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ANALYSIS OF OPTIMIZATION FUNCTIONS FOR CHEST CT IMAGE SUPER RESOLUTION USING DEEP LEARNING

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Abstract: Deep learning leverages optimization functions to minimize the loss function while training a neural network. Several optimization functions are prevalent in deep learning for this purpose, such as SGD, Adagrad, RMSProp, Adam, Adamax, ASGD (Average Stochastic Gradient Descent). Selection of best optimization functions helps to avoid under-fitting or over-fitting situations and helps to converge training faster. All the optimization functions were trained and tested on SRCNN model. This paper addresses the problem of selecting the best optimization function as one of the hyper parameters to train the SRCNN model for TCIA NSCLC chest CT images to enhance the quality of LR chest CT images into Super Resolved images. The experimental results show that Adam is the best optimization function with better PSNR values.

Index Terms- Deep Learning, Optimization functions, PSNR, SRCNN, TCIA.

1. INTRODUCTION

Single Image Super Resolution (SISR) is the process of translating Low Resolution image into High Resolution image [1]. Super Resolution process is widely applicable in many domains such as Satellite Imagery [2], Medical domain [3], Object detection [4], Astrology [5], Crime detection [6] and more. This paper aims to super resolving chest CT medical images to upscale and improve the details using deep learning models. There are certain limitations in CT scanning process. First, the patient is given a dose of radiation, so that the lungs can clearly visible. The higher the radiation dose, the clearer the image is. But it increases the risk of cancer in a patient. Second, the high number of sensors used in CT machine, the more high-resolution image is generated. But such machines are costly. To avoid the mentioned limitations, usage of the deep learning models by training low-resolution images and generate high-resolution images as a post processing step can be a better choice.

Hyper parameters play a major role in converging the training process faster and performance improvement. The appropriate selection of different hyper parameters, such as loss function, filter size, batch size, optimization function, activation function, number of epochs can improve the performance significantly. The various existing optimization functions such as Stochastic Gradient Descent (SGD), Adaptive Gradient (AdaGrad), Root Mean Square Propagation (RMSProp), Adaptive momentum (Adam), Adamax, ASGD (Average Stochastic Gradient Descent) as optimization function hyper parameter are trained for 200 epochs on SRCNN deep model. The experimental results depict that Adam optimizer converges training faster with stable Peak-Signal-to-Noise-Ration (PSNR) [7] compared to other optimization functions.

2. RELATED WORK

For the task of Super-Resolution (SR), various methods have been employed over time. Initially, traditional image processing interpolation techniques like bilinear [8], bicubic [9], and nearest neighbour [10] were utilized. These methods employ basic mathematical formulas to estimate missing pixels when upscaling an image. While computationally straightforward and using only a single Low-Resolution (LR) image, they exhibit drawbacks such as blurring, pixel repetition, and jagged edges, resulting in subpar quality in the reconstructed SR image.

Subsequently, reconstruction-based techniques were introduced. These methods employ different image priors, including gradient priors, soft-cuts, and gradient profile priors [11], [12], to reconstruct the SR image. However, they demand significant computational resources and may yield lower quality SR images when dealing with high upscaling factors.

Following this, learning-based methods, also known as example-based methods, emerged. These approaches leverage multiple High-Resolution (HR) images as examples to learn features and reconstruct the HR image through LR-HR mappings. Yet, they often come with high computational costs, making them less practical for real-world applications.

Sparse coding techniques [13], fuzzy-based methods [14], and soft computing methods were subsequently proposed for SR. These methods necessitate background knowledge, exhibit non-linear time complexities, and may be susceptible to certain artifacts.

Later, diverse machine learning approaches were applied to the SR process, such as Nearest Neighbour Embedding, Markov Random Field, and Random Forest, leading to the generation of high-quality SR images. Nonetheless, they require manual pre-processing of the input dataset, thereby increasing time complexity.

In recent times, advances in hardware resources, such as GPUs and other programming frameworks, have alleviated computational time constraints. Deep learning neural networks have revolutionized the SR process, offering reduced computational time and enhanced performance compared to existing methods.

Furthermore, a plethora of deep learning-based neural network models have been introduced in the literature. These encompass linear models, residual network models, recursive network models, generative adversarial network models, attention-based deep models, autoencoders, and more.

The initial linear deep neural network model, SRCNN [15], resembled sparse coding techniques but employed a convolutional neural network for the SR process. It set a benchmark for deep neural networks, surpassing earlier methods in performance. Other linear models like FSRCNN [16] and ESPCNN [17] followed, achieving even greater performance gains.

Residual networks like VDSR [18] and EDSR [19] were subsequently proposed, leading to improved performance through the use of residual connections. Generative adversarial networks like SRGAN [20], incorporating two networks (Generator and Discriminator), significantly enhanced the perceptual quality of SR images. Attention-based networks [21] further advanced the objective quality of reconstructed SR images, employing mechanisms like channel attention [22], spatial attention [23], and pixel attention [24][25]. Notably, pixel attention mechanisms, when combined with residual networks, have recently garnered attention in the SR research community, enabling the creation of lightweight network models with improved performance. Ongoing research aims to develop even more sophisticated deep models to further enhance performance in SR.

In all the deep learning models in literature, optimization function as one of the important hyper parameters, plays an important role to minimize the loss function and converge training the model faster, which can also help in avoiding gradient vanishing problem and even overfitting and underfitting issues.

3. METHOD AND APPROACHES

As the primary motivation for this study, explored the impact of optimizers on the process of updating the weights in a Convolutional Neural Network (CNN). It is our hypothesis that various optimizers will yield distinct sets of weights, thus helping to mitigate issues related to underfitting and overfitting. Essentially, different optimizers guide the training process in unique ways. For instance, the gradient descent method can be thought of as navigating a local minimum by moving along the steepest descent path, as depicted in Figure 1.

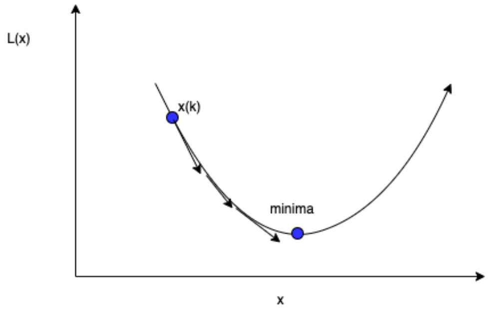

Figure 1: Stochastic Gradient Descent optimizer

Nevertheless, the efficacy of minimizing a function using the steepest descent approach is contingent on various external factors, such as the choice of loss function and learning rate. These factors significantly influence the overall cost of training and directly impact the performance of Super-Resolution (SR).

Given these considerations, it is essential to determine which optimizer strikes the right balance between performance and computational efficiency. In this study, the benchmarking deep model, SRCNN is trained with different optimization functions such as SGD, AdaGrad, RMSProp, ASGD, Adam, Adamax with other hyper parameters using TCIA dataset. SGD (Stochastic Gradient Descent) is a basic optimization method, updates parameters with fixed learning rate per sample. AdaGrad (Adaptive Gradient) adjusts learning rates for each parameter based on historical gradients, useful for sparse data. RMSProp (Root Mean Square Propagation) is an extension of AdaGrad with adaptive learning rates, preventing aggressive decay. Adam (Adaptive Moment Estimation) combines momentum and RMSProp, widely used due to efficiency and robustness. Adamax is a variant of Adam using max norm, designed for stability and efficiency in certain scenarios. ASGD (Averaged Stochastic Gradient Descent) computes average parameter values over time for better convergence. The SRCNN model architecture is shown in Figure 2.

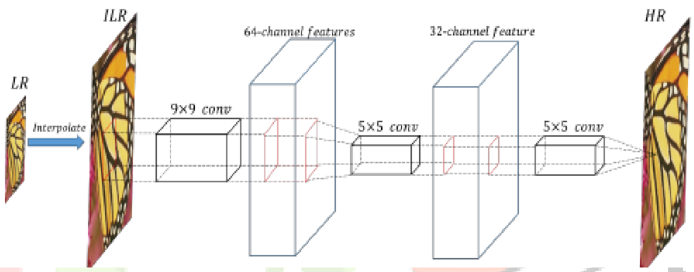

Figure 2: SRCNN Model

The model is trained with 100 chest CT images from TCIA dataset, considering 80 images for training and 20 images for validation. Input image size is 512x512 and the patch size extracted is 32x32, generating a total of 62720 patches. The model is trained for 200 epochs. The loss function is Mean Square Error (MSE). The batch size 16.and initial learning rate 0.0001 filter size 9x9, 3x3, 5x5 Using a basic CNN architecture, each optimizer generated distinct weight sets for super-resolution. The performance metric PSNR is evaluated for each of the optimization function.

4. EXPERIMENTAL RESULTS

4.1 Dataset

The SRCNN model underwent training and testing using the dataset of Chest CT Scan Images. The dataset originates from TCIA Non-Small Cell Lung Cancer (NSCLC) Chest CT Scan Images [26], encompassing clinical findings from 56 patients with CT images, each sized at 512 × 512 pixels. These CT scans consist of multiple slices. This dataset serves as a valuable resource for research in lung cancer screening and diagnosis. The TCIA NLCSC dataset is sourced from the National Lung Cancer Screening Trial (NLST) and is meticulously annotated and indexed to facilitate advanced studies in lung cancer screening. It offers a diverse range of imaging modalities, including CT scans, chest x-rays, and PET scans. The dataset is partitioned in an 80:20 ratio, with 100 images allocated for training and validation, while 10 images are reserved for testing. The model is trained and tested for 2x scale factor and evaluated PSNR value.

4.2 Results

Table 1 presents the experimental results of different optimization functions. It is observed that Adam resulted high PSNR with faster convergence and minimized loss. The time also noted, and observed that time has no significant role.

Table 1: Results of different optimization functions

Optimization function	PSNR (dB)	Time (Seconds)
SGD	10.60	70.218
Adagrad	21.42	69.57
RMSProp	36.36	70.73
Adam	**36.45**	**73.43**
Adamax	34.07	72.02
ASGD	10.60	73.39

Figure 3 shows the plots of SGD for Loss Vs Epochs and PSNR Vs Epochs. It is observed that SGD leads to underfitting and training converged slowly and it requires a greater number of epochs to converge and the PSNR value is also not increased much.

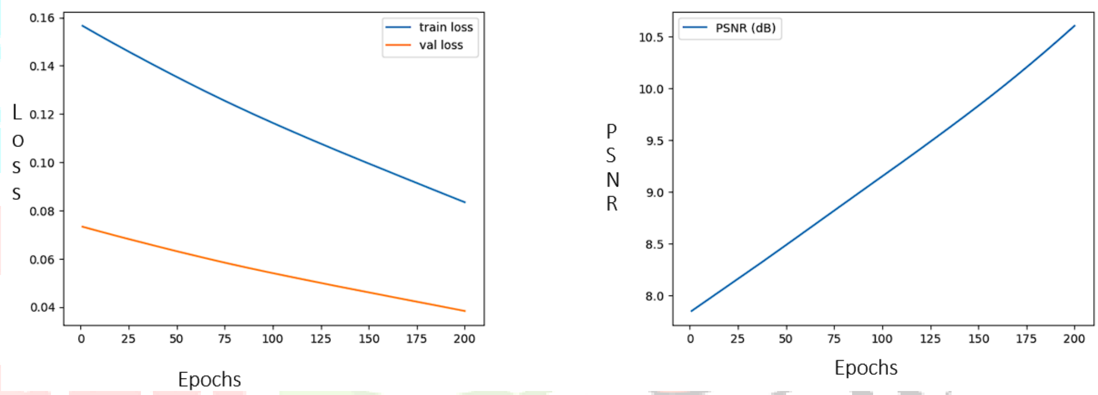

Figure 3: SGD Loss and PSNR plots

Figure 4 depicts AdaGrad optimization function plots. The plots show that the training converged faster than SGD and PSNR also increasing for the epochs, but shows slow stabilization. The Loss plot leads to good fit. Figure 5 shows RMSProp optimizer plots. It is observed that Loss is minimized faster and increased PSNR value for the number of epochs. Here, the PSNR is fluctuating, though it has increased value.

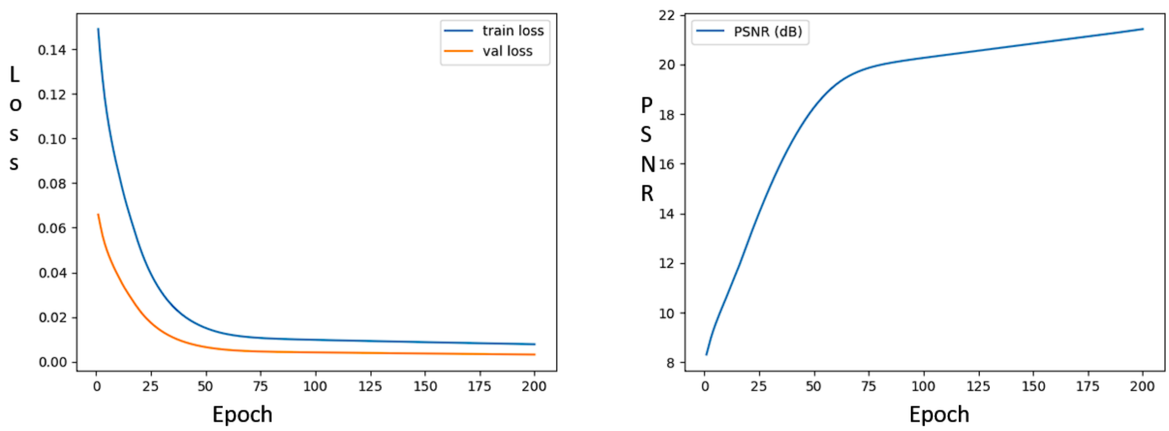

Figure 4: AdaGrad Loss and PSNR Graphs

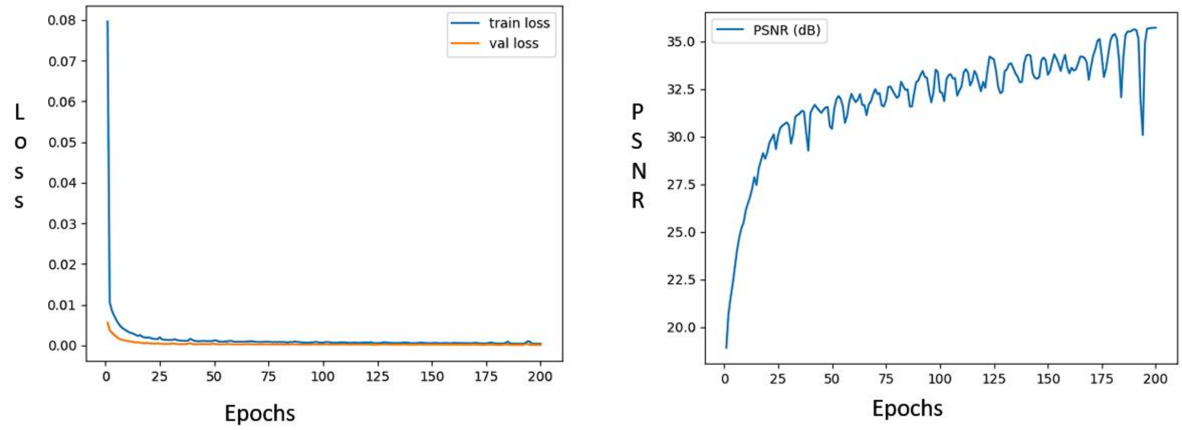

Figure 5: RMSProp Loss and PSNR plots

From Figure 6, the observation is that a good fit and stable PSNR value with a smaller number of epochs. So, it leads to minimized loss and stable increased PSNR value. It is observed that, Adam leads to faster convergence than other optimization functions.

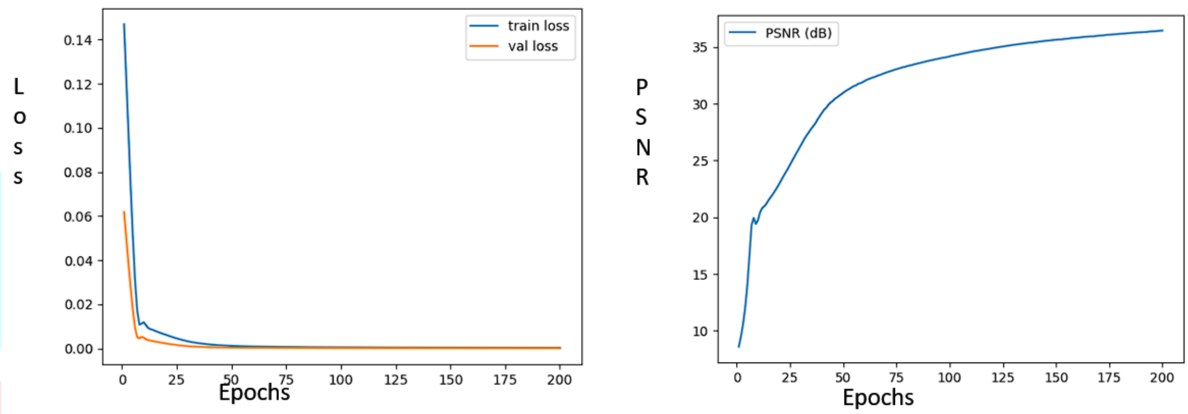

Figure 6: Adam Loss and PSNR plots

Figure 7 shows that the training converged by minimizing loss and slow increase in PSNR for the Adamax optimization function

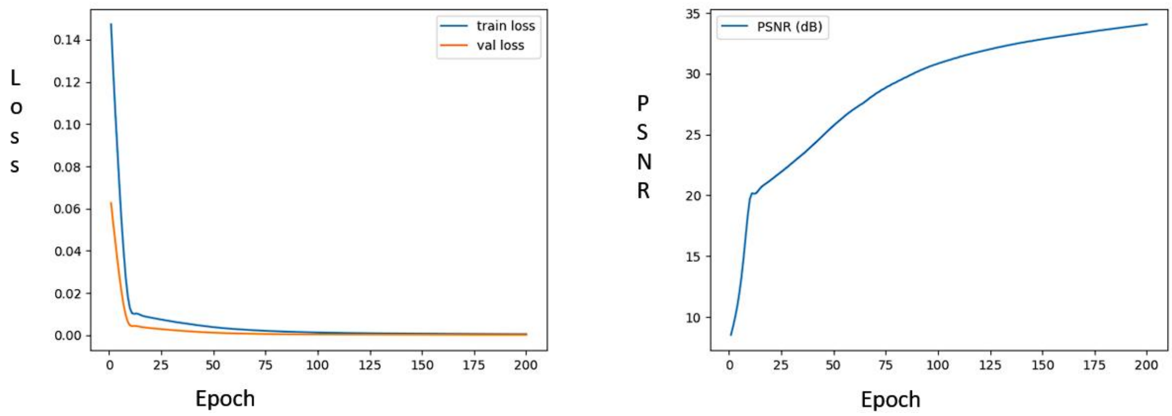

Figure 7: Adamax Loss and PSNR plots

Figure 8 shows the plots for Average SGD (ASGD) for Loss and PSNR values. It is observed that the plot for Loss leads to underfitting and requires a greater number of epochs to converge training and low PSNR values.

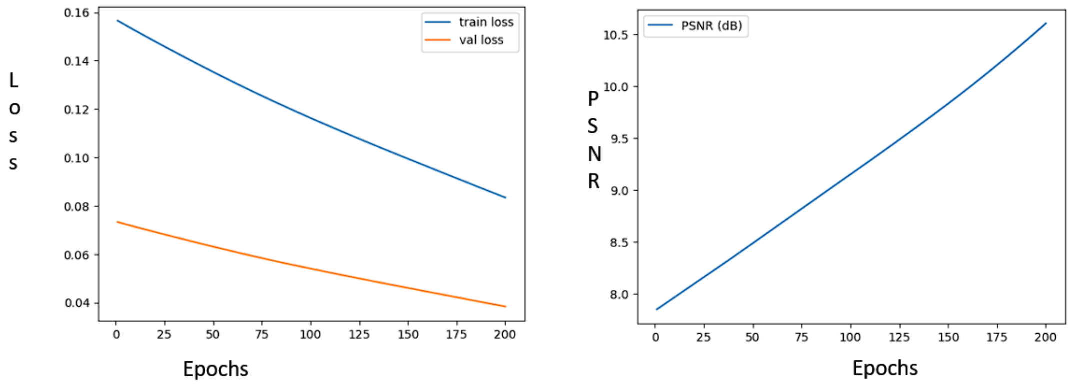

Figure 8: ASGD Loss and PSNR plots

Table 2 shows the comparative results compared to the existing work. The authors [27], trained and tested with SRCNN model with T91 dataset and this work also trained with SRCNN model on TCIA chest CT Dataset. This shows the improved results.

Table 2: Comparative Results with existing work

Optimization Function	**Anagun et al [27] Dataset-T91 for Training** **Model-SRCNN**	**Our Results Dataset- 80 CT images from TCIA** **Model- SRCNN**
SGD	28.95dB	10.60dB
Adagrad	29.50dB	21.42dB
RMSProp	31.51dB	36.36dB
Adam	31.92dB	36.45dB
Adamax	31.77dB	34.07dB

5. CONCLUSION

Super resolution is important in many real time applications. In recent times, Deep learning models achieved promising performance compared to traditional image processing methods. In training the deep models, it is always important to tune the hyper parameters correctly to avoid the issues like overfitting/underfitting. One of the important hyper parameters is selection of appropriate optimization function to minimize loss and converge the training process faster. This study aims this and experimental results show that Adam optimizer is leading to faster convergence and increased PSNR compared to other optimizers.

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