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Review on Application of Image Super-Resolution Technology Based on Deep Learning

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Abstract. With the rapid development of information and intelligent technology, high-resolution images play an increasingly important role in medical imaging, remote sensing monitoring, security monitoring, intelligent transportation and industrial detection. Traditional image super-resolution (SR) methods have limitations in improving image detail and visual quality, while the introduction of deep learning has brought new breakthroughs in image super-resolution. In this paper, the development status and application progress of image super-resolution technology based on deep learning are systematically summarized. From the basic principle of super-resolution, mathematical model, benchmark dataset and performance evaluation index, the functions and advantages of convolutional neural network (CNN), upsampling method, residual network, sharpening layer, structure reparameterization and Patch technology in image reconstruction are analyzed. The typical applications of super-resolution technology in medical imaging, security monitoring, satellite remote sensing, high-definition video and image editing are further discussed, and its important value in detail recovery, vision enhancement and intelligent recognition is revealed. Finally, the main challenges facing current super-resolution technologies are summarized, including real degradation modeling, model complexity, perceptual quality balance and insufficient generalization ability, and the future development trends are prospected, such as lightweight network design, multimodal fusion, Transformer and diffusion models. This paper aims to provide systematic theoretical summary and application reference for deep learning-driven image super-resolution research, and promote the implementation and innovation of this technology in more practical scenes.

Keywords: image super-resolution, deep learning, CNN, GAN, Transformer, multimodal fusion

1. Introduction

1.1. Research background and significance

With the rapid development of informatization and intelligence, high-resolution images play a key role in medical imaging, remote sensing monitoring, security monitoring, intelligent transportation and industrial detection, which not only enhance the visual perception experience, but also provide

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high-quality input for computer vision tasks. However, limited by sensor performance, environmental conditions and data transmission, it is expensive and difficult to obtain high-resolution images. Therefore, reconstruction of high-resolution images from low-resolution images by algorithmic means has become an important research direction [1]. Super-resolution (SR) technology came into being and made breakthroughs under the promotion of deep learning, especially CNN, GAN and Transformer models greatly improved the image detail recovery and perception quality, and promoted its wide application in medicine, remote sensing, video surveillance, automatic driving and other fields.

1.2. Development history of super-resolution technology

Super-resolution has evolved from traditional interpolation, reconstruction model based, sparse representation learning to deep learning. Early methods such as bilinear and bicubic interpolation are simple but lack of detail recovery; reconstruction methods enhance high-frequency details but rely on accurate degenerate models; sparse representation methods enhance reconstruction but have limited generalization. The proposal of SRCNN in 2014 marked the beginning of the dominant phase of deep learning, and subsequent models such as VDSR, EDSR and SRGAN significantly improved reconstruction performance through residual learning and adversarial training, making the results clearer and more realistic. Deep learning methods rely on end-to-end feature learning and large-scale data training to become the current mainstream and promote their landing in multiple fields.

1.3. Overview of research objectives and content

This paper aims to systematically review image super-resolution techniques based on deep learning, covering theoretical models, datasets and performance evaluation methods, focusing on key mechanisms such as CNN, upsampling, residual network, sharpening layer, structural reparameterization and Patch technology, and to explore its challenges and development directions in medical imaging, remote sensing and Media Processing Service applications. Through systematic combing, the evolution and application prospect of super-resolution technology driven by deep learning are revealed, which provides theoretical support and method reference for subsequent research.

2. Super-resolution technology basis

2.1. Problem definition

Image Super-Resolution (SR) aims to recover high-resolution (HR) images from low-resolution (LR) images, and its core task is to make up for the information lost in the degradation process and reconstruct as clear details as possible. Formally, a low resolution image may be generated from a high resolution image by a degradation model:

$$I_{LR} = D(I_{HR};\theta) + n \tag{1}$$

where, I_{HR} representing the high-resolution image, $D(\cdot)$ is the degradation mapping function, θ is the parameters of the degradation process (such as the blur kernel size, downsampling factor, etc.), and n is the noise term. The super-resolution task is to recover the high-resolution image

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I_{HR} approximately from the low-resolution observation I_{LR} using a learned model $f(\cdot;\phi)$, namely:

$$\widehat{I}_{HR} = f(I_{LR};\phi) \tag{2}$$

Among them, ϕ denotes the parameters of the network to be learned ,which are continuously adjusted through the training process to improve the recovery accuracy.

In practical applications, the real degradation process is often complex and unknown, and may include blur, noise, compression artifacts and other factors. Due to the difficulty of accurate modeling, most research efforts are reduced to a single downsampling operation. Common methods include bilinear interpolation, bicubic interpolation, nearest neighbor downsampling, etc. However, there is a gap between this simplified method and the real degradation process, and it is difficult to fully improve the effect in practical applications. For this reason, researchers have proposed more realistic modeling methods in recent years, such as fuzzy kernel-based degenerate modeling, noise or compression process and blind super-resolution (Blind SR) method, aiming at improving the generalization ability and practical applicability of the model.

The training objective for super-resolution is usually achieved by minimizing the loss function between the generated image and the real image:

$$L = \ell(\widehat{I}_{HR}, I_{LR}) + \lambda R(\phi) \tag{3}$$

Where $(\cdot)$ is the reconstruction loss (such as mean square error, perceptual loss, adversarial loss, etc.), $R(\phi)$ is the regularization term used to control the model complexity and prevent overfitting, and λ is the trade-off coefficient. In this way, the model is able to strike a balance between pixel accuracy and perceptual quality, resulting in high-fidelity reconstruction of low-resolution images.

2.2. Introduction to baseline data sets

Released in 2017, the DIV2K dataset is an important benchmark dataset for image super-resolution (SR) research, providing 2650 high-resolution (HR) images and their low-resolution (LR) versions, of which 2400 are used for training and 250 for testing. The original version contained only HR images, and researchers needed to generate LR images by bicubic downsampling, fuzzy convolution plus downsampling, and noise addition to simulate the real degradation process. DIV2K's high-quality images, diverse scenes and large-scale validation sets have greatly promoted the development of image super-resolution technology. With the rise of deep learning, researchers continue to improve the detail recovery ability and generalization performance of models by introducing generative adversarial networks (GAN), attention mechanisms, cross-domain data enhancement and multi-task learning, and continue to promote computer vision dataset standardization and technological innovation [2]

2.3. Performance index evaluation

Peak Signal-to-Noise Ratio (PSNR) is one of the most commonly used objective evaluation indexes in image superresolution and other image reconstruction tasks. Its core idea is to evaluate the reconstruction quality by measuring the pixel error between the reconstructed image and the reference image. The definition of PSNR depends on Mean Squared Error (MSE), which is

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$$PSNR = 10 \cdot \log_{10}(\frac{MAX_I^2}{MSE}) \tag{4}$$

where MAX_I is the maximum pixel value of the image (e.g. 255 in an 8-bit image) and MSE is the squared average of the pixel-by-pixel differences between the predicted image and the reference image. A smaller MSE and a larger PSNR indicate a higher similarity between the reconstructed image and the reference image. Because of its simplicity and intuitive results, it has been widely used in comparison of algorithms for a long time. However, $PSNR$ focusing only on pixel-level differences ignores the sensitivity of the human visual system to structure and semantics, and thus often fails to accurately reflect the subjective perceived quality of images. For example, two images are close in PSNR, but visually there may be significant sharpness or texture differences. Even so, due to the lack of unified and better perceptual evaluation indicators and the need for repeatable comparative experiments in scientific research, PSNR is still the most commonly used benchmark indicator at present. At the same time, there are also studies on constructing real-scene super-resolution quality datasets and proposing no Reference evaluation indicators are used to make up for the shortcomings of PSNR/SSIM [3].

To compensate for this deficiency, Structural Similarity Index Measure (SSIM) is proposed for image quality assessment closer to human visual perception. $SSIM$ Based on the sensitivity of human visual system to image structure,

Compare the similarities between the two images in terms of brightness, contrast and structure. The calculation formula is usually expressed as:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{5}$$

where μ_x and μ_y represents the average brightness of the image, σ_x and σ_y represents contrast (variance), σ_{xy} represents the covariance of the two images, and C1 and C2 is a stability constant that avoids zero denominator. $SSIM$ The results range from -1 to 1, with closer to 1 indicating more similar structures. Different from PSNR, it can comprehensively consider brightness consistency, contrast preservation and structural information similarity, which is more in line with the subjective perception of human vision. Therefore, it has been widely used in the perceptual quality evaluation of super-resolution, image compression, denoising and other tasks, and is considered to be a better index than.

However, the agreement (correlation) between PSNR and SSIM and human subjective perception is not high. They measure pixel-level error and structural similarity, but they don't do a good job of reflecting "realism","naturalness", and "visual comfort" perceived by the human visual system. Therefore, it is a challenge and innovation to develop a new index (KLTSRQA) that is more subjective to human eyes and does not need reference images, and compare it fairly with other NR-IQA indexes of the same type.

3. Deep learning-based super-resolution core technology

3.1. CNN basics

A typical CNN model consists of an input layer, a convolutional layer, a pooling layer, a fully connected layer, and an output layer. Convolutional layers are the cornerstones of CNNs, which extract local features by sliding window operations on an input image or feature map through a set of learnable convolution kernels (or filters). After convolution operation, nonlinear activation

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functions (such as ReLU) are usually introduced to enhance the expressive ability of the model. The pooling layer follows the convolution layer and achieves translation invariance by reducing the spatial dimension of the feature map, reducing computation and enhancing feature robustness while effectively controlling overfitting.

3.2. Upsampling technique

Upsampling is a typical scaling operation in image processing and computer vision. Its core goal is to map a low-resolution image to a higher-resolution space, thereby generating a larger size and richer detail image. In practical applications, upsampling can not only improve the visual effect of images, but also provide higher quality inputs for subsequent detection, recognition and analysis tasks, as shown in Figure 1.

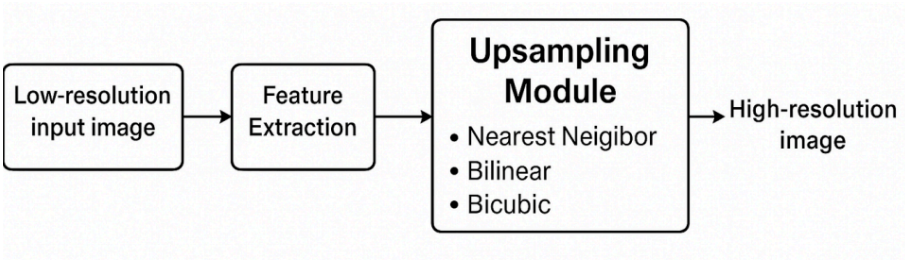

Figure 1. Upsampling pipeline: a low-resolution input image is processed by feature extraction layers and then upsampled using interpolation methods (nearest neighbor, bilinear, bicubic) to obtain a high-resolution image

In the upsampling process, pixels in the original image are projected onto a denser pixel grid. Since there are a large number of unknown pixel values in the newly generated high-resolution grid, how to reasonably infer and fill these pixels becomes a key problem. Intuitively, this process is actually an interpolation problem: we need to estimate the gray or color values of unknown pixels from known discrete pixels to ensure that the resulting image is as close to the true high-resolution image as possible in terms of spatial continuity and perceptual quality. Upsampling is a key step in super-resolution to generate high-resolution output from low-resolution input. This paper analyzes how different upsampling methods work together with other modules of convolutional neural network, such as extracting low-resolution image features by convolution layer, then upgrading the resolution of feature map to high-resolution image size by upsampling method, and finally generating final high-resolution image by reconstruction module. The influence of upsampling method selection on super-resolution image quality is expounded.

3.3. Residual neural network helps super-resolution

With the increase of the layers of deep neural networks, traditional convolutional networks are prone to gradient disappearance and performance degradation during training, which makes it difficult for the model to effectively learn complex high-low resolution mapping relations. To solve this problem, Residual Neural Network (ResNet) introduces the idea of "skip connection", that is, the input is directly transferred to the later layer through identity mapping in the network, so that the model can learn the residual information between the input and the output. This structure not only alleviates the gradient vanishing problem, but also improves the convergence speed and stability of the network, making deeper networks possible. In image super-resolution tasks, typical models such

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as EDSR (Enhanced Deep Super-Resolution Network) use a large number of residual blocks to build deep structures, and retain low-level feature information through skip connections, thus performing well in recovering high-frequency textures and details. The core advantage of residual structure is that it allows the network to focus on learning compensation parts of high-frequency information rather than reconstruction of complete images, greatly improving image detail restoration and visual perception quality. Overall, it is one of the key supporting frameworks for current deep learning super-resolution technology [4].

3.4. Sharpen layer enhances image detail

In the task of image super-resolution, how to recover high-frequency detail and edge information effectively is the key factor to determine image quality. Sharpening Layer aims to highlight the edge contour and texture structure by enhancing the high frequency components of the image, so as to make the reconstruction result clearer and more natural. The basic principle is to enhance gradient regions of an image by using filters (such as Laplacian, high-pass filters, or self-learning convolution kernels) to improve local contrast and detail representation. Unlike traditional post-processing sharpening, sharpening layers in deep networks are usually embedded into the model structure, working in conjunction with convolution layers, residual blocks, and upsampling modules to enable the network to automatically learn the optimal sharpening strategy during the feature extraction phase. In this way, the model can not only effectively suppress blur effects, but also achieve better perceptual quality in texture restoration and edge enhancement. Practice shows that the sharpness and visual realism of images can be improved significantly by introducing sharpening layer into super-resolution network, and more fine details can be provided for high-resolution reconstruction.

3.5. Structural reparameterization optimization network

Structural reparameterization is a network optimization method that considers both model performance and inference efficiency. Its core idea is to use multi-branch and complex structures in training phase to improve model representation ability, and convert these structures into single convolution form equivalently in inference phase, thus significantly reducing computational complexity and memory consumption. By adopting structural equivalence transformation in different stages, the method can make the model have higher inference speed and lower hardware overhead while maintaining high accuracy. Specifically, the network can include structures such as multiple convolutional branches, batch normalization layers, and nonlinear activations during training to enhance feature learning and robustness, while at the inference stage, these branches are mathematically combined into an equivalent convolutional layer for structural simplification and performance optimization. In image super-resolution task, structural reparameterization can effectively improve the application value of the model in mobile and real-time scenes. For example, by reparameterizing the multi-branch residual block into a single convolution module, the model greatly improves computational efficiency while maintaining the quality of super-resolution reconstruction. The introduction of this technology provides a new way of thinking for lightweight super-resolution network design, enabling deep learning models to better balance accuracy and speed, and promoting the development of super-resolution algorithms in an efficient and practical direction.

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3.6. Application of patch technology in super resolution

Patch technology is a key strategy commonly used in image super-resolution training. Its core idea is to divide the whole image into several local patches so that the model can focus on learning local features and texture details. Because high-resolution images are often large in size and information-intensive, direct overall input will lead to high computational resource consumption, so Patch partitioning can significantly reduce training costs and improve the learning ability of models for local structures. During the training phase, the model learns the mapping relationship between low resolution (LR) and high resolution (HR) patches in pairs, enabling the network to capture local feature changes and enhance detail recovery. Patch extraction methods include sliding window with fixed size, random sampling and dynamic extraction based on feature adaptation. Different methods can balance computational efficiency and feature diversity. In the reconstruction stage, the network re-assembles the processed high-resolution patches into a complete image, and ensures the continuity and consistency of the overall image through edge fusion and overlapping area weighting, providing a reliable basis for high-quality image reconstruction [5].

4. Industrial applications of super-resolution technology

4.1. Field of medical imaging

In the field of medical imaging, high-resolution images are crucial for accurate diagnosis and lesion identification of diseases. Whether it is X-ray film, CT tomography image or MRI magnetic resonance imaging, the diagnostic effect is highly dependent on the clarity and detail of the image. However, limited by the physical resolution of imaging equipment, radiation dose control and imaging time, it is often difficult to obtain high-quality medical images, resulting in blurred images and serious noise interference, thus increasing the risk of misdiagnosis and missed diagnosis. Therefore, image super-resolution technology based on deep learning is widely used in medical image reconstruction and enhancement tasks. Through convolutional neural network (CNN), generative adversarial network (GAN) or residual network, the model can learn detailed features and structural information of organ tissues from low-resolution medical images to generate high-quality, high-fidelity images [6].

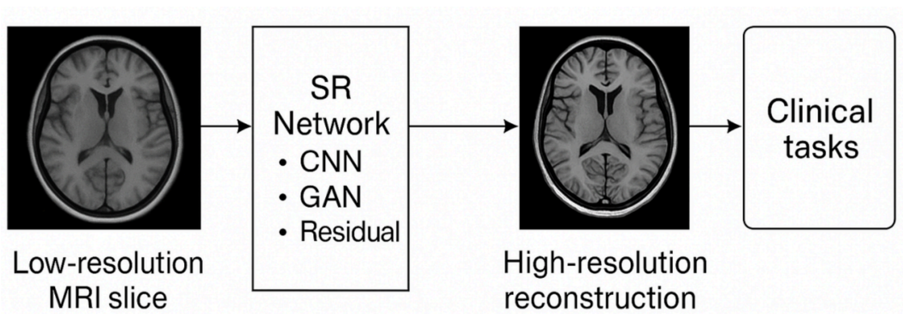

Figure 2. Deep learning-based super-resolution pipeline for medical MRI, from low-resolution input to high-resolution reconstruction and downstream clinical tasks

Current research shows that super-resolution technology has achieved remarkable results in tasks such as lung nodule detection, brain tumor segmentation, and retinopathy identification. For example, in CT imaging, SR model can effectively improve edge definition, enabling doctors to more accurately identify lesion contours in early screening;GAN structure can enhance texture

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information while maintaining tissue structure consistency, improving lesion area discrimination [7]. However, medical image super-resolution still faces many challenges, such as limited medical data acquisition, high labeling costs, large domain differences caused by different equipment and imaging parameters, and insufficient interpretability of models in clinical scenarios. Future research can start with multi-modal fusion, small sample learning and interpretable artificial intelligence to further improve the stability and reliability of medical image super-resolution technology and provide stronger technical support for intelligent diagnosis and auxiliary decision-making.

4.2. Field of security monitoring

In the field of security monitoring, the clarity of images and videos is directly related to the accuracy of personnel identification, behavior analysis and event tracking. However, subject to factors such as hardware resolution, installation distance, lighting conditions and network transmission bandwidth of surveillance cameras, surveillance images often present problems such as low resolution, high noise, blurred details, etc., which seriously affect the effect of target recognition and behavior judgment. Deep learning-based image super-resolution (SR) provides an effective solution to this problem. Through end-to-end learning, the model can automatically recover high-resolution images from low-resolution surveillance images, such as face features, license plate numbers [8] and target contours, thus significantly improving the recognition accuracy and reliability of the surveillance system.

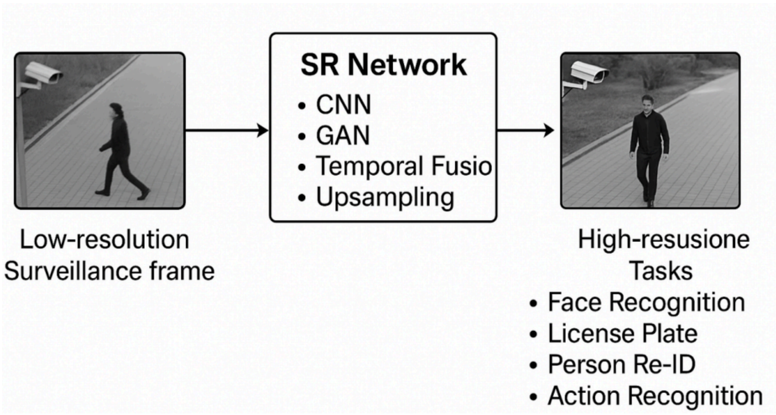

Figure 3. Deep learning-based super-resolution framework for surveillance video enhancement

In specific applications, the researchers combined convolutional neural networks (CNN) with generative adversarial networks (GAN) to monitor the spatiotemporal feature enhancement of video, enabling the model to recover compressed or blurred details by integrating successive frame information. For example, super-resolution networks based on temporal information can enhance image quality in low-light or long-distance scenes and improve the recognition rate of faces and objects; while lightweight SR models are suitable for real-time video stream processing to achieve a balance between high-resolution output and low-delay response, and the identifiability and target detection accuracy of surveillance images are significantly improved [9]. In addition, in terahertz (THz) imaging scenarios such as postal security, there are also efforts to improve the spatial resolution and detail reconstruction quality of THz images using multi-scale super-resolution networks, thereby enhancing nondestructive inspection and security performance [10].

However, super-resolution reconstruction in security surveillance scenes still faces several challenges, including high real-time requirements, complex environmental changes (such as

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lighting, weather, occlusion, etc.), and insufficient generalization ability of models between different scenes. In order to solve these problems, future research directions can focus on lightweight network structure design, multi-frame fusion algorithm, scene adaptive modeling and joint optimization with tasks such as target detection and behavior recognition, so as to promote the deep fusion and landing application of super-resolution technology in intelligent security systems.

4.3. Super-resolution of satellite remote sensing images

In the field of satellite remote sensing, image resolution is a key factor affecting the accuracy of ground observation and the quality of geographic information analysis. High-resolution remote sensing images can show more clearly the details of land surface structure, such as buildings, roads, water bodies and vegetation distribution, which is of great significance for urban planning, land use monitoring, resource exploration and environmental protection. However, due to the limitations of satellite sensor resolution, imaging distance, meteorological conditions and cost, obtaining high-resolution images is often costly and difficult to popularize. Image super-resolution technology based on deep learning provides a new solution to improve the quality of low-resolution satellite images.

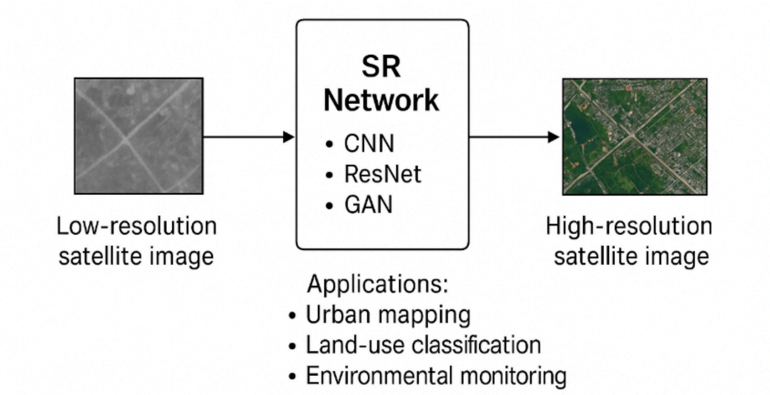

Figure 4. Deep learning-based super-resolution for satellite remote sensing imagery

Using models such as convolutional neural networks (CNN), residual networks (ResNet), and generative adversarial networks (GAN), researchers were able to reconstruct high-resolution images with richer details and sharper edges from low-resolution satellite images. For example, in urban area monitoring, SR technology can effectively improve the accuracy of building edge recognition; in agriculture and forestry remote sensing, super-resolution reconstruction can enhance texture features for classification and pest detection; in environmental monitoring, it can improve the spatial accuracy of remote sensing indicators such as surface temperature and pollution distribution [11-13]. However, satellite remote sensing image super-resolution still faces challenges such as multi-source data heterogeneity, sensor differences and image distortion. Future research can continue to explore new architectures such as multimodal fusion (optical, radar, infrared, etc.), adaptive degradation modeling, and Transformer to further improve the robustness and generalization ability of the model in complex remote sensing scenarios [14].

4.4. HD video and image editing field

In the field of Media Processing Service and Image Editing, super-resolution technology is widely used to improve image quality, repair details and enhance visual experience. With the rapid growth

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of HD and Ultra HD content demand [15,16], traditional video enhancement and frame interpolation algorithms are difficult to meet. Deep learning-based super-resolution method can automatically recover high-resolution content from low-resolution video or images through end-to-end learning mechanism, effectively enhancing picture details, texture levels and visual realism.

Temporal Consistency is a key issue in Media Processing Service. To this end, researchers combine convolutional neural networks (CNN) with recurrent neural networks (RNN), transformers and other structures to jointly model video using multi-frame information, thereby improving resolution while maintaining inter-frame smoothness and dynamic stability. For example, the VSR (Video Super-Resolution) model can improve sharpness and reduce flicker artifacts in low frame rate video. In the field of image editing, super-resolution is used for tasks such as restoration of old photos, digital magnification, denoising and enhancement. By introducing Generative Adversarial Networks (GAN) or Perceptual Loss, the model is able to generate high-definition images with natural texture and realistic detail. Future research directions include real-time video super-resolution, multi-task fusion (such as denoising and enhancement synchronization), and adaptive super-resolution generation in interactive image editing, which will bring higher quality visual experiences to film production, virtual reality and digital content creation.

5. Challenges and future directions

Although image super-resolution technology based on deep learning has achieved remarkable results in many fields, it still faces problems such as imperfect modeling of real degradation, high computational complexity of models, difficulty in balancing perceptual quality, and insufficient cross-domain generalization ability [17]. Future research will focus on accurate modeling of real scene degradation mechanisms and optimization of blind super-resolution methods, combining lightweight design, structural reparameterization and knowledge distillation to improve model efficiency and deployability. At the same time, multi-modal fusion and multi-task learning will become an important development trend. By fusing multi-source information such as semantics, depth and timing, more robust and adaptive high-quality reconstruction will be realized. In addition, the introduction of new architectures such as Transformer and Diffusion Model provides a new breakthrough direction for super-resolution technology in detail recovery and global modeling. In general, future super-resolution research will gradually move from the pursuit of reconstruction accuracy to intelligent, real-time and multi-scene adaptation, promoting the technology to achieve a wider range of landing applications in medical imaging, security monitoring, satellite remote sensing and video editing.

6. Conclusion

In this paper, the research status and application progress of image super-resolution technology based on deep learning are systematically reviewed. Firstly, the theoretical basis is expounded from the definition of super-resolution problem, mathematical model, typical data set and performance evaluation index. Then, the core technologies driven by deep learning are systematically analyzed, including convolutional neural network (CNN), upsampling method, residual network, sharpening layer, structure reparameterization and Patch technology, and their mechanism in improving image reconstruction quality and detail recovery is revealed. On this basis, the paper further discusses the typical application scenarios of super-resolution technology in medical imaging, security monitoring, satellite remote sensing, high-definition video and image editing, and demonstrates the wide applicability and potential value of this technology in different industrial environments.

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Finally, the main challenges and future development directions are summarized, and it is pointed out that super-resolution research is evolving towards real degradation modeling, lightweight networks, multimodal fusion and high perceptual quality optimization. In general, the introduction of deep learning has made breakthrough progress in both theory and practice of image super-resolution technology. In the future, with algorithm optimization and hardware computing power improvement, it will play a more important role in intelligent vision, medical diagnosis, remote sensing monitoring and content creation.

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