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Advances in Image Super-Resolution: A Comprehensive Review of Machine Learning and Deep Learning Techniques

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***Abstract*—This review paper examines current ML and DL approaches for image super-resolution, including advancements in network architectures, loss functions, and optimization techniques that address key challenges such as computational efficiency, model generalize ability, and robustness to real-world variations. The paper further explores specialized techniques like multi-scale and hybrid models, as well as domain-specific SR solutions tailored for high-stakes applications like medical and satellite imaging. Additionally, it highlights emerging trends in evaluation metrics that capture both fidelity and perceptual quality, alongside strategies for real-time SR and model deployment on resource-constrained devices. By providing a comprehensive overview of current methodologies and identifying existing challenges and future research directions, this paper aims to support further innovation in the field of image super-resolution through machine learning and deep learning techniques.**

Keywords— Image Super resolution, machine learning, deep learning, SR, SISR.

I. Introduction

In recent years, SISR has been a major issue of discussion among scientists. Different high-resolution picture identification techniques have been developed, including single-image super-resolution. These answers appear to be very dependent on specific datasets and observations, as well as a range of conditions. The single-image super resolution is displayed in fig. 1.The process of turning low-resolution photos into high-resolution photographs is known as "super-resolution" (SR). In other words, LR denotes a single picture input, high-resolution is the actual data, and SR denotes the anticipated high-resolution. synthetic aperture radar images (SAR). The main objective of proposed research work to improve the visual quality of satellite and SAR images. [27]. "Remote sensing" refers to the study and method of learning about a thing, area, or phenomenon by analyzing data gathered by a machine that is not in contact with the thing, location, or activity being studied [20]. The remote sensing picture, collected by sensor spectral remote sensing techniques, provides a lot of information for monitoring the land temperature, and has a wide spectrum of uses in the areas of image corresponding and sensing, land surface identification, urban economic evaluation, energy investigation, and so on [19]. There is evidence to support the critical role of high-resolution satellite imagery. However, because of issues including long-range imaging, erratic weather, broadcast distortion, and mobility distortion, remote sensing photography has lower resolution and less geographic clarity than synthetic photos. The scales of surface elements in remotely sensed photography are also often different, which makes the items and their surroundings work together in the combined distribution of their picture patterns [18].

Image super-resolution (SR) is a pivotal task in computer vision that seeks to enhance the resolution of low-quality images, reconstructing fine details and textures that are otherwise lost in the downsizing process. This capability is essential in a variety of fields, including medical imaging, satellite imaging, security surveillance, and consumer photography, where high-resolution imagery is crucial for accurate analysis, interpretation, and decision-making. Traditional SR methods, such as interpolation techniques, often fail to preserve image quality and cannot recover intricate details, particularly for high-upscaling factors. The advent of machine learning (ML) and deep learning (DL) has ushered in new approaches to SR, enabling models to learn complex mappings from low-resolution to high-resolution images. Deep neural networks, especially convolutional neural networks (CNNs), Generative Adversarial Networks (GANs), and more recently, Transformer-based architectures, have demonstrated significant advancements in generating visually realistic, high-fidelity images. These models leverage large datasets to learn patterns and textures, thus producing sharper, more accurate outputs. However, challenges such as computational efficiency, model robustness, and generalization to varied real-world scenarios continue to drive research in this field.


Fig. 1 Shows the Single Image Super Resolution (SISR)

Single Image Super Resolution

A super-resolution network, as seen in fig. 1, at the earth's cubic, may be employed in a variety of procedures. It will be used to improve the process of categorizing photographs and make it simpler for users. They spend several hours subdividing automobiles or categorizing military aircraft, so improving the quality of the photos they're viewing speeds up their job, improves the quality of their categorization, and improves their overall well-being [14]. It is something that a large number of individuals might benefit from as well. This improvement may be beneficial to people as well as robots. The purpose of single image super-resolution (SISR) is to boost image resolution beyond the limitations of the sensor. That also means growing in terms of visual elements without maintaining greater location data than the initial acquisition equipment acquired. There are two types of SR approaches, single-image and multi- image, that may be used according to the input pictures. Multi-image SR methods need numerous scene images to be obtained concurrently at various places, while single- image SR approaches employ a single image of the target scene to get the super-resolved output [15]. The single-image technique is often used in remote sensing because it gives a more flexible strategy for super-resolving any kind of imaging sensor without requiring a satellite constellation. This problem is usually solved by using strong information from a group of images to narrow down the number of possible solutions.

A CNN [16] is a kind of neural network that specializes in processing data with an energy structure as well as images. A digital graphic is an output of visual information. The SRCNN [14] is a deep CNN that learns how to translate low-resolution images to high-resolution images from start to finish. As a consequence, authors may use it to enhance the picture quality of low-resolution photographs. This network's performance will be evaluated. The low-information, smooth interpolation between known pixels is used in the super resolution approach for picture up sampling. These approaches may be thought of as convolutional with a kernel that contains no information about the original image. Despite the fact that they improve picture resolution, they do not generate the clarity required for the super-resolution job. CNNs are a generalization of such algorithms that use trained kernels with nonlinear activations to encode generic properties about photos that may provide structure to the low-resolution input. The super-resolution challenge has been successfully applied to CNN [24] systems such as SRCN [17].

High resolution may be achieved by using predictable results and intersecting areas that be the images as well as analysis. It may also be feasible to create a single high-resolution picture. to improve the spectral characteristics and eliminate the performance degradation and limits of the pixel level imaging technology and method. The need for high resolution is ubiquitous, especially in computer vision applications. Pattern recognition and image analysis performance. In the medical profession, high resolution is critical. Many applications require zooming in on a particular region of interest in an image where high resolution is required. "Super-resolution imaging" (SR) is a group of methods that improve an imaging system's resolution [26]. The diffraction limit of systems is overcome in visual super resolution, while the resolution of digital image sensors is improved in topological super resolution. The finer the spectral resolution, the smaller the frequency ranges are for a dedicated channel or spectrum [25]. The time between images is referred to as temporal resolution. Since the start of the space era, sensors' capacity to give photos of the same geographic region more frequently has improved substantially. There are lots of aesthetically stunning satellite photographs that may be found on the internet. Instrument measurements on a space-based station give so much more than photos; they often provide geographical information. Understanding and comprehending earth system principles requires the capacity to assess and analyze spatial data [18].

II. LITERATURE REVIEW

Zhang, et.al, (2020), “Remote sensing image super-resolution via mixed high- order attention network”, In this article, the researcher has introduced a new network named MHAEN (Multi-Head Attention Enhanced Network) for Remote Sensing Image Super-Resolution (SR). This network fully leverages the benefits of ordered Hierarchical Order Attention (HOA) modules applied to feature maps from different frequency bands. Compared to commonly used Spatial Channel Attention (SCA), the presented HOA module is capable of modeling complex and high-order statistics. Due to the concatenation of feature maps in the channel-wise concatenation (WS-Cat), the ratio between nonlinear and identification mapping branches can be adaptively adjusted, enhancing the representational capacity of the model. Additionally, the Feature Attention Calibration (FAC) is introduced to effectively combine feature extraction and feature refinement networks. Extensive experimental results indicate that the proposed MHAEN can outperform modern methods with less computational time and GPU cost, demonstrating its superiority in terms of efficiency and performance in Remote Sensing Image Super-Resolution techniques [1].

Li, et.al. (2019),"Feedback network for image super-resolution", In this study, the researcher has introduced a novel network designed for image super-resolution, termed as the Super-Resolution Feedback Network (SRFBN). This network effectively reconstructs images by elevating low-level representation while preserving high-level representation. Incorporated within the network is a Feedback Block (FB) that adeptly manages the flow of feedback information along with the efficient reuse of features.Moreover, a curriculum learning strategy has been presented to adapt the network for more intricate tasks, particularly where low-resolution images are affected by a complex degradation model. Comprehensive experimental results reveal that the SRFBN, utilizing minimal parameters, can either match or outperform modern techniques [2].

Dai, et.al. (2019), "Second-order attention network for single image super- resolution." The researcher has introduced a comprehensive Second Order Attention Network (SOAN) designed for precise image super-resolution. Particularly, this network incorporates the Non-Local Residual Groups (NLRG) structure, allowing it to grasp distant dependencies and structural information while facilitating the skip connection of low-frequency information from LR images through source connections. Furthermore, the researcher has presented the Second Order Channel Attention (SOCA) module to enhance global feature interdependence learning through global average pooling. In addition to exploiting spatial relationships for local improvement, the SOCA module demonstrates its efficacy in achieving more distinctive representation. The experimental results, conducted on super-resolution tasks with Bicubic and BSD degradation models, highlight the effectiveness of SOAN in delivering both quantitative and visual improvements [3].

Zhao, et.al, (2019), "FC2N: Fully Channel-Concatenated Network for Single Image Super-Resolution." In this study, the researcher has presented a novel and simplified network structure, FC2N, aiming to achieve efficient image super-resolution (SR). Instead of initiating all skip connections as the Weighted Contextual Connections (WCC) in the network, FC2N adopts residual learning. Utilizing Differentiable Weighted Skip Connections (DWSC), the model not only can selectively adapt effective inter-layer skips and fully exploit ordered features but also attend to both linear and non- linear features. The incorporation of Channel Interaction Context (CIC) with the Channel Group Interaction (CGI) structure can facilitate learning local representations, enabling the model to effectively merge features at fine and coarse levels.

Comprehensive experiments demonstrate that the FC2N model surpasses the most advanced models in both lightweight and large-scale deployments, affirming its effectiveness in extracting model representation capabilities [4].

Hou, et.al (2017), "Adaptive super-resolution for remote sensing images based on sparse representation with global joint dictionary model", in this study, the researcher combined a GJDM with an adaptable SR for remote sensing pictures based on sparse representation. The NL feature was added to the SR model to improve the reconstructed HR pictures' naturalness and edge clarity. In order to properly depict the textures and edges of the picture, the researcher first chose an appropriate image feature to train the joint dictionary using. In order to enhance the rebuilt HR image's realism, the study also employed a global constraint. Finally, the researcher used Algorithm 1 to get the best outcome. The researcher's technique produced good results in terms of visual perception and PSNR when compared to three other methods [5].

Chang, et.al (2018), "Single image super-resolution using collaborative representation and non-local self-similarity", This study investigates a competitive reconstruction-based framework that simultaneously incorporates external and internal priors of natural images. Initially, it gathers appropriate local neighbors from external data to establish the Competitive Reconstruction Residual (CRR) prior. Following this, to enhance the super-resolution (SR) results, the algorithm integrates the Non-Local Residual (NLR) prior, which exploits Non-Local Self-Similarity (NLSS) in natural images. The effectiveness of the proposed Competitive Reconstruction-based Natural image Super-resolution (CRNS) algorithm is demonstrated through experimental results, comparing it with various SR methods. Notably, CRNS exhibits an average improvement over NCSR (ranking second among all tested methods) of 0.40 dB in PSNR, 0.0068 in SSIM, and 0.0059 in FSIM. However, it is important to note that CRNS comes with a higher computational burden compared to other benchmark methods [6].

Zhang, et.al. (2018), "Residual dense network for image super-resolution", In this study, residual dense block (RDB) is used as the fundamental construction module in a very deep residual dense network (RDN) for image SR. Each RDB's extensive connections between its levels enable the complete utilization of its local layers. In addition to stabilising the training broader network, local feature fusion (LFF) determines adaptively how much data from previous and current RDBs is preserved. Contiguous memory (CM) is made possible by RDB's additional allowance of direct connections between each layer of the current block and the previous RDB. The gradient and information flow are further enhanced by the local residual leaning (LRL). Global feature fusion (GFF), another method the researcher described, is used to extract hierarchical features from the LR space. Deep supervision and dense feature fusion are achieved by researching RDN with the complete use of local and global features. Three degradation models and real-world data are handled by researchers using the same RDN framework [7].

Zhang,et.al. (2018), "Image super-resolution using very deep residual channel attention networks", Very deep residual channel attention networks (RCAN) for extremely accurate image SR were provided by the researchers. More specifically, RCAN can achieve extremely big depth with LSC and SSC thanks to the residual in residual (RIR) structure. In the meanwhile, RIR enables a multitude of skip connections to circumvent copious amounts of low-frequency information, allowing the main network to concentrate on acquiring high-frequency information. Additionally, by taking into account the interdependencies across channels, the researcher proposed the channel attention (CA) mechanism, which enhances the network's capacity to adaptively rescale channel-wise characteristics. The efficacy of the researcher's proposed RCAN is demonstrated by extensive studies on SR using BI and BD models. RCAN demonstrates encouraging outcomes in object recognition as well [8].

Haris, et.al. (2018), "Deep back-projection networks for super-resolution", A researcher has introduced a novel deep back-projection network designed for single- image super-resolution. Unlike previous methods that rely on feed-forward approaches for predicting high-resolution images, this research emphasizes the improvement of direct super-resolution features by incorporating multiple upsampling and downsampling stages. At each depth of the network, error feedback is introduced to refine the samples, and self-improvements from each upsampling stage are aggregated to generate the super-resolution image. The researcher leverages error feedback from both up and down-scaling stages to guide the network towards better outcomes. The results illustrate the efficacy of the proposed network, outperforming other contemporary techniques, particularly demonstrating superior performance in scenarios with large scaling factors, such as 8×. This work has received partial support from FCRAL [9].

Lei, et.al. (2017), "Super-resolution for remote sensing images via local–global combined network", To fully use the representations of deep CNNs for the super resolution of remote sensing pictures, researchers created a unique network called LGCNet. The LGC Net learns multilayer representations of ground objects and environmental priors with the goal of reconstructing residuals between pairs of low- resolution and related high-resolution images. The experimental findings demonstrate that combining several layers yields more precise reconstruction outcomes. Using a variety of cutting-edge algorithms, the researcher's strategy produces overall increases in accuracy and visual performance (for all 21 classes). Furthermore, real-world trials validate the resilience of the researcher's LGCNet, and the addition of extra layers to the representation portion slows down the rate of quality improvement [10].

Tong, et.al. (2017), "Image super-resolution using dense skip connections", Researchers have introduced a unique network in this study that uses dense skip links for support resolution (SR). On four benchmark datasets, the provided methodology significantly outperforms state-of-the-art solutions in terms of PSNR and SSIM. The rebuilding findings visually show a significant improvement. Additionally, researchers have shown that enhancing SR performance might benefit from the combination of characteristics at various levels. In order to recreate photo-realistic HR pictures, future work will concentrate on integrating perceptual loss into the network that has been shown [11].

Table.1 Different Method Comparison of previous year

Year / Ref	Journal	Adopted Methodology	Remark/ Data Set	Outcomes / Result
2020/[1]	IEEE	reconstruction- based methods	RSSCN7	PSNR- 34.28 SSIM- 0.953
2019/[2]	IEEE	deep learning based methods	DIV2K	PSNR- 39.28 SSIM- 0.9784
2019/[3]	IEEE	CNN-based methods	DIV2K	PSNR- 39.72 SSIM- 0.9797
2019/[4]	Elsevier	convolutional neural networks (CNNs)	DIV2K	PSNR- 39.68 SSIM- 0.9792
2018/[5]	IEEE	learning based methods	USC_SIPI	GJDM (TD1) -37.O7 GJDM (TD2) -37.013

2018/[6]	ELSEVIER	Collaborative-Representation-Based	BSD100	PSNR- 27.54 d SSIM- 0.8479

III. Problem Formulation

Identifying the main problems in image super-resolution (SR) using machine learning is essential for creating effective solutions and understanding research directions. Here are some key problem areas:

1. Data Quality and Quantity

- **Limited High-Resolution Data**: High-quality image datasets for training SR models are limited, especially for specific domains like medical imaging.
- **Image Quality Variability**: Real-world images can have noise, blurriness, and compression artifacts, which complicate the SR process.
- **Synthetic vs. Realistic Data**: Many SR datasets are generated by artificially downsampling high-resolution images, but these synthetic low-resolution (LR) images do not always represent real-world scenarios.

2. Model Complexity and Efficiency

- **Large Model Sizes**: Many SR models, especially deep neural networks, require extensive memory and computational resources.
- **Slow Inference Speed**: Achieving high-quality SR often requires deep, complex networks that may be computationally intensive, impacting real-time performance.
- **Hardware Limitations**: Deploying SR models on resource-constrained devices, such as mobile phones, is challenging due to the model size and computation requirements.

3. Generalization and Robustness

- **Overfitting to Training Data**: SR models trained on specific datasets may not generalize well to images from different domains or conditions.
- **Sensitivity to Noise and Artifacts**: Many SR methods struggle with images that have heavy noise, compression artifacts, or unusual textures, leading to artifacts in the SR output.
- **Scale Variability**: Different applications may require different upscaling factors, but training for multiple scales simultaneously can reduce model performance.

4. Loss Function Design

- **Choice of Loss Function**: SR models often rely on pixel-wise losses (e.g., MSE or L1), which may not capture perceptual quality well. This can result in blurry outputs, especially for high-upscale factors.
- **Balancing Perceptual Quality and Fidelity**: Perceptual losses (e.g., perceptual loss, GAN-based loss) can improve visual quality but may create artifacts and reduce fidelity, leading to a Trade-off between sharpness and faithfulness to the original image.

5. Evaluation Metrics

- **Subjective Nature of Image Quality**: Objective metrics (PSNR, SSIM) may not correlate well with human perception of image quality, especially at high resolutions.
- **Inconsistency Across Applications**: SR performance metrics may vary by application (e.g., medical, satellite, or general images), requiring custom metrics to evaluate model effectiveness accurately.

6. Domain-Specific Challenges

- **Medical Imaging**: High-stakes fields like medical imaging require SR models to enhance image details while preserving diagnostic information, with minimal artifacts.
- **Real-Time Applications**: In applications like video SR or streaming, real-time processing is necessary, which requires balancing quality with speed.

IV. Expected Solution

1) Advanced Network Architectures for SR

- **Convolutional Neural Networks (CNNs)**: Standard CNNs are powerful for SR, with architectures like SRCNN (Super-Resolution CNN) providing a basic yet effective structure. These can be improved by adding residual connections (ResNet) or dense connections (DenseNet) to make deeper networks trainable and to enhance feature propagation.
- **Residual and Recursive Networks**: Architectures like VDSR (Very Deep Super-Resolution Network) and EDSR (Enhanced Deep Super-Resolution Network) use residual learning to improve performance on higher upscaling factors. Recursive SR networks like DRCN (Deeply-Recursive Convolutional Network) reuse parameters, making models smaller and more efficient.
- **Transformer-based Architectures**: Vision Transformers (ViTs) and Swin Transformers are gaining traction in SR as they can capture global context better than traditional CNNs. Models like SwinIR (Swin Transformer for Image Restoration) show promising results in SR by integrating both local and global features.
- **Generative Adversarial Networks (GANs)**: GANs, especially SRGAN (Super-Resolution GAN) and ESRGAN (Enhanced SRGAN), use adversarial training to improve perceptual quality. They create more realistic textures by training a

generator and a discriminator network, which can make the output appear sharper and more visually appealing.

2) **Hybrid and Multi-Scale Approaches**

- **Multi-Scale SR Models**: Networks like LapSRN (Laplace Pyramid SR Network) handle different upscaling factors within a single architecture by creating intermediate layers, improving flexibility and consistency.
- **Hybrid Architectures**: Combining CNNs with other approaches like Transformers or Recursive Networks can leverage the strengths of both. For example, hybrid CNN-Transformer models can capture both local features and long-range dependencies, leading to high-quality SR results.

3) **Specialized Loss Functions for Better Quality**

- **Perceptual Loss**: Using feature maps from a pretrained network (e.g., VGG) as a loss function can encourage the model to produce images that look more natural to the human eye by focusing on perceptual quality rather than pixel accuracy.
- **Adversarial Loss**: GAN-based SR models often include adversarial loss, where a discriminator network penalizes images that look less realistic, pushing the generator to produce high-quality textures and details.
- **Content-Aware Losses**: Structure-aware or edge-preserving loss functions help SR models maintain structural integrity, especially for applications where details are critical, such as medical or satellite imaging.

4) **Efficient Model Optimization Techniques**

- **Pruning and Quantization**: Model compression techniques like pruning and quantization reduce model size and computation without heavily sacrificing accuracy, which is especially useful for deploying SR models on mobile or embedded devices.
- **Knowledge Distillation**: Training a smaller “student” SR model to mimic a larger “teacher” model’s output can reduce complexity, making the model more efficient for real-time applications.
- **Lightweight SR Models**: Architectures like MobileNet and EfficientNet, adapted for SR, use depthwise separable convolutions to reduce computational cost while retaining high quality.

5) **Data Augmentation and Realistic Data Generation**

- **Realistic Data Augmentation**: Instead of simply downsampling high-resolution images, applying various types of noise, blur, and compression artifacts during training can make SR models more robust to real-world data.
- **Synthetic Data Generation with GANs**: GANs can simulate realistic LR images that mimic real-world conditions, improving model robustness. For instance, CycleGAN can be used for unsupervised domain adaptation in SR, enabling models to generalize better on data with different distributions.

V.CONCLUSION

In conclusion, image super-resolution (SR) has made substantial strides through the application of machine learning and deep learning, establishing itself as a key tool in enhancing visual clarity across various high-impact domains, including medical diagnostics, remote sensing, and video streaming. Deep learning models, particularly CNNs, GANs, and Transformer-based architectures, have significantly advanced the state of SR by achieving higher fidelity and perceptual quality than traditional methods. While these methods have shown impressive results, challenges remain, particularly in balancing computational efficiency with image quality, improving generalization across diverse real-world datasets, and ensuring robustness against noise and artifacts. Efforts to address these challenges have led to novel architectures, sophisticated loss functions, and efficient optimization techniques, all contributing to more versatile and powerful SR models. Domain-specific SR applications have also emerged, tailoring solutions to unique demands in fields like medical and satellite imaging, where image accuracy is critical.

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