A Review of Deep Learning in Inverse Problem Imaging Using Super-Resolution Reconstruction Algorithms

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***Abstract*—This review summarizes the objectives of applying deep learning in the inverse problem of super-resolution reconstruction, including basic concepts, principles, and common model architectures. The rapid development of deep learning technology has brought a breakthrough for super-resolution reconstruction, which can model complex mapping relationships and automatically extract features. In addition, deep learning also has wide applicability and potential for image denoising and repair. This paper also discusses the challenges that deep learning faces in inverse problem imaging, such as data requirements and computational complexity, and suggests directions for future research, such as model complexity, cross-domain learning, and interpretability. To address these challenges, future research can improve the model performance by exploring more complex deep learning architectures to enhance model capacity while optimizing model complexity, leveraging external data to enhance model generalization, improving model interpretability by integrating expert knowledge with traditional methods, and enhancing the robustness of the model in complex conditions. With the above improvements, deep learning will provide more accurate, high-quality, and interpretable super-resolution reconstruction solutions, driving the field of inverse problem imaging.**

***Keywords*—deep learning, inverse problem imaging, super-resolution reconstruction, image denoising, image restoration**

I. Introduction

The super-resolution reconstruction algorithm, as an important research direction in the field of image processing, has a wide range of background and significance. This section will introduce the background and significance of super-resolution reconstruction algorithms, as well as their applications in fields such as image enhancement, video processing, and medical imaging.

A. Background and Significance of Super-Resolution Reconstruction Algorithms

Super-resolution reconstruction algorithms are of great significance and widely used in the field of image processing. The main goal is to recover high-resolution images from low-resolution images. This is important for many fields, including computer vision, digital photography [1], medical imaging [2], unmanned driving, surveillance systems [3], satellite images [4], etc.

The application of the super-resolution reconstruction algorithm has the following aspects:

- Image enhancement: Low-resolution images usually lack detail and clarity, unable to meet the requirements of the human eye for image quality. With the super-resolution reconstruction algorithm, more detail and clarity can be recovered from the low-resolution images, making the image more realistic and easy to analyze [5].
- Medical imaging: In the field of medical imaging, high-resolution images are crucial for diagnosis and treatment. However, access to high-resolution medical imaging can be challenging due to cost and radiation dose. Through the super-resolution reconstruction algorithm, clearer and more detailed images can be recovered from low-resolution medical images, which can help doctors make accurate diagnoses and treatment decisions [6].
- Video compression: In video compression, high-resolution video needs to be compressed to reduce the file size. However, the image quality is lost in the uncompressed low-resolution video. Through a super-resolution reconstruction algorithm, high-resolution images can be recovered in the compressed low-resolution video to improve the visual quality of the video [7].
- Restore old images: For some historical and cultural heritage or old photos, super-resolution reconstruction algorithms can help restore and

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restore the details of the image, to protect and preserve important cultural and historical information [8].

- Remote monitoring and security: In the monitoring system, due to the limitation of the camera or the network transmission limitation, the acquired image often has a low resolution. This can affect the identification and analysis of the details. Through a super-resolution reconstruction algorithm, high-resolution images can be recovered from low-resolution monitoring images, provide clearer visual information and improve the monitoring effect [3].
- Promoting the research of computer vision and image processing: super-resolution reconstruction algorithms involve the intersection of image processing, pattern recognition, machine learning and other fields, promoting the research and technological progress in the field of computer vision and image processing [9].

In conclusion, super-resolution reconstruction algorithms are important in image processing and can improve image quality, enhance detail, and play a key role in multiple domains.

B. The Application of Deep Learning in Inverse Problem Imaging

Inverse problem imaging involves the process of inferring raw information or images from observed data [10]. Traditional methods are limited by model assumptions, computational complexity, and noise interference when dealing with complex inverse problems. Deep learning, as a powerful machine learning technique with the ability to automatically learn features and nonlinear mapping, has been widely applied in the field of inverse problem imaging (Table I). Its applications include image restoration and reconstruction (such as denoising [11], super-resolution and restoration [12]), compressive sensing [13] and image reconstruction [14], inverse problem solving [15], and data reconstruction and enhancement. Deep learning models can automatically learn the features and structures of images by learning a large amount of training data, and reconstruct high-quality images from observation data. It can also be used in compressive sensing to recover images from a small amount of observation data by learning sparse representation models. In inverse problem solving [16], deep learning achieves accurate estimation from observed data to raw information by designing appropriate neural network structures and training algorithms. In addition, deep learning can be applied to data reconstruction and enhancement tasks [17], by learning noise or artefact models, repairing and enhancing observation data, and improving image quality and accuracy of information restoration.

Deep learning shows great potential in the real-world applications of solving super-resolution reconstruction. In the field of medical imaging, deep learning can improve the resolution of medical images such as CT (Computed Tomography) and MRI (Magnetic Resonance Imaging), and help doctors to better diagnose and analyze the condition. In the field of remote sensing, deep learning can be applied to the super-resolution reconstruction of satellite and aerial images to improve image details and provide higher-quality data for environmental monitoring, urban planning and so on. In the field of surveillance, deep learning can improve the resolution of surveillance camera images, and enhance the target recognition and tracking performance.

TABLE I. APPLICATIONS OF DEEP LEARNING IN INVERSE PROBLEM IMAGING

Application Field	Deep Learning Methods	Advantages
Image Restoration and Reconstruction [11, 12]	Denoising, Super-resolution, Inpainting	Automatically learn image features and structures, reconstruct high-quality images from observation data
Compressed Sensing [13, 14]	Learning sparse representation models	Recover images from limited observation data
Inverse Problem Solving [15, 16]	Designing appropriate neural network structures and training algorithms	Achieve accurate estimation from observation data to original information
Data Reconstruction and Enhancement [17]	Learning noise or artifact models	Repair and enhance observation data, improve the accuracy of image quality and information restoration

In addition, deep learning also shows advantages in image denoising and recovery. A deep learning model can effectively remove image noise and retain more useful details. Deep learning also performs in image repair and reconstruction, recovering high-quality complete images from partial information. These applications help to improve image quality and provide better input data for subsequent computer vision tasks. Future research directions can include the exploration of more complex deep learning models, the generalization ability of the models, and the new methods of efficient integration of the two by combining the traditional image processing methods and the advantages of deep learning.

C. Purpose of the Research

Super-resolution reconstruction is an important task in the field of inverse problem imaging, and deep learning has shown great potential in this task. The goal of this study is to review and summarize the deep learning applications of super-resolution reconstruction algorithms in inverse problem imaging.

- Specific study objectives include a review of the background and significance of super-resolution reconstruction: to introduce the basic concepts of super-resolution reconstruction, application scenarios and importance in inverse problem imaging.

- The basic principle of deep learning in super-resolution reconstruction: To explain the working principle of deep learning in super-resolution reconstruction, including network architecture, training methods and optimization strategies.
- Existing deep learning models and methods: Review the current proposed deep learning models and methods, including convolutional neural networks, generative adversarial networks and attention mechanisms, to compare their advantages and disadvantages and applicable scenarios.
- Experimental research and results analysis: Review the existing experimental studies, evaluate the performance and effects of different models and methods in super-resolution reconstruction tasks, and analyze their advantages and disadvantages.
- Other application fields and expansion directions: discuss other application fields of deep learning besides super-resolution reconstruction, such as medical images, satellite images, etc., and discuss the future expansion directions and challenges.

By accomplishing the above research objectives, we will get a comprehensive and systematic review to provide an important reference and guidance for the application of deep learning in super-resolution reconstruction and inverse problem imaging.

D. Research Questions

The research problem in this paper is the deep learning application of super-resolution reconstruction algorithms in inverse problem imaging. Traditional methods have limitations in reconstruction details, while deep learning techniques can improve reconstruction quality by learning image features in a large number of training samples. Our goal is to comprehensively evaluate the performance and effects of different deep learning methods in super-resolution reconstruction and to explore their advantages and challenges in inverse problem imaging. The motivation of this paper is to promote the research and development of this field, provide guidance for researchers and practitioners, and promote the performance improvement and effect optimization of super-resolution reconstruction algorithms in practical application. We believe that the application of deep learning in super-resolution reconstruction will lead to important advances in the field of inverse problem imaging.

II. Overview of Super-Resolution Reconstruction Algorithms

The super-resolution reconstruction algorithm is an image processing technique aimed at reconstructing images with higher resolution and more details from low-resolution images. It is widely used in fields such as surveillance video enhancement [18], medical image analysis [19], and drone image processing [20]. Traditional super-resolution reconstruction methods can be divided into interpolation methods [21] and learning-based methods. Interpolation methods estimate missing high-frequency details by interpolating pixels in low-resolution images but often result in blurring and distortion. Learning-based methods have been a research hotspot in recent years, including sparse representation methods [22], regression models [23], and deep learning methods [24]. Sparse representation methods reconstruct high-resolution images by optimizing the process of sparse representation, regression models use the relationship between features and labels in the training dataset for prediction, and deep learning methods use deep neural network models to learn the mapping relationship between low resolution and high-resolution images. Deep learning methods have made breakthroughs in super-resolution reconstruction, enabling the generation of more realistic and detailed high-resolution images.

In addition to these methods, there are also some other super-resolution reconstruction algorithms, such as edge-based methods [25] and image statistical methods [26], which recover missing details by utilizing the structure and statistical patterns of the image.

In summary, super-resolution reconstruction algorithms have broad application prospects in the fields of image processing and computer vision.

III. The Application of Deep Learning in Super-Resolution Reconstruction

Super-resolution reconstruction is a key issue in the field of image processing, and the introduction of deep learning technology provides new opportunities for achieving more accurate and high-quality super-resolution reconstruction.

A. The Basic Concepts and Commonly Used Model Architectures of Deep Learning

Deep learning of super-resolution reconstruction algorithms in inverse problem imaging is an important research direction in the field of computer vision and image processing. The following is an analysis of the current research status in this field (Fig. 1).

1) Deep learning-based method

Deep Convolutional Neural Network (CNN) is one of the most commonly used deep learning models in super-resolution reconstruction [27]. By training the mapping relationship between low-resolution images and corresponding high-resolution image pairs, CNN can learn features and structural information in the images and be used to reconstruct high-resolution images. In recent years, researchers have proposed various CNN-based architectures, such as Super-Resolution Convolutional Neural Network (SRCNN), Very Deep Super-Resolution (VDSR), Efficient Sub-Pixel Convolutional Neural Network (ESPCN), etc., to continuously improve the performance of super-resolution reconstruction.

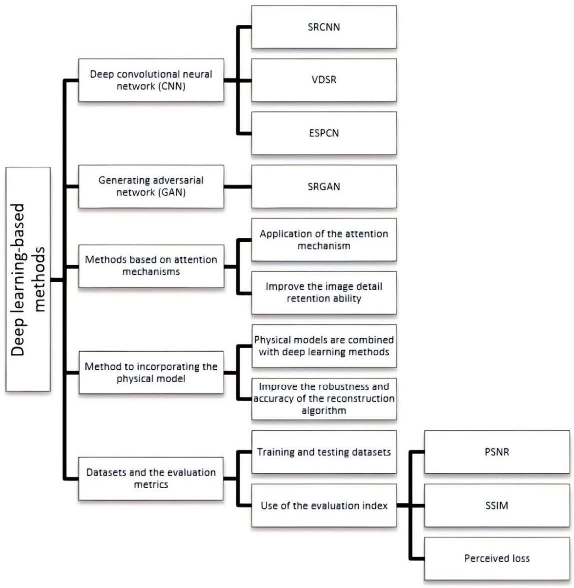

Fig. 1. Status of deep learning in super-resolution reconstruction algorithms in inverse problem imaging.

2) Method based on Generative Adversarial Network (GAN)

Generative Adversarial Network (GAN) is a model of adversarial training through a generator and discriminator network. In super-resolution reconstruction, the generator network is responsible for mapping low-resolution images to high-resolution images, while the discriminator network evaluates the authenticity of the generated images [28]. Through the training of GAN, more realistic and highly detailed high-resolution images can be obtained. For example, Super-Resolution Generative Adversarial Network (SRGAN) is a GAN-based super-resolution reconstruction method that provides more natural reconstruction results while maintaining the image details.

3) Methods based on the attention mechanism

The attention mechanism can be used to guide the model to pay attention to the important areas in the image [29], to improve the effect of super-resolution reconstruction. Some research efforts have introduced attention mechanisms to enhance the detail retention of images. By adaptively allocating attention, the model can better reconstruct subtle texture and structure information.

4) Methods of combining physical models

Some researchers combine physical models with deep learning methods to better solve the problem of super-resolution reconstruction. These methods use physical models to model imaging systems and use deep learning for optimization and reconstruction processes. By combining physical constraints with deep learning capabilities, the robustness and accuracy of the reconstruction algorithm can be improved [30].

5) Data sets and evaluation indicators

The researchers have constructed various training and test datasets for super-resolution reconstruction, such as DIV 2 K, Set5, Set14, etc. At the same time, to evaluate the performance of the algorithm, some evaluation indicators are also widely used, such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), perceived loss and so on.

Overall, super-resolution reconstruction algorithms have made significant progress in deep learning research in inverse problem imaging. Researchers constantly propose new network structures, loss functions, and training strategies to improve the quality and efficiency of super-resolution reconstruction. Future research directions may involve more complex network architectures, finer attention mechanisms, and more accurate physical models combined to further drive the development of super-resolution reconstruction algorithms.

B. *Application Methods and Algorithms of Deep Learning in Super-Resolution Reconstruction*

The application of deep learning techniques in the field of super-resolution image reconstruction is considered a new idea and is rapidly evolving. Based on the authors' query of related papers from the Scopus database from 2014 to 2023, a total of 9,643 papers related to the application of deep learning methods in super-resolution image reconstruction (Fig. 2). Among them, there are 3,543 methods based on Convolutional Neural Network (CNN), 1,770 based on Generative Adversarial Network (GAN), 2,560 based on attention mechanism, and 1,770 based on residual learning. In the past few years, these deep learning methods have been widely extended for super-resolution image reconstruction. Fig. 2 demonstrates the demand and prevalence of deep learning methods in the field of super-resolution image reconstruction. It should be noted that the application of deep learning methods has continuously grown in super-resolution image reconstruction from 2014 until 2023.

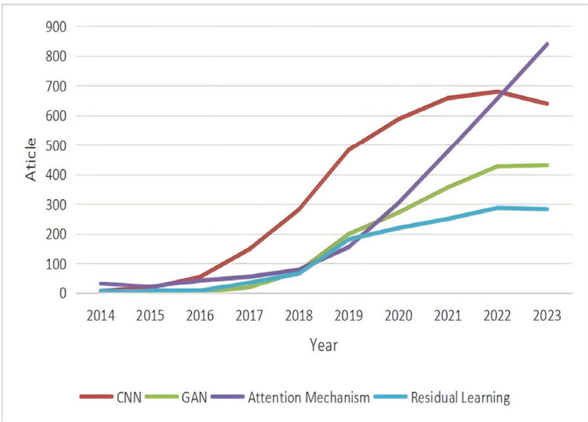

Fig. 2. The popularity of deep learning methods in super-resolution reconstruction.

Deep learning has made remarkable progress in super-resolution reconstruction and has become one of the most effective methods. The following are several common deep learning application methods and algorithms:

1) The method based on Convolutional Neural Networks (CNN)

Convolutional neural networks are commonly used models in deep learning, which can effectively learn feature representations of images. In super-resolution reconstruction, CNN models can be designed and trained to predict high-resolution images from low-resolution images. For example, SRCNN was initially proposed by Dong *et al.* [31] in their 2014 paper. SRCNN is a classic CNN-based super-resolution method. It consists of multiple convolutional layers and nonlinear activation functions, which can map low-resolution images to high-resolution image space (Fig. 3). SRCNN learns the weights of convolution kernels by training a large number of image pairs to achieve image super-resolution. This method improves the quality and detail retention ability of super-resolution to a certain extent but also faces challenges such as data dependency and computational complexity.

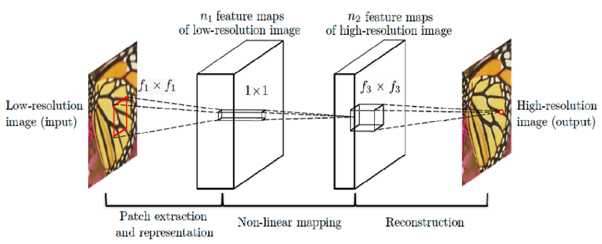

Fig. 3. SRCNN network structure [31].

2) The method based on Generative Adversarial Networks (GANs)

Generative Adversarial Networks are adversarial models composed of generators and discriminators. In super-resolution reconstruction, GAN models can be designed and trained to generate realistic high-resolution images. A common method is Super Resolution Generative Adversarial Network (SRGAN), where the generator network is responsible for converting low-resolution images into high-resolution images, while the discriminator network is used to distinguish between generated images and real high-resolution images. Through adversarial training, the generator can gradually improve the quality of the generated images. For example, Ledig *et al.* [32] introduced the SRGAN method in their 2017 paper, which is a photo-realistic single image super-resolution reconstruction method based on generative adversarial networks. The SRGAN method achieves high-quality image super-resolution reconstruction by introducing two adversarial networks, a generator and a discriminator (Fig. 4). The generator network is responsible for mapping low-resolution images to high-resolution images, while the discriminator network is used to distinguish the differences between the generated images and the real high-resolution images. The author provides a detailed description of the network structure and training strategy of SRGAN and demonstrates its realistic and detailed results in image super-resolution tasks. It has made significant improvements in the visual quality of super-resolution images but still faces challenges such as training stability and data requirements. This method provides a new direction for the study of single-image super-resolution and has had a wide impact in this field.

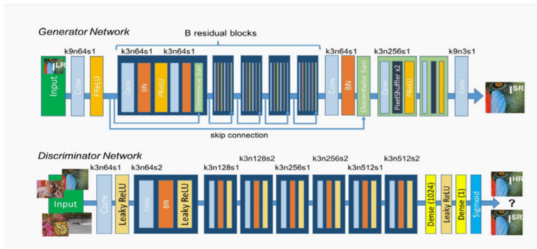

Fig. 4. SRGAN network structure [32].

3) Attention-based methods

Attention mechanisms can help networks better focus on important information in images. In super-resolution reconstruction, a model with an attention mechanism can be designed to enable the network to adaptively reconstruct different regions of low-resolution images. A common method is Spatial Attention Network (SAN), which guides the reconstruction process of the network by learning the spatial relationships between pixels. For example, Vaswani *et al.* introduced a neural network structure called a Transformer based on attention mechanism [29] for sequence modeling in natural language processing tasks, especially machine translation tasks (Fig. 5). Although this paper mainly explores the field of natural language processing, its idea of attention mechanism has also been widely applied in other fields, such as computer vision and speech recognition. The breakthrough work of this paper provides new directions and insights for the research and application of attention mechanisms and has become one of the milestones in the field of natural language processing. Another common method is Dense Attention Network (DAN), which introduces dense attention mechanisms in multiple network layers to improve the representation ability of features.

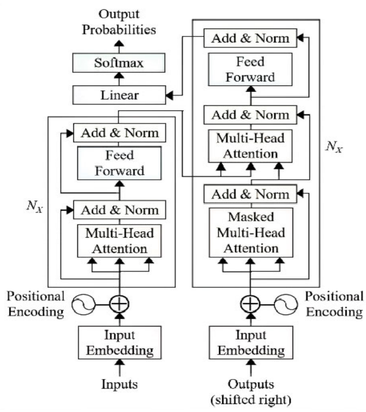

Fig. 5. Transformer model architecture [29].

4) Residual learning-based method

Residual learning can improve the performance of the network by learning residual mapping. In super-resolution reconstruction, a model with residual connections can be designed to enable the network to learn the mapping relationship between low resolution and high resolution. For example, Lim *et al.* [33] introduced the Enhanced Deep Super-Resolution Network (EDSR) method, which is a method of improving super-resolution quality by utilizing residual blocks and dense connection layers (Fig. 6). The EDSR method reconstructs high-resolution images by learning residual mapping. The experimental results and analysis in the paper indicate that this method has achieved good performance in super-resolution reconstruction tasks and has made important contributions in this field. However, the evaluation of the paper also needs to consider other factors comprehensively, such as the complexity of the method and computational efficiency.

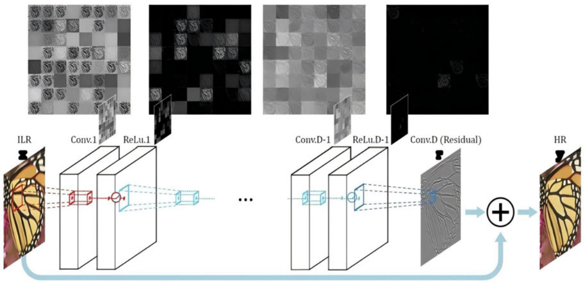

Fig. 6. EDSR network structure [33].

TABLE II. COMPARISON AND ANALYSIS OF COMMONLY USED METHODS AND ALGORITHMS IN DEEP LEARNING FOR SUPER-RESOLUTION RECONSTRUCTION

Method/ Algorithm	Function Description	Advantage	Disadvantage
RDN (Residual Dense Network) [2]	Network-based on residual and dense connections for super-resolution reconstruction	High reconstruction quality and strong reconstruction ability	The model is complex and the training process takes longer
SRCNN [31]	Using convolutional neural networks for super-resolution reconstruction, including convolutional layers and upsampling layers	Simple and easy to implement	Requires a large amount of training data
EDSR [33]	Using residual networks for super-resolution reconstruction, including residual blocks and upsampling layers	Has a strong reconstruction ability and can restore more details	The model is complex and requires more computing resources
DBPN (Deep Back-Projection Networks for Super-Resolution) [34]	Bidirectional pyramid network, achieving super-resolution reconstruction through stepwise upsampling and downsampling	Has strong reconstruction ability and can capture multi-scale information	The training process is relatively complex and requires more computing resources
ESPCN [35]	Using convolutional neural networks for super-resolution reconstruction and pixel recombination layers for upsampling	High computational efficiency	Limited ability to recover image details
RCAN（Residual Channel Attention Network）[36]	Residual network based on channel attention mechanism for super-resolution reconstruction	Has strong reconstruction ability and can adaptively allocate attention	The training process requires a longer time

Table II only provides a brief comparative analysis of some common deep learning methods and algorithms. In practical applications, selecting the most suitable method and algorithm also requires consideration of specific task requirements, data characteristics, computing resources, and feasibility of implementation. These methods and algorithms all utilize the powerful representation learning and pattern recognition capabilities of deep learning, which can learn advanced features and mapping relationships of images from a large amount of training data, thus achieving excellent performance in super-resolution reconstruction tasks.

IV. THE ADVANTAGES AND CHALLENGES OF DEEP LEARNING ALGORITHMS

In the field of image processing, deep learning algorithms have shown unique advantages in super-resolution reconstruction. Their powerful modeling ability and automatic feature extraction make them an ideal choice for achieving high-quality super-resolution reconstruction. However, deep learning algorithms also face some challenges, such as data requirements and model complexity. Understanding the advantages and challenges of deep learning algorithms is of great significance for a deeper understanding of their applications in super-resolution reconstruction.

A. The Advantages of Deep Learning Algorithms in Super-Resolution Reconstruction

Deep learning algorithms have multiple advantages in super-resolution reconstruction. Firstly, deep learning can learn complex image mapping relationships and capture image details through multi-layer neural networks. Secondly, deep learning can automatically extract features without the need for manual design of feature extractors, adapting to different scenarios and data changes. Thirdly, deep learning relies on large-scale data-driven learning, utilizing rich image data to learn accurate feature representations and mapping relationships. Fourthly, deep learning supports end-to-end learning, directly generating high-resolution images from low-resolution images to reduce information loss and error propagation. Finally, deep learning has flexibility and scalability, allowing for network structure adjustments and loss function improvements based on tasks and data, and efficiently processing large-scale image data. In summary, the advantages of deep learning in super-resolution reconstruction have made it a mainstream method and achieved significant results.

B. The Challenges Faced by Deep Learning Algorithms in Super-Resolution Reconstruction

The training process of deep learning models for super-resolution reconstruction faces several challenges and considerations, including data requirements, computational complexity, overfitting problems, balance between performance and efficiency, and adversarial sample attacks.

1) Data requirements

Training deep learning models requires large-scale and high-quality matching image pairs. This means that a large number of high-resolution images with their corresponding low-resolution images are needed. However, acquiring such images can be challenging for pairs because data acquisition and annotation can be difficult and expensive tasks. One of the approaches to this problem is to expand the training set with synthetic data, which may not fully simulate real-world images [37].

2) Computational complexity

Deep learning models require a lot of computational resources and memory when processing high-resolution images. Because high-resolution images have more pixels and more complex features, the training and inference process of models becomes more time-consuming and expensive. To meet the challenges of computational complexity, techniques such as distributed training, model pruning, and quantification can be used to reduce the demand for computational resources, or hardware accelerators such as GPU (Graphical Processing Unit) or TPU (Tensor Processing Unit) can be used to speed up the computational process [38].

3) Overfitting problem

In the case of insufficient training data or lack of diversity, deep learning models are prone to overfitting problems. Overfitting means that the model performs well on the training data but generalized poorly on the test data. To solve the overfitting problem, we can use regularization methods such as L1 or L2 regularization, Dropout, etc., or use data augmentation techniques to expand the training data set to increase the diversity of the data [38].

4) Balance of performance and efficiency

In super-resolution reconstruction, there is a tradeoff between high performance and computational complexity. On the one hand, deep learning models need to have sufficient representation capability and complexity to capture the details and textures in an image. On the other hand, the computational complexity of the model should enable to achieve efficient inference speed in practical applications. Technologies such as designing lightweight models, network architecture optimization, model pruning, and quantification can help balance performance and efficiency [39].

5) Adversarial sample attack

Deep learning models also face the challenges of adversarial sample attack in super-resolution reconstruction. Adversarial sample attacks can fool the model by making small perturbations to the input images, resulting in unreal details or distortion of the resulting high-resolution images. To counter adversarial sample attacks, defence techniques such as adversarial training can be used to improve the robustness and generalization of the model. The performance of the model is crucial to the speed of convergence [40].

The hyperparameters include learning rate, batch size, selection of optimizer, etc. Different combinations of hyperparameters may have significant effects on the model training and performance. Usually, the tuning and validation of the hyperparameters are required, which can select the best combination of the hyperparameters to achieve better model performance.

In conclusion, the training process of deep learning models for super-resolution reconstruction faces many challenges and considerations, including data requirements, computational complexity, overfitting problems, balance between performance and efficiency, and anti-sample attacks. Addressing these challenges requires a comprehensive consideration of data acquisition and annotation, model design and optimization, and computational resource benefits.

V EXPERIMENTS AND APPLICATIONS

Super-resolution reconstruction is one of the important applications of deep learning algorithms in the field of image processing. Through deep learning algorithms, researchers have conducted extensive experimental research aimed at improving the quality and performance of super-resolution reconstruction, and have achieved remarkable results in various application scenarios. Deeply understanding the experimental research of deep learning algorithms for super-resolution reconstruction not only helps to grasp its technical principles but also provides important references for future applications and improvements.

A. Experimental Research on Deep Learning Algorithms for Super-Resolution Reconstruction

A large amount of experimental research has been conducted on deep learning algorithms for super-resolution reconstruction. These studies typically involve the use of different datasets, evaluation metrics, and experimental results. The following is a summary of these aspects:

1) Data set

The dataset used by deep learning algorithms for super-resolution reconstruction can vary depending on specific research and application needs. Here are some examples of datasets used in commonly used super-resolution reconstruction deep learning algorithms:

(1) The Set5: Set5 dataset is a commonly used dataset for evaluating super-resolution algorithms, containing 5 classic natural images such as “baby”, “bird”, “butterfly”, etc.

(2) Set14: The Set14 dataset is another commonly used dataset for evaluating super-resolution algorithms, consisting of 14 natural images covering a wider range of scenes and content.

(3) BSDS100: The BSDS100 dataset is a subset of the Berkeley Segmentation Dataset, which contains 100

natural images for image segmentation and evaluation of super-resolution algorithms.

(4) DIV2K: The DIV2K dataset is a large-scale super-resolution dataset that contains 800 high-quality images collected from the Internet for training and evaluating super-resolution algorithms.

(5) CelebA: The CelebA dataset is a dataset containing a large number of facial images of celebrities, commonly used in the research and evaluation of facial super-resolution reconstruction algorithms.

(6) Manga109: The Manga109 dataset is a dataset used for super-resolution reconstruction of Japanese comics, containing 109 different comics, used to study super-resolution algorithms for comic images.

These datasets are just some examples, and there are many other datasets available for deep learning algorithm research in super-resolution reconstruction. Researchers can choose suitable datasets based on specific research objectives and application fields. In addition, data augmentation techniques can be used to process the data, generate more training samples, and improve the algorithm's generalization ability.

2) Evaluation indicators

Peak Signal to Noise Ratio (PSNR): PSNR is a commonly used indicator to measure the difference between a reconstructed image and the original high-resolution image. The higher the PSNR value, the closer the reconstructed image is to the original image [41].

Structural Similarity Index (SSIM): SSIM is an indicator that measures the structural similarity between a reconstructed image and the original image, taking into account the relationship between brightness, contrast, and structure [41].

Root Mean Square Error (RMSE): RMSE is an indicator that measures the pixel level difference between the reconstructed image and the original image. The lower the RMSE value, the closer the reconstructed image is to the original image [41].

3) Experimental results

a) Traditional deep learning methods.

Early deep learning methods such as SRCNN [31], VDSR [42], and DRCN (Deep Recursive Convolutional Network) [42] have achieved significant performance improvements in super-resolution reconstruction tasks. These methods typically use Convolutional Neural Network (CNN) architectures to learn the mapping relationships of images through multi-layer networks, achieving high PSNR and SSIM values. Haris *et al.* [34] proposed a super-resolution method based on deep back projection networks. and compared and analyzed them with methods such as SRCNN, LapSRN (Laplacian Pyramid Super-Resolution Network) [35], DRCN, VDSR, and ESPCN [35], exploring their differences in reconstruction quality and computational efficiency. This paper introduces the method of SRGAN and conducts experimental evaluation. The following is an analysis of the advantages and disadvantages of the author's experimental results:

According to the experimental findings by Haris *et al.* [34], D-DBPN (Deeply-Recursive Densely-Connected Pyramid Network) exhibited notable performance in 4x magnification and surpassed other methods. D-DBPN demonstrated the ability to generate patterns that closely resembled actual edges, surpassing EDSR in this regard (Fig. 7). On the Manga109 dataset, D-DBPN achieved a PSNR of 31.5 dB, which outperformed EDSR by 0.09 dB. Similarly, on the Set14 dataset, D-DBPN achieved a PSNR of 28.82 dB, surpassing EDSR by a mere 0.02 dB. These results highlight that D-DBPN excels particularly in processing images with intricate structural details.

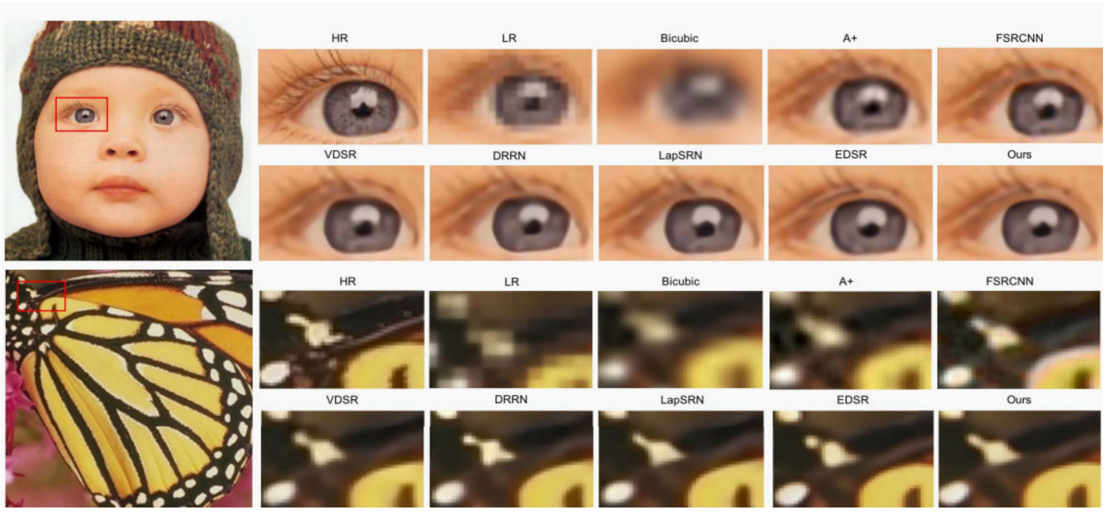

Fig. 7. Qualitative comparison of our models with other works on 4× super-resolution [40].

(1) Advantages

Experimental verification: The author verified the effectiveness of deep back projection networks in super-resolution tasks through experiments. By presenting the actual reconstruction results, readers can intuitively understand the performance and capability of this method.

Quantitative evaluation: The paper may have used quantitative evaluation metrics such as PSNR and SSIM to measure the performance of deep back projection networks. These indicators provide objective measurements that can be used to compare performance differences between different methods.

Visual result analysis: In addition to quantitative evaluation, the paper may provide visual result analysis to demonstrate the effectiveness of deep back projection networks through visual reconstruction results. These results can help readers intuitively understand the details and texture information that the network can recover.

Computational complexity and efficiency: The author discusses the computational complexity and efficiency of deep backprojection networks. The authors proposed a lightweight SS network (T = 2), using only conv (3,64) and conv (1,18) for feature extraction. Surprisingly, the SS network outperforms the SRCNN, Fast Super-Resolution Convolutional Neural Network (FSRCNN), and VDSR at 4 and 8 magnification. Compared to the VDSR, the SS network performs better with 72% and 37% reduced parameters. In 4 amplification, the SS network has 27% fewer parameters than the LapSRN and has a higher PSNR (Fig. 8). Compared with EDSR, D-DBPN reduced 76% of parameters and the PSNR remained close. In 8 magnification, D-DBPN reduced the parameters by 47%. This proves that our network achieves the best trade-off in performance and number of parameters (Fig. 9). This is crucial for feasibility and efficiency in practical applications, which can understand the training time, inference time and the required computational resources.

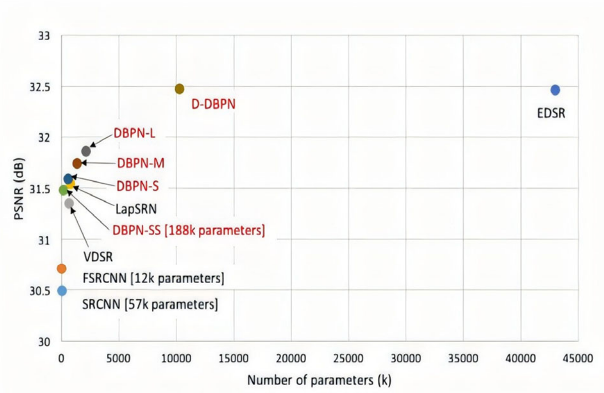

Fig. 8. Performance vs number of parameters. The results are evaluated with Set5 dataset for 4× enlargement [40].

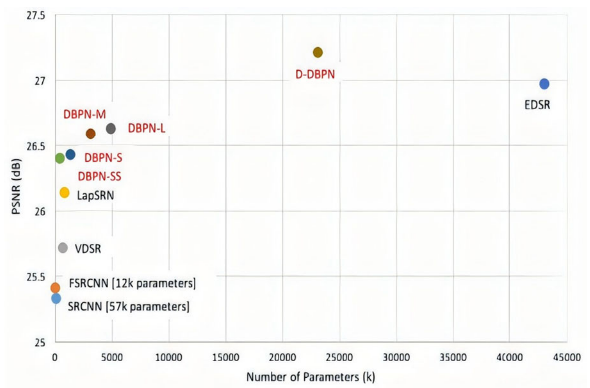

Fig. 9. Performance vs number of parameters. The results are evaluated with Set5 dataset for 8× enlargement [40].

(2) Disadvantages

Lack of comparative methods: The paper may not have been compared with other popular super-resolution methods. The lack of comparative methods makes it difficult to evaluate the performance of deep back projection networks compared to other methods.

Dataset selection: The dataset used in the experiment may be limited and cannot represent various real-world images. The characteristics of different datasets in terms of content, noise, and resolution may have an impact on the performance of the method.

Selection of evaluation indicators: The paper may only use one or a limited number of evaluation indicators to measure the performance of the network. These indicators may not fully capture the human eye's perception of image quality.

Lack of quantitative and qualitative analysis: The paper may have shortcomings in the quantitative and qualitative analysis of experimental results. More comprehensive quantitative and qualitative analysis can provide a deeper understanding of network performance.

In summary, the analysis of experimental results in Deep back projection networks for super-resolution has some advantages and disadvantages. Advantages include experimental validation, quantitative evaluation, visual result analysis, and discussion of computational complexity. Disadvantages include a lack of comparative methods, limitations in dataset selection, limitations in indicator selection, and a lack of comprehensive quantitative and qualitative analysis. These factors require readers to consider comprehensively and objectively when evaluating the performance and applicability of the method.

b) Methods based on Generative Adversarial Networks (GANs).

With the rise of Generative Adversarial Networks, some GAN-based methods, such as SRGAN and ESRGAN (Enhanced Super-Resolution Generative Adversarial Networks) [43], have achieved better performance in super-resolution reconstruction tasks. These methods can generate more realistic and detailed high-resolution images by introducing adversarial loss functions, improving visual quality and perceptual realism. Ledig *et al.* [32] introduced a deep learning-based image super-resolution method, which is the original paper of SRGAN and introduces the method of using GAN for super-resolution. It improves the quality of generated images by introducing adversarial and perceptual losses, and its performance is validated through quantitative and qualitative evaluations. This paper introduces the method of SRGAN and conducts an experimental evaluation of it. The following is an analysis of the advantages and disadvantages of the author's experimental results.

Analyzing the experimental results from Ledig *et al.* [32], it is evident that both SRGAN-MSE (Super-Resolution Residual Network) and SRGAN achieve new state-of-the-art results in super-resolution reconstruction, as demonstrated through quantitative evaluations on three benchmark datasets. The Mean Opinion Score (MOS) on the BSD100 dataset reveals that SRGAN outperforms all reference methods, establishing a new state-of-the-art. Notably, all MOS differences were statistically significant in the BSD100 dataset, except for the difference between SRCNN and SelfExSR. For more detailed information, please refer to Fig. 10.

This figure showcases the results of 4 super-resolution reconstruction methods: SRResNet, SRGAN-MSE, SRGAN-VGG (Super-Resolution Generative Adversarial Network with VGG loss) 2.2, and SRGAN-VGG54. Among them, SRGAN-VGG54 achieves the best performance, with rich details and the highest visual quality, almost indistinguishable from the high-resolution reference image. GAN-based methods, especially SRGAN leveraging VGG features, can maintain excellent visual quality while enhancing the resolution, making them highly valuable for applications requiring super-resolution.

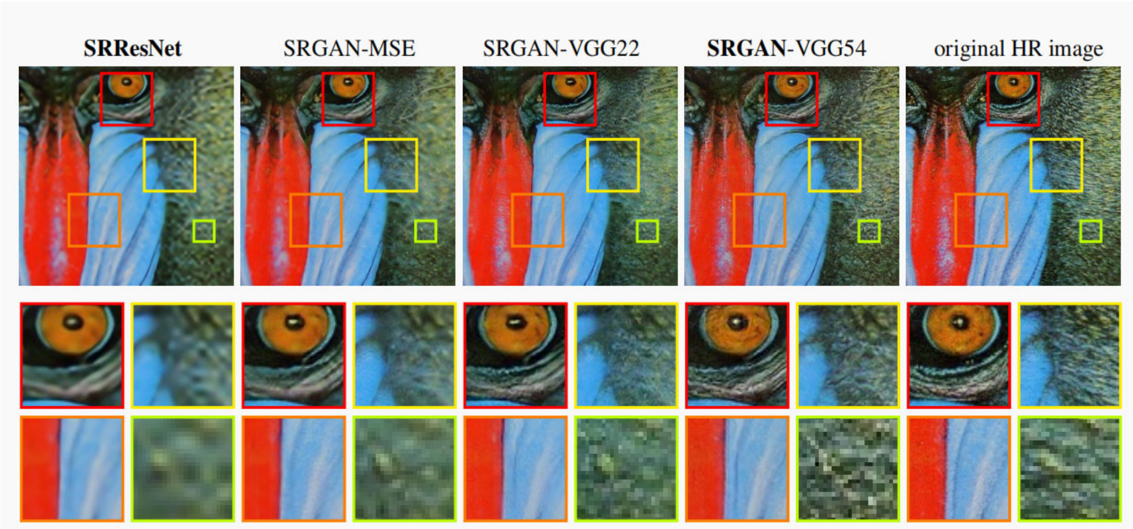

Fig. 10. Showcases the reconstruction outcomes of SRResNet , SRGAN-MSE, SRGAN-VGG2.2, and SRGAN-VGG54, along with the corresponding reference high-resolution image. The image resolution has been enhanced by a factor of 4× [32].

(1) Advantages:

High-quality image reconstruction: SRGAN can generate super-resolution images with higher visual quality and realism by introducing adversarial and perceptual losses. Compared with traditional methods, SRGAN generates clearer and more detailed images, while avoiding artifacts and blurring.

Improvements to multiple evaluation metrics: The paper utilized multiple objective evaluation metrics, such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), and compared them with other methods. The experimental results indicate that SRGAN has achieved significant performance improvements on these indicators.

Improvement of subjective quality: In addition to objective evaluation indicators, the paper also conducted subjective evaluation. Through experiments on human eye perception of image quality, it was verified that the visual quality of SRGAN-generated images is higher. The user is satisfied with the images generated by SRGAN and believes that they have better realism and detail restoration ability.

(2) Disadvantages

The complexity of the training process: The training process of SRGAN is relatively complex, requiring both the generator and discriminator networks to be trained simultaneously, and a carefully designed loss function to balance the quality and realism of the generated images. This may require more computing resources and training time.

Sensitivity to hyperparameters: There are some hyperparameters in SRGAN, such as learning rate, loss weight, etc., and the selection of these parameters may have an impact on the final result. Different hyperparameter settings may lead to different performance, which requires tuning and experimental verification.

Challenges in processing partially complex textures: When dealing with complex textures, SRGAN may face some challenges, such as handling small details in images or texture changes. In some cases, there may be some artifacts or unnatural details generated.

Overall, SRGAN demonstrated good performance and visual quality improvement in the experimental results, but there are also issues with training complexity and sensitivity to hyperparameters. In addition, there may be some challenges when dealing with complex textures. These advantages and disadvantages can serve as a reference for evaluating the SRGAN method.

c) Attention based methods.

In recent years, some attention based methods, such as RCAN [36], SAN [44], etc., have received widespread attention. These methods can dynamically adjust the network's reconstruction attention to different regions of the image by introducing attention modules, thereby improving reconstruction quality and preserving details.

Zhang *et al.* [2] introduced Residual Dense Network (RDN), a novel image super-resolution method. By introducing dense Residual Blocks (RDB) and feature fusion mechanisms, RDN has achieved significant improvements in detail preservation and computational efficiency. Experimental results have shown that RDN outperforms other methods in terms of super-resolution quality and computational efficiency. This paper introduces the method of SRGAN and conducts experimental evaluation on it. The following is an analysis of the advantages and disadvantages of the author's experimental results:

The experimental results indicate that RDN performs well on all datasets and with different scaling factors (such as ×2, ×3 and ×4) Performed the best on. Compared with persistent CNN models (SR DenseNet and MemNet), RDN exhibits better performance. RDN effectively extracts and reuses feature information through Residual Dense Blocks (RDB), achieving optimal results on various datasets. Compared to other models, RDN achieves the best average results in most cases. Especially in × Under a scale factor of 2, RDN performs best on all datasets. When the scaling factor increases (such as ×3 and ×4) RDN and MDSR (Multi-Scale Deep Super-Resolution) have similar performance advantages.

The experimental results presented by Zhang *et al.* [2] reveal that RDN+ achieves excellent Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) on various datasets. For instance, under the 4× scaling factor of the Set5 dataset, RDN+ achieves a PSNR of 32.61 and an SSIM of 0.9003. Similarly, with the 4× scaling factor on the Set14 dataset, RDN+ achieves a PSNR of 28.92 and an SSIM of 0.7893. For the B2 dataset at the 4× scaling factor, RDN+ yields a PSNR of 27.80 and an SSIM of 0.7434. Notably, under the 4× scaling factor of the Urban100 dataset, RDN+ achieves a PSNR of 31.39 and an SSIM of 0.9184. These results demonstrate the high PSNR and SSIM values achieved by RDN+ across different datasets, indicating superior image reconstruction quality and structural similarity. Refer to Fig. 11 for a visual representation of these findings.

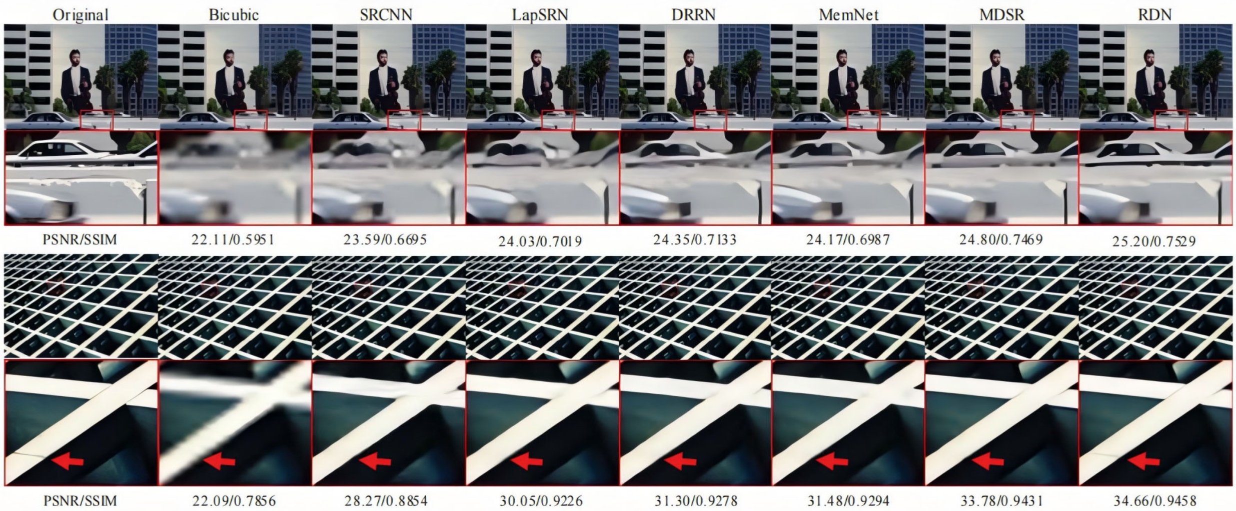

Fig. 11. Visual results with BI (Bicubic Interpolation) model (×4). The SR (Super-Resolution) results are for image "119082" from B100 and "IMG 043" from Urban100 respectively [2].

(1) Advantages

High quality super-resolution reconstruction: RDN can generate high-quality super-resolution images, restore details, and maintain edge clarity through effective feature extraction and reuse of Residual Dense Blocks (RDBs).

Multi scale feature fusion: RDN utilizes multiple residual dense blocks for feature extraction, and performs feature fusion within and between blocks. This multi-scale feature fusion helps to capture image information at different scales and improve the accuracy of super-resolution results.

Relatively fewer network parameters: Compared to some complex super-resolution methods, RDN has relatively fewer network parameters, resulting in lower computational costs for training and inference.

Competitive performance: RDN exhibits superior performance on multiple datasets and different scaling factors, and can achieve better average results compared to persistent CNN models and other methods.

(2) Disadvantages

High training complexity: RDN training may require longer time and larger computing resources, especially when using large-scale datasets and deep network structures.

For extremely high magnification super-resolution tasks, the performance of RDN may be limited.

The processing of complex textures and fine structures may be limited: although RDN has achieved certain results in extracting image structures and details, there may be challenges in processing complex textures and fine structures.

It should be noted that different studies may use different datasets, evaluation metrics, and experimental settings, so specific experimental results may vary. In addition, researchers are constantly proposing new datasets, improving evaluation metrics, and exploring higher performance and more efficient super-resolution reconstruction algorithms.

d) Gap analysis between the super-resolution reconstruction algorithms

In the super-resolution reconstruction algorithms in inverse problem imaging, deep learning methods show differences from the conventional methods in different aspects. Here is a summary of some of the major differences.

- Modeling capabilities: Deep learning methods can flexibly model the complex mapping relationships between images through deep neural networks. In contrast, traditional methods are usually based on hand-designed feature extractors and statistical models, with relatively weak modelling power for complex image content and change patterns. Deep learning methods can better capture the detail and texture information in the image and improve the accuracy of super-resolution reconstruction.
- Data requirements: Traditional methods usually require a large number of paired low-resolution and high-resolution image pairs, while deep learning methods can reduce the dependence on large amounts of paired data through end-to-end training. Deep learning methods can learn the statistical features and complex mapping relationships of images from limited training data, resulting in better generalization ability when processing new images.
- Adaptive feature extraction: Deep learning methods can automatically learn the feature representation of images, while traditional methods usually require the manual design of feature extractors. Deep learning model can automatically extract the features in the image through the multi-layer convolutional neural network, to better capture the detailed and structural information in the image.
- Model complexity: Deep learning models usually have high complexity, including a large number of parameters and computational requirements. In contrast, conventional methods usually have a simpler model structure and lower computational complexity. Therefore, in practice, deep learning methods may require more powerful computational resources and longer training time.

Overall, deep learning methods have clear advantages in the field of super-resolution reconstruction in inverse problem imaging. They can provide more accurate, high-quality super-resolution reconstruction results through flexible modelling capabilities, adaptive feature extraction, and end-to-end training methods. However, the complexity and computational requirements of deep learning methods also need to be considered and may be challenging in either insufficient data-based or domain-specific applications. Therefore, factors such as specific application scenarios, available data and computational resources should be considered comprehensively when choosing the appropriate method.

B. Other Application Areas of Deep Learning in Inverse Problem Imaging

The wide application areas of deep learning in inverse problem imaging include image denoising, image restoration, super-resolution reconstruction, and compressive sensing. Traditional methods are usually based on manually defined filters or statistical models, while deep learning methods have achieved significant results by learning features and mapping relationships from large-scale image datasets. In terms of image denoising, models such as DnCNN (Denoising Convolutional Neural Network) and FFDNet (Flexible Factorized Denoising Convolutional Neural Network) have achieved excellent denoising results by learning the noise features of images through convolutional neural networks. In image restoration tasks, models such as Pix2Pix and Impainting GAN use autoencoders or generative adversarial networks to recover predictions of missing or damaged areas. In super-resolution reconstruction tasks, models such as SRCNN, SRGAN, and ESRGAN have achieved remarkable results by learning the mapping relationship between low-resolution images and high-resolution images. In terms of compressive sensing, models such as Deep K-SVD and ISTA Net achieve high-quality recovery by learning sparse representations of signals. Deep learning methods have brought breakthroughs and developments in the field of inverse problem imaging by utilizing large-scale datasets and complex network structures.

VI CONCLUSION

Deep learning has achieved remarkable results in super-resolution reconstruction. By modelling complex relationships and automated feature extraction, deep learning improves image detail and clarity. While still challenged with data requirements and computational complexity, future research could focus on balancing model complexity and efficiency, improving realism and detail retention, multimodal and multiscale reconstruction, cross-domain and transfer learning, and interpretability. Deep learning is important in the field of super-resolution reconstruction and is expected to make greater progress in the future.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this paper.

AUTHOR CONTRIBUTIONS

Rongfu Wang and Mary Jane C. Samonte contributed to foundational concepts, while Rongfu Wang handled the implementation and experimentation. The analysis phase involved collective efforts from all authors. All authors had approved the final version.

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