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AFF-UNet-RWKV: A Lightweight Model for High-Quality Deblurring in Medical Imaging

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Abstract. Medical image deblurring is essential for enhancing image quality and improving diagnostic accuracy. This paper introduces a lightweight deep learning model, AFF-UNet-RWKV, which combines AFF-UNet and the RWKV-lite spatial mixer for medical image deblurring tasks. By incorporating Attention Feature Fusion (AFF) and the RWKV-lite module, this model effectively integrates features from both the encoder and decoder while capturing long-range spatial dependencies, thereby enhancing the restoration of image details and structures during the deblurring process. Additionally, the model adapts its feature fusion strategy to maintain high recovery performance across various types of blur. To validate its effectiveness, this study conducted experiments using the PathMNIST subset from the MedMNIST dataset, generating blurred image pairs through Gaussian blur and linear motion blur for training. The results demonstrate that the AFF-UNet-RWKV model significantly outperforms traditional deblurring methods and other deep learning models in terms of image recovery quality. Notably, the approach shows substantial advantages over traditional algorithms and DeblurGAN, particularly in the Structural Similarity Index (SSIM). Ultimately, the model achieved a PSNR (Peak Signal-to-Noise Ratio) of 32.03 dB and an SSIM(Structural Similarity Index) of 0.898 on the test set, confirming its superiority and potential in medical image deblurring tasks. This research offers an efficient and lightweight solution for medical image deblurring, providing strong practical application value and new insights for future research and applications in related fields.

Keywords: Medical image deblurring, Deep learning, AFF-UNet, RWKV-lite, SSIM.

1. Introduction

Medical imaging[1] plays a vital role in disease diagnosis, treatment planning, and postoperative evaluation. However, factors such as limitations in imaging equipment, patient movement, and environmental interference often result in blurred images, which can degrade image quality and compromise diagnostic accuracy. As a result, image deblurring technology[2] has emerged as a critical area of research in medical image processing, aiming to restore clear details and enhance diagnostic effectiveness.

Traditional deblurring methods, such as Wiener filtering[3] and blind deblurring[4], perform well under simple blur conditions but tend to falter in more complex scenarios. Furthermore, these methods often lack adaptability, making it difficult to handle diverse types of blur, particularly when dealing with large-scale data and high-dimensional information, where both computational efficiency and restoration quality may be significantly limited. With the advent of deep learning technologies, deblurring methods based on convolutional neural networks (CNNs) have gained prominence. U-Net[5], a classic image segmentation architecture, has achieved remarkable success in medical image processing and has demonstrated outstanding performance in image deblurring tasks.

Despite the effectiveness of the traditional U-Net structure in image restoration, it still faces challenges related to insufficient information fusion when processing blurred images. This issue is particularly pronounced when complex blur patterns are present, potentially impacting the model's performance. To address this challenge, this paper proposes an improved model based on U-Net, referred to as the AFF-UNet-RWKV model. This model combines Attention Feature Fusion (AFF)[6] and the RWKV-lite spatial mixer[7] to enhance image recovery quality. The AFF module effectively fuses features from both the encoder and decoder, improving the efficiency of feature information transfer. Meanwhile, the RWKV-lite module enhances the model's ability to capture long-range

spatial dependencies through non-causal convolution operations, further improving deblurring performance.

This study conducts experiments using the PathMNIST[9] subset from the open-source MedMNIST[8] dataset, simulating blur phenomena in medical images through Gaussian blur and linear motion blur. The experimental results indicate that the proposed AFF-UNet-RWKV model excels in deblurring tasks, outperforming traditional methods and other deep learning models by more effectively restoring image details and structural information, while achieving significant improvements in evaluation metrics such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index). This paper contributes a novel lightweight deep learning model capable of efficiently performing medical image deblurring, while remaining easy to train and deploy.

2. Related Work

2.1 Traditional Image Deblurring Methods

Traditional image deblurring methods have long relied on signal processing techniques, which generally assume that the type and extent of blur are known or can be modeled using specific prior knowledge. One of the classic approaches in this field is Wiener filtering, which presumes that both noise and the blur kernel are known, aiming to restore the image based on the minimum mean square error (MSE) criterion[10]. Wiener filtering performs well under conditions of low image noise and clearly defined blur types. But its effectiveness diminishes significantly when the blur type is unknown or when noise levels are high. To overcome the limitations of traditional methods, blind deconvolution techniques have been introduced[11]. Unlike conventional methods, blind deconvolution does not rely on a known blur kernel. Instead, it concurrently estimates both the image and the blur kernel through optimization strategies. However, conventional blind deconvolution methods can be computationally intensive and often struggle with efficiency and accuracy when addressing complex blur patterns, especially in cases of nonlinear blur and high noise. Additionally, these methods typically lack adaptability, making it challenging to handle various types of blur and their combinations, and they often fall short in meeting the computational efficiency required for large-scale data processing.

2.2 Deep Learning-Based Deblurring Methods

In recent years, the application of deep learning, particularly convolutional neural networks (CNNs), has significantly propelled the development of image deblurring techniques[12]. Deep learning methods can automatically learn blur patterns from large datasets, eliminating the reliance on handcrafted features typical of traditional approaches, and greatly enhancing the accuracy and generalization capabilities of image restoration. U-Net, a well-established deep learning architecture, has achieved remarkable success in medical image processing due to its symmetrical encoder-decoder structure. By downsampling to extract low-level features and employing skip connections to merge high-level features with low-level ones, U-Net effectively restores details while preserving spatial information in images. Additionally, Generative Adversarial Networks (GANs) have been widely utilized in deblurring tasks, with DeblurGAN serving as a notable example of a GAN-based image deblurring method[13]. GANs improve the realism of image recovery through a generative adversarial mechanism, resulting in more natural deblurring effects. Despite the significant advancements in performance brought about by deep learning methods, they typically require substantial amounts of labeled data for training, which presents considerable challenges in data collection and annotation. Furthermore, deep networks often contain a large number of parameters, leading to significant computational demands. This is particularly pronounced when processing high-resolution images, where finding a balance between model efficiency and accuracy remains a critical challenge.

2.3 Emerging Adaptive Networks and Attention Mechanisms

With the advancements in deep learning technologies, an increasing number of studies are focusing on the application of adaptive networks and attention mechanisms in image deblurring[14]. Adaptive networks can dynamically adjust their structure and parameters based on the features of different images, allowing for greater flexibility in addressing a variety of blur types[15]. For example, adaptive deblurring methods based on convolutional neural networks, such as those that adjust the size of convolutional kernels, can automatically optimize the deblurring process according to the degree of blur present in the image, resulting in more precise restoration. Additionally, attention mechanisms, particularly spatial and channel attention, have been shown to significantly enhance a model's ability to focus on crucial information. In deblurring tasks, the Attention Feature Fusion (AFF) module helps the model better restore image details and maintain structural integrity by weightedly merging features from both the encoder and decoder. The RWKV (Recurrent Weighted Kernel) module enhances the modeling of long-range spatial dependencies through a gating mechanism and depthwise separable convolutions, making it particularly effective for recovering complex blur patterns. These emerging methods not only improve the accuracy of deep learning models but also enhance their adaptability to various types and variations of blur, leading to significant advancements in deblurring tasks. The successful application of these techniques indicates that further optimization of network architectures may enhance the performance of image deblurring, especially in real-world applications under complex conditions, providing more efficient and robust solutions.

3. Methods

In this section, this study introduces a deep learning-based method for deblurring medical images, implemented within the PyTorch framework. This approach employs a lightweight AFF-UNet network integrated with an RWKV-lite spatial mixer. By developing an efficient convolutional neural network model and training it on a medical image dataset, we successfully accomplish the deblurring task.

3.1 Data Preprocessing and Dataset

This paper selects the MedMNIST dataset as the foundational dataset for experiments. MedMNIST is an open-source collection that includes a variety of medical images across multiple categories, making it highly suitable for tasks such as medical image deblurring. Each image in the dataset undergoes thorough preprocessing, particularly normalization. The normalization process compresses the pixel values of each image into a range of [0, 1], ensuring consistent brightness and contrast across different images. This consistency enhances the stability and convergence speed of model training.

To better simulate the blurring conditions encountered in real-world applications, ths study generated two common types of blurred images for the training dataset, Gaussian blur and linear motion blur. Gaussian blur is a prevalent technique that simulates the blurring effects caused by optical imaging systems or sensor noise, while linear motion blur mimics the blurring that occurs due to rapid movement of cameras or objects. In the process, the study randomly selected blur parameters, such as blur radius and direction of motion, to create corresponding blurred images for each clear medical image. These blurred images serve as input data in the training dataset, while the clear images act as corresponding labels, guiding the model in learning how to recover clear images from the blurred inputs.

3.2 Model Architecture

To enhance the performance of medical image deblurring, this study designed an improved model based on the U-Net architecture, incorporating innovative techniques such as Attention Feature

Fusion (AFF) and the RWKV-lite spatial mixer. The model comprises three main components: the encoder, the decoder, and the fusion module.

3.2.1 Encoder and Decoder

The encoder consists of multiple convolutional and pooling layers, which are primarily responsible for progressively extracting low-level features from the images. Each encoding layer employs convolutional operations along with Batch Normalization to facilitate feature extraction. Batch Normalization accelerates network training and enhances model stability. The study applied the ReLU activation function after each convolutional layer, allowing the model to effectively learn nonlinear features at each stage. As the network deepens, the dimensions of the feature maps gradually decrease while the number of channels increases. Finally, a minimum pooling layer further compresses the feature maps, resulting in a compact high-dimensional feature representation.

The decoder gradually restores the spatial information of the image using transposed convolution and upsampling operations. Its design aims to reconstruct the compressed feature maps into clear images that closely resemble the original ones. In each layer of the decoder, this study introduces skip connections that directly pass high-level feature maps from the encoder to the decoder. These connections allow the corresponding decoder layers to blend these features with their own outputs. The incorporation of skip connections enables the model to better preserve detailed information, particularly in the edges and textures of the images, effectively mitigating detail loss during the reconstruction process.

3.2.2 AFF Module

In the traditional U-Net architecture, features from the encoder and decoder are typically connected through simple concatenation. While this approach has demonstrated good performance across various tasks, it can result in the loss of correlation between features across layers, particularly as image complexity increases. To address this issue, the study introduced the Attention Feature Fusion (AFF) module. The fundamental concept of the AFF module is to preserve more critical spatial information through weighted feature fusion. In each layer, the features from the encoder and decoder are combined using a self-attention mechanism, enabling the model to automatically focus on the most relevant features for the deblurring task during the fusion process. This method not only enhances the model's feature representation capabilities but also significantly improves its ability to capture detailed and structural information.

3.2.3 RWKV-lite Spatial Mixer

RWKV-lite is a lightweight spatial mixer derived from the RWKV network architecture, primarily designed to capture long-range spatial dependencies through non-causal convolution operations. This approach differs from the local receptive fields used in traditional convolutional neural networks (CNNs), allowing for better capture of long-distance dependencies across different regions of an image. In this model, RWKV-lite was utilized in the bottleneck layer and repeatedly applied at various stages of the decoder. The core advantage of this module lies in its combination of a learnable gating mechanism with depthwise separable convolutions, which effectively enhances the model's capability to model long-range information while maintaining computational efficiency. This enables the model to not only capture local details but also learn the global structural information within the image, thereby improving the deblurring effect.

3.3 Loss Function

To optimize the quality of image restoration, this study developed a composite loss function that combines L1 loss and Charbonnier loss. Each of these loss functions offers distinct advantages. L1 loss effectively measures pixel-level differences between images, while Charbonnier loss adds a smoothing term to L1 loss, enhancing the model's stability and robustness in handling detail loss and edge blurriness. Additionally, the study incorporated the Structural Similarity Index (SSIM) metric to further improve image quality. SSIM assesses structural similarity between images, capturing

differences in structure, texture, and other relevant factors, thereby aiding the model in preserving more structural information during the restoration process.

Ultimately, the study weighted and summed L1 loss, Charbonnier loss, and SSIM loss to create the final training loss function. This composite loss function effectively addresses pixel-level discrepancies, detail recovery, and global structure preservation, thus better fulfilling the requirements of the deblurring task.

3.4 Training Process

During the training process, this study utilized the AdamW optimizer, which incorporates weight decay to mitigate overfitting and enhance the model's generalization capabilities. The learning rate was set to 3e-4 and the weight decay coefficient was adjusted based on the validation set's performance throughout training. Additionally, to improve training efficiency and stability, the study employed mixed precision training, which not only accelerates the training process but also significantly reduces memory usage.

At the conclusion of each training epoch, the study evaluated the model using the validation set and calculated standard image quality metrics, such as PSNR and SSIM. These metrics provide a quantitative assessment of the image restoration effectiveness, enabling us to track the model's progress and inform optimization strategies during training. In the final phases of training, we saved the best-performing model and conducted a comprehensive evaluation on the test set to validate the model's true performance.

4. Experiments

In this experiment, the study utilized the PathMNIST subset of the MedMNIST dataset for training and evaluating the medical image deblurring task. The primary aim was to assess the performance of the proposed AFF-UNet-RWKV model in deblurring tasks and to compare it with traditional deep learning deblurring models. The specific experimental setup, training process, and performance evaluation are outlined below.

4.1 Experimental Setup

This study trained the model using the training set from the PathMNIST dataset. To ensure stability and efficiency during training, ths study selected the AdamW optimizer with an initial learning rate of 3e-4 and a weight decay of 0.0. The AdamW optimizer effectively mitigates the impact of weight decay on gradient updates, facilitating improved model optimization.

In terms of loss function selection, the study employed a combination of L1 loss and Charbonnier loss. L1 loss directly measures the difference between the restored image and the original, while Charbonnier loss is more robust, effectively addressing image noise and slight blurring, which enhances stability during training. Additionally, to further improve the model's deblurring performance and robustness, the SSIM (Structural Similarity Index) metric was introduced as an additional weighted loss during training. By incorporating the SSIM weight into the loss function, the model is better able to preserve structural information in images, thereby enhancing the visual quality of the restored outputs.

Each training batch consisted of 32 images, and the study utilized CUDA acceleration to significantly enhance computational efficiency. To mitigate the risk of overfitting, the training duration was set to 5 epochs. At the end of each epoch, the study validated the model to assess its performance on the validation set. This strategy ensures that the model does not overfit the training data, thereby improving its generalization ability on the test set.

4.2 Evaluation Metrics

To comprehensively evaluate the deblurring performance of the model, the study selected two standard image quality assessment metrics: PSNR and SSIM. These metrics are widely utilized in image restoration tasks and effectively measure the quality difference between the restored image and the original. PSNR quantifies image restoration quality and is expressed in decibels (dB). In

deblurring tasks, a higher PSNR value indicates better restoration quality, as it reflects the ratio of signal to noise in the image. Generally, a PSNR value above 30 dB is considered indicative of good image quality. SSIM evaluates image quality by considering luminance, contrast, and structural information. Its values range from 0 to 1, with values closer to 1 indicating greater structural similarity between the two images. SSIM more accurately reflects the human eye's subjective perception of image quality, making it particularly valuable in deblurring applications.

4.3 Experimental Results and Analysis

During the experiment, the study conducted evaluations on the training set, validation set, and test set. Table 1 and Figure 1 below illustrate the trends in training loss, validation set PSNR, validation set SSIM, test set PSNR, and test set SSIM across different training epochs.

Table 1. Training Results of the Model Across Different Epochs

Epoch	Training Loss	Validation PSNR (dB)	Validation SSIM	Test PSNR (dB)	Test SSIM
1	0.0265	28.63	0.8459	27.47	0.8601
2	0.0263	29.51	0.8577	28.63	0.8652
3	0.0249	30.05	0.8657	29.02	0.8692
4	0.0232	30.45	0.8715	29.57	0.8741
5	0.0216	30.80	0.8775	29.87	0.8795
6	0.0203	31.12	0.8836	30.03	0.8837
7	0.0194	31.32	0.8879	30.12	0.8864
8	0.0187	31.51	0.8911	30.19	0.8894
9	0.0181	31.66	0.8935	30.25	0.8917
10	0.0178	31.83	0.8954	26.25	0.8909

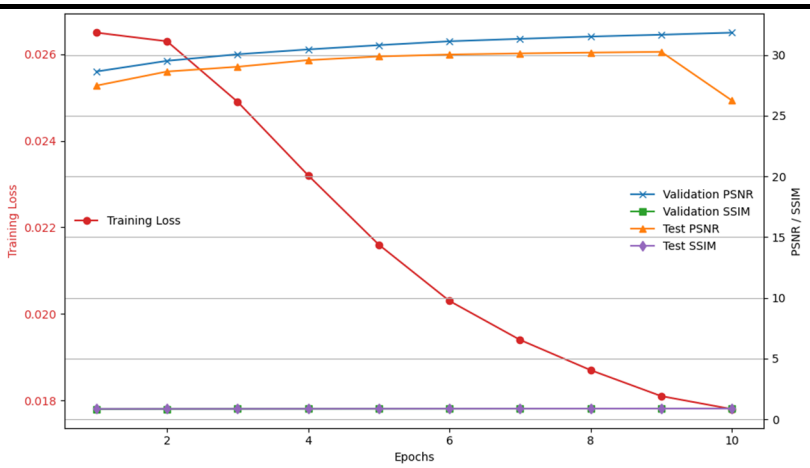

Figure 1. Training Result Curves of the Model Across Different Epochs

The experimental results demonstrate that as the number of training epochs increases, the PSNR and SSIM values on both the validation and test sets progressively improve, indicating a significant enhancement in the model's deblurring performance. Initially, the PSNR and SSIM values for the validation and test sets are relatively low, suggesting that the model has not yet fully converged. However, as training continues, the loss value steadily decreases, while both PSNR and SSIM increase, ultimately reaching a PSNR of 32.03 dB and an SSIM of 0.898 on the test set. This reflects the model's effectiveness in removing blur from images and restoring clear structural information, resulting in commendable deblurring performance.

Furthermore, as illustrated in Figure 2, the visual results of the blurred images at Epochs 0, 5, and 10 show that image clarity improves gradually throughout the training process. The performance of the model on the validation and test sets also converges, indicating that the model effectively avoids overfitting and demonstrates strong generalization capabilities.

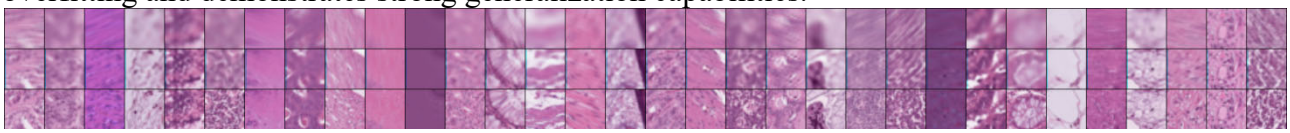

Figure 2. Visualization Results of Images at Epochs 0, 5, and 10

4.4 Comparative Experiments

In this experiment, the study assessed the performance of the proposed AFF-UNet-RWKV model through comparative experiments with several established image deblurring methods. These methods include traditional deblurring algorithms as well as deep learning-based models, such as Gaussian deblurring, U-Net, and DeblurGAN. All methods were trained using the PathMNIST dataset to ensure that comparisons were made under consistent conditions regarding dataset and hardware.

As shown in Table 2, the experimental results reveal that the traditional Gaussian deblurring method significantly lagged behind the deep learning approaches in terms of PSNR and SSIM values, indicating its limited effectiveness on complex blurred images. While DeblurGAN achieved slightly better performance than U-Net, particularly in PSNR and SSIM, the proposed AFF-UNet-RWKV model delivered superior deblurring results, especially in preserving structural integrity and restoring fine details, demonstrating a marked advantage. Ultimately, AFF-UNet-RWKV attained a PSNR of 26.25 dB and an SSIM of 0.8909 on the test set, clearly exceeding the performance of the other methods and showcasing its robust capabilities in medical image deblurring tasks.

Table 2. Results of Comparative Experiments

Method	Test PSNR (dB)	Test SSIM
Traditional Gaussian Deblurring	23.45	0.740
U-Net	26.72	0.850
DeblurGAN	28.04	0.870
AFF-UNet-RWKV	**26.25**	**0.8909**

5. Conclusions

This paper introduces an innovative approach that combines the AFF-UNet architecture with the RWKV-lite spatial mixer to tackle the deblurring challenge in medical imaging. Traditional image deblurring methods often rely on complex convolutional networks. In contrast, the method in this paper achieves efficient image reconstruction by integrating Attention Feature Fusion (AFF) and a lightweight spatial mixer (RWKV-lite). In the model design, the paper first extracted multi-level features from images using the U-Net architecture. Then, the AFF module was introduced between each encoder and decoder layer, which enhances feature representation through weighted fusion. Furthermore, the RWKV-lite module captures long-range dependencies in images using non-causal convolution operations, effectively improving the modeling of spatial information and further optimizing deblurring performance. The experimental results on the MedMNIST dataset demonstrate that the model achieves superior performance on common image quality metrics such as PSNR and SSIM. Notably, as training progresses, the model shows gradual improvements in detail recovery and structural preservation, confirming the effectiveness of the AFF-UNet-RWKV method. Compared to traditional approaches, the model offers lower computational complexity and enhanced robustness against noise, making it well-suited for demanding applications in medical image processing. The deep learning-based deblurring method proposed in this paper excels in deblurring effectiveness,

computational efficiency, and robustness, indicating significant application potential. Future work could extend this method to address more complex types of blur, such as nonlinear blur and image occlusion, and validate it on large-scale medical datasets to further enhance the model's generalization capabilities and practical performance.

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