9}$$

As a fractional number, it is evident that if the reconstruction is flawless, meaning the Mean Squared Error (MSE) is zero, the Peak Signal-to-Noise Ratio (PSNR) attains an infinite value.

PSNR=14dB PSNR=16dB PSNR=28dB PSNR=50dB

Fig. 2. Reconstructed Images with Various PSNR Values

In Figure 2, the reconstructed image is presented with diverse Peak Signal-to-Noise Ratio (PSNR) rates, demonstrating a clear relationship between increasing PSNR rates and enhanced image quality. The visual representation underscores the importance of higher PSNR values in achieving superior reconstruction quality, highlighting the significance of PSNR as a metric for assessing the fidelity and precision of the reconstructed image.

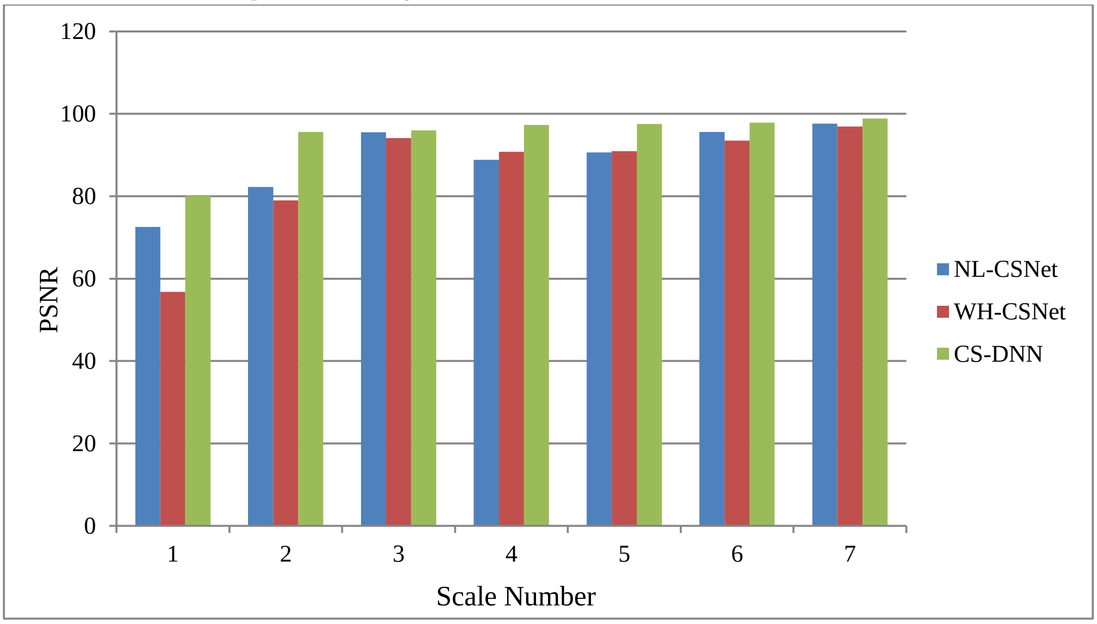

Fig. 3. Performance Comparison (Sampling rate=0.1)

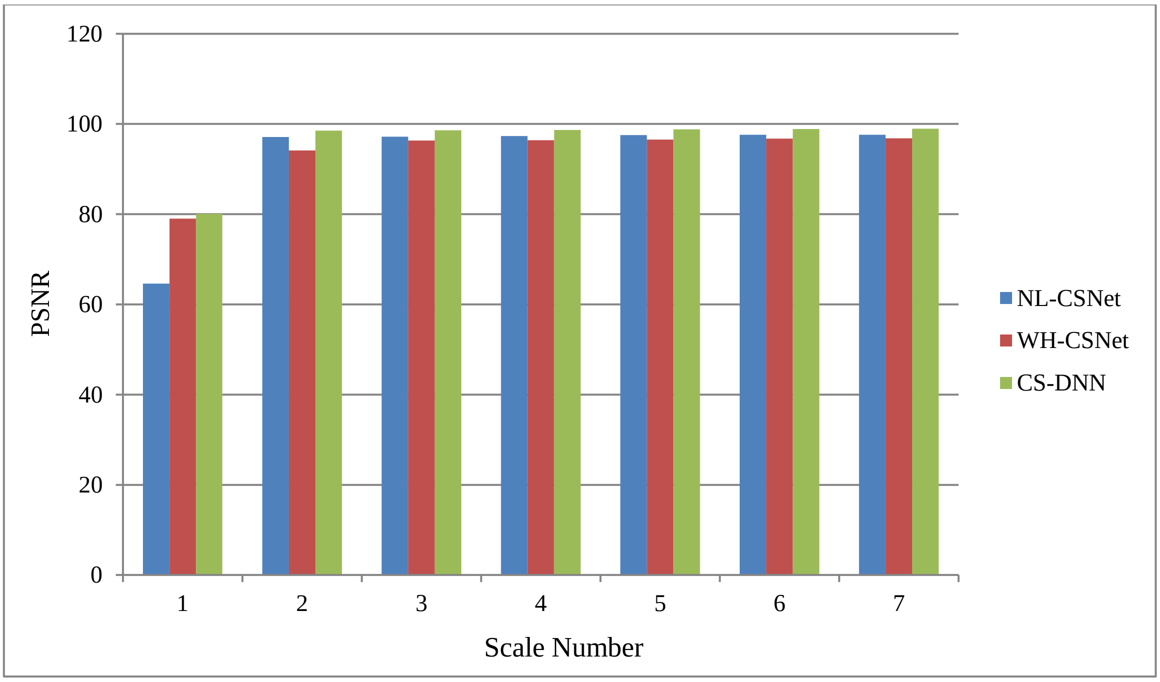

Fig. 4. Performance Comparison (Sampling rate=0.5)

The suggested model's efficacy is evaluated by comparing it to well-established methods with a particular emphasis on Peak Signal-to-Noise Ratio (PSNR). The performance comparison at a sample rate of 0.1 is shown in Figure 3, and the performance at a sampling rate of 0.5 is shown in Figure 4. The outcomes show that the suggested CS-DNN strategy outperforms the compared methods in both scenarios. While some approaches exhibit accuracy levels similar to the proposed technique, none outperform it. This underscores the superiority of the CS-DNN method in achieving higher fidelity and accuracy in image reconstruction, particularly at lower sampling rates, substantiating its effectiveness as a robust approach in comparison to established methods.

5. Conclusion

In the current scenario, the foremost challenges in image processing and, particularly, transmission pertain to resource constraints, notably in terms of memory and time. This has prompted an increased focus on the exploration and utilization of Deep Learning and Compressed Sensing within the realm of image processing. Currently, the significant challenges in image processing and transmission revolve around resource limitations such as memory and time constraints. Deep Learning (DL) and Compressed Sensing have become increasingly vital in addressing these challenges within the image processing domain. This paper delves into DL-based methods applied to compressed sensed images, aiming to achieve efficient reconstruction in a short timeframe. The primary emphasis is on the sensing process using a stable sensing matrix. Two distinct approaches were explored, involving experiments with both block-based and full-image-based methodologies. Reconstructed images are provided with step by step process. Results indicate that a block-based approach exhibits significantly better performance than the trained sensing matrices. The performance comparison shows that the implemented algorithm showed better performances than the compared algorithms.

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