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An Extensive Review of Developments and Methods in Super-Resolution Image Reconstruction

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ABSTRACT

Super-resolution (SR) image reconstruction plays a vital role in enhancing the resolution of low-resolution (LR) images, benefiting various fields such as remote sensing, medical imaging, and surveillance. The SR problem entails reconstructing high-resolution (HR) images from LR inputs, typically due to the loss of high-frequency information and the problem's ill-posed nature. This review study presents a comprehensive overview of recent developments and approaches in SR image reconstruction. This study primarily presents three approaches: methods based on learning, methods based on reconstruction, and methods based on interpolation. Despite the fact that interpolation-based approaches, such as bicubic interpolation, are straightforward and quick, they frequently result in blurring and loss of high-frequency features. Reconstruction-based methods leverage prior knowledge of image characteristics to recover HR images, often through optimization techniques. However, these methods may suffer from slow convergence and high computational cost. Because of their capacity to learn complicated mappings between LR and HR picture spaces, learning-based methods—and deep learning approaches in particular—have been the center of a lot of attention lately. These methods leverage large datasets to train convolutional neural networks (CNNs) for image super-resolution, achieving remarkable performance in terms of visual quality and computational efficiency. Furthermore, we discuss the challenges and future directions in SR research, including the development of more robust and efficient algorithms, handling noisy real-world data, and exploring novel architectures and loss functions to further improve SR performance. The purpose of this review paper is to provide a comprehensive overview of strategies for SR image reconstruction. It focuses on the progression from conventional interpolation methods to cutting-edge deep learning approaches. They hope that this publication will serve as a valuable resource for scholars and practitioners in the field of computer vision and image processing.

keywords - Super-resolution, Image reconstruction, Low-resolution images, High-resolution images, Interpolation-based methods

I INTRODUCTION

A wide range of industries, including agriculture, meteorology, geography, the military, and others, have found widespread applications for remote sensing imaging technology. Remote sensing photographs are extremely useful in a variety of contexts, including the monitoring of pests and diseases, the forecasting of climate change, the surveying of geological features, and the marking of military targets. High-resolution photos can be difficult to capture due to the fact that the quality of remote sensing images can be negatively impacted by a variety of variables, including interference from the surroundings around the sensor, optical distortion, and noise from the sensor system itself. Image SR, a technique that attempts to reconstruct high-resolution (HR) images from low-resolution

(LR) photographs, can enhance the resolution of remote sensing images. This is because SR helps offset the impacts of acquisition equipment and ambient conditions. The SR problem is ill-posed because low-pass filtering and secondary sampling processes obliterate high-frequency data. The inherent difficulty in solving it accounts for this. Because the SR operation requires several mappings from the LR space to the HR space, it results in multiple solution spaces for any LR input. Because of this, it is vital to establish which solution is the desired one. The three major categories that summarize the various approaches suggested as potential solutions to the SR problem are interpolation-based methods, reconstruction-based methods, and learning-based methods. Despite the fact that interpolation-based methods are straightforward and quick, there is a possibility that they will result in a reduction in model fidelity because of the removal of high-frequency information that occurs during upsampling. It is possible for reconstruction-based methods to suffer from poor convergence speed and high computational cost. However, these methods incorporate past image information into the surface reconstruction (SR) process. Learning-based approaches necessitate a significant number of LR and HR image pairs to gain the necessary knowledge for mapping between LR and HR image spaces. Deep learning-based algorithms have gained popularity for SR due to their ability to effectively predict when low-resolution photos would lack high-frequency information. This is because these approaches save both time and computational resources
[1].

Figure 1.SR aims to reconstruct a high-resolution (HR) image from its degraded lowresolution (LR) counterpart.

Deep learning is a research topic that is always undergoing development. In recent years, deep learning-based SR models have proliferated. These models have helped to achieve significant results on benchmark SR test datasets. Furthermore, the use of SR models to perform super-resolution activities on remote sensing photographs has emerged as a growing topic within SR. This is due to the numerous uses for SR models in the field. Researchers have put in a tremendous deal of effort to enhance the performance of SR models when applied to remote sensing photos.
The first step involved building a model with three CNN layers, known as SRCNN [2]. This led Kim et al. to raise DRCN's network depth to twenty nodes [3], which yielded drastically better experimental results than SRCNN [4]. As a result, Liebel et al. [20] modified SRCNN [4] to accommodate the multispectral properties of remote sensing data by retraining it using satellite image datasets. VDSR [5] also addressed the problem of processing multi-scale images within a single framework, incorporating residual learning and gradient cropping into its solution. Additionally, to achieve this, VDSR increased the number of network layers. Lei et al. [6] proposed a hybrid local-global network known as LGCnet. This network, as a hybrid model, uses VDSR as its foundation. This network's branching structure, which incorporates both shallow and deep features, addresses the issue of losing local details in remote sensing images. This structure extensively utilizes both local and global data. Combining shallow and deep characteristics is the solution to this challenge. Guo and colleagues created a dual regression model, known as DRN [7], to tackle the discomfort resulting from image superresolution. This model directly learns the mappings from the LR images, eliminating the need to

rely on the HR images. Generally, they optimize most SR approaches based on the following factors to achieve superior results: Creating the learning strategy, choosing the loss function, and designing the network architecture are all examples of such labor. Deep learning-based SR approaches are receiving increasing attention due to their superior performance. SR has been the subject of numerous published survey articles. The majority of these studies, on the other hand, highlight a variety of evaluation metrics for the reconstruction results of statistical reconstruction algorithms.

The purpose of this research was not merely to present a summary of the survey works that are currently available; rather, they aimed to provide a full overview of systematic review approaches. The primary focus was on the concepts and methods of deep learning, aiming to demonstrate its performance, originality, strengths and weaknesses, relevance, and issues. They also focused on the specific applications of these techniques for remote sensing graphical representations.

The main contributions of this paper are as follows:

- In order to give this study with a comprehensive basis, we will first provide an introduction to the technique of super-resolution that is performed using deep learning. This introduction covers all the bases: problem definitions, datasets, learning procedures, including evaluation methods.
- We classify the SR algorithms based on the design requirements they meet. On top of that, they study the effectiveness of various performance metrics for popular SR algorithms on benchmark domains. Furthermore, they review several recent papers that discuss super-resolution techniques for remote sensing image creation. This article aims to present and debate the visual effects of typical SR methods on remote sensing images.
- The authors evaluate the current issues and limits of super-resolution remote sensing images from many perspectives, offer useful recommendations, and describe future trends and prospects for improvement.

In addition, we present the results.

What follows is a timeline of the remaining sections of this evaluation.

The definition of deep learning-based SR, common datasets, and assessment metrics are covered in Section 2. You can find a detailed discussion of representative topologies for SR jobs in Section 3, which is available here. Section 4 employs several assessment criteria to evaluate the effectiveness of the SR techniques discussed in Section 3 and their use in remote sensing examples. In the fifth section, they will discuss the uses of SR in remote domains. Section 6 of this report discusses the current issues and probable future paths of SR. Section 7 concludes the effort.

Deep-Learning-Based Super-Resolution

Over the past few years, super-resolution deep learning [8] has experienced remarkable development as a result of advancements in computational capacities. Artificial neural networks established the concept of deep learning, an extension of machine learning [9]. Deep learning utilizes neural networks in its learning process. Artificial neural networks use artificial neurons as computational units to replicate the method by which the human brain processes information. The structure of the artificial neural network reflects the connections these neurons have with each other. Finding the data's feature distribution is the goal of deep learning, which entails learning a hierarchical representation [10] of the underlying features. In particular, deep learning is a strategy that employs a variety of learning strategies in order to continuously improve the performance of the super-resolution algorithm application. The deep network architecture, optimizer design, and loss function design are all examples of these tactics. Deep learning also aids in addressing the ill-posed problem of concurrent superresolution. Most of the time, the LR picture Ix is depicted as the result of the deterioration indicated in the following sentence:

$$Ix = I_x = I_y \otimes k\downarrow_s + n, \qquad (1)$$

The notation Iy k represents the HR image fusion with the degenerate blur kernel k, which includes the double cubic blur kernel, the Gaussian blur kernel, and more blur kernels. It is essential to note this fact. Furthermore, the down sampling operation with scale factor s is represented by the symbol <0xD3>s, whereas the reference to the typical Gaussian white noise is represented by the symbol n.

Deep learning is able to convert the operations mentioned above into an end-to-end framework, which enables significant time and efficiency savings. This is in contrast to classical algorithms, which deep learning cannot do. Looking at Figure 3, it is clear that SRCNN's network topology is responsible for achieving this target. When it comes to the process of super-resolution of photographs, there are normally three stages involved. These steps include the extraction and representation of features, the visualization of non-linear mapping, and the reconstruction of images. The first phase is the extraction of feature blocks from the low-resolution image, which is accomplished by employing 9xC3>0x97>9 convolution. This is to provide a more specific explanation. Next, we create a highdimensional representation for each feature block. Then, using a 5<0x5E>5 convolution, the method comprises non-linearly mapping two high-dimensional vectors. The process is mapping-based, with each vector representing a high-resolution patch. By integrating the high-resolution patches mentioned earlier using the 5-convolution technique, the final highresolution image will be created in the following phase.

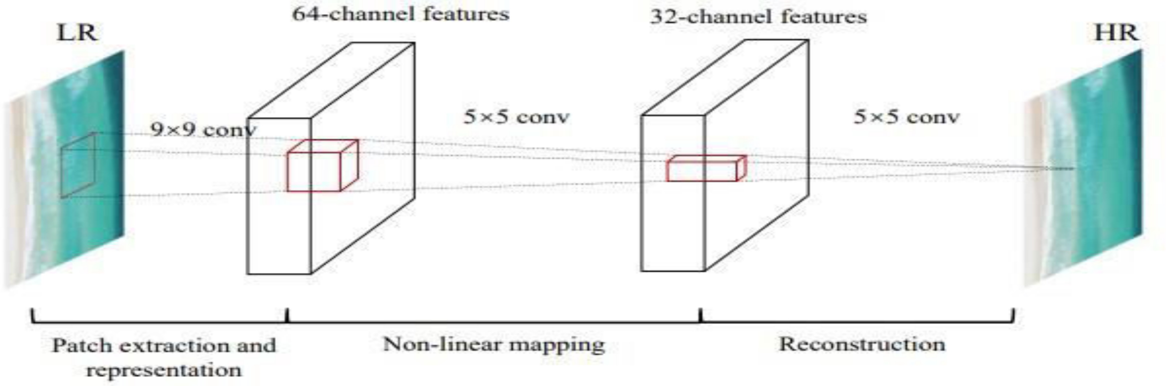


Figure 3. The network structure of SRCNN [18].

One thing that sets remote sensing images apart from natural ones is that they often depict large-scale scenes with small objects and varying distributions. Additionally, aerial photography, land and ocean satellites, and other methods typically capture these scenes from high above the earth, and different weather conditions can alter the quality of remote sensing images due to variations in sensor lighting and the obscuring effect of clouds and fog. Before we can consider super-resolution remote sensing picture reconstruction successful, we need to meet a number of conditions. Collecting remote sensing images from grasslands and woodlands results in extremely homogeneous scenery coloration. In this scene, using color alone to classify objects is difficult. When looking at these images at super-resolution, it's simple to tell the difference between the "rough" forest and the "smooth" grass. We achieve this by utilizing the texture elements in the image.

Training and Test Datasets

One way to train a model is with high-quality data; this technique is known as deep learning, and it uses the data to train its model. High-quality data has the potential to enhance the reconstruction performance of a deep learning SR-based model. Deep learning is a way of knowledge acquisition. Previous proposals have included a wide variety of datasets for training and testing SR tasks. We frequently use certain datasets, like BSDS300 [11], BSDS500 [12], DIV2K [13], and others, to train SR models. Similarly, we can utilize BSD100 [14], Set5 [15], Set14 [16], Urban100 [17], and other similar models to efficiently test the prototype's performance. When it comes to super-resolution activities involving remote sensing photos, databases like AID [38], RSSCN7 [18], and WHU-RS19 [40] have seen heavy use. Most SR models train on the DIV2K [34] dataset, which is considered the most representative among these datasets. The DIV2K [19] dataset has a variety of images, each with its own distinct qualities. It includes 800 training shots, 100 validation images, and 100 test images. It is possible for Set5 and Set14 to appropriately reflect the performance of the model because they are traditional test datasets for SR tasks. The outside Scene [41] dataset includes plants, animals, landscapes, reservoirs, and other types of outdoor settings. Initially, we used AID [38] to identify objects in remote sensing photos. This particular task encompasses a total of 10,000 remote sensing images, each measuring 600 x 600 pixels. These images depict various scenes, such as airports, beaches, deserts, and more. RSSCN7 [20], comprising 2800 remote sensing photos from a variety of seasons and grouped at four distinct sizes, depicts a variety of settings, including farmland, parking lots, residential areas, and industrial regions. The WHU-RS19 collection includes remote sensing photos from 19 different scenarios. Each category has a total of fifty photographs. Remote sensing photographs represent 21 different categories of scenes at the University of California, Merced. Each category has 100 images, and the size of each image is 256 x 256 pixels. Northwestern Polytechnic University is responsible for publishing NWHU-RESISC45 magazine. Northwestern Polytechnic University organizes the photographs into 45 distinct categories of scenes, each containing seven hundred photographs. RSC11, a collection of eleven distinct categories of scenes, each containing one hundred specific photographs, originates from Google Earth. The SR task also incorporated several datasets, such as ImageNet, VOC2012, and Celeb A, previously used for other image processing tasks. These datasets were introduced in addition to the ones that were presented above.

II RESEARCH METHODOLOGY

The study that was conducted for this work was a comprehensive review; yet, despite the fact A scoping review is similar to a systematic literature review but has more extensive research objectives. This study examines the ways in which artificial intelligence (AI) interacts with education by analyzing its applications, advantages, and challenges. There is a wealth of relevant literature on this subject. We also provide a clear image of the amount of literature and studies currently available, along with an outline of their subject matter, regardless of its broadness or specificity [22]. Two students, physically separated from one another, conducted these searches in May and June 2023. Both the Scopus and Google Scholar systems were the primary areas of focus from 2005 to 2023. The search yielded a total of ninety matches. The investigation initially identified ninety recordings for inclusion. We removed duplicate records to reduce the dataset to 78 for eligibility screening. The subsequent screening procedure eliminated five records from consideration. We evaluated the complete texts of the remaining 73 articles after determining their eligibility. They excluded thirteen articles due to insufficient full-text availability. The final analysis included a comprehensive selection of research articles pertinent to the study's aims, totaling fifty publications. This painstaking method not only adhered to strict eligibility requirements, but also thoroughly evaluated and included relevant literature in the study.

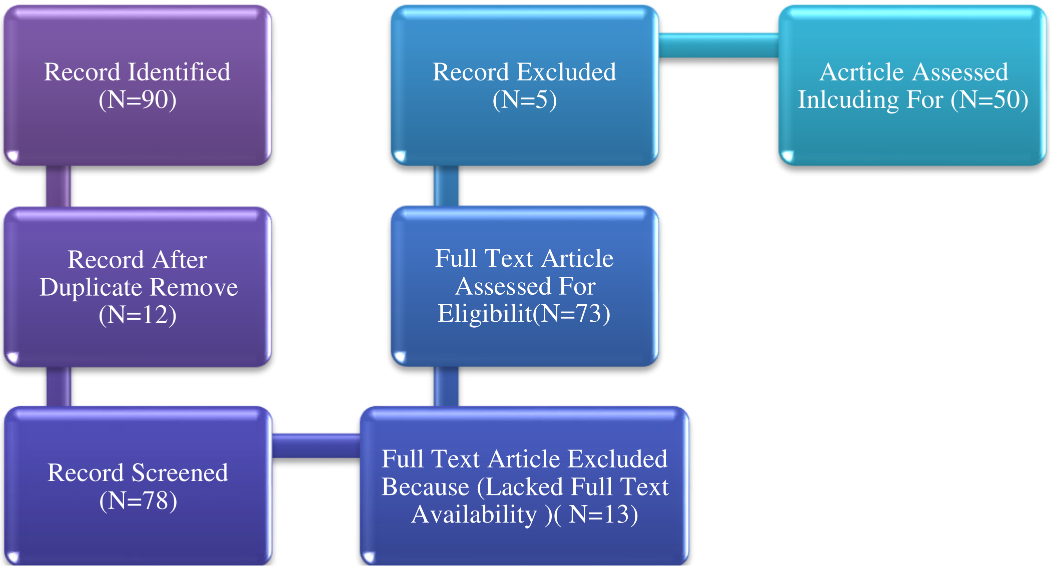


Figure 5.Overview of literature search process **Defining the Search String:**

Determine search phrases relevant to the topic of interest, focusing on titles, abstracts, and keywords.

Selecting Digital Libraries:

Utilize the following digital libraries:
ACM Digital Library (dl.acm.org)
IEEE Xplore (ieeexplore.ieee.org)
Science Direct (sciencedirect.com)
SpringerLink (springerlink.com) Scopus (scopus.com)

Conducting a Pilot Search:

Conduct an initial search in each digital library using the search phrases that have been identified in order to evaluate the results in terms of their relevance and coverage.

Refining the Search String:

By taking into consideration additional synonyms, different spellings, and antonyms for the keywords, the search string should be refined based on the results of the pilot search. When constructing a comprehensive search string, it is necessary to make any necessary adjustments to the Boolean logic (AND, OR). **Retrieving a Preliminary Set of Primary Studies:**

A preliminary collection of primary studies that are a match for the search parameters should be retrieved by executing the narrowed search string throughout the digital libraries that have been chosen. **Evaluation Methods**

Depending on the circumstances, the evaluation index of image reconstruction quality may reflect the reconstruction accuracy of an SR model. Conversely, we can express the performance of an SR model through the number of parameters, the duration of its execution, and the computations carried out.

This section presents techniques for assessing the quality of picture reconstruction and the effectiveness of reconstruction.

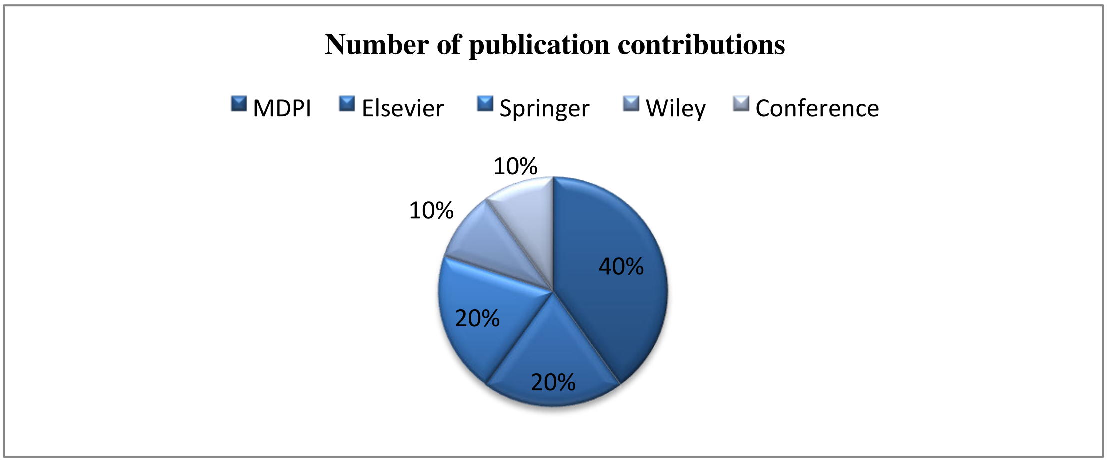
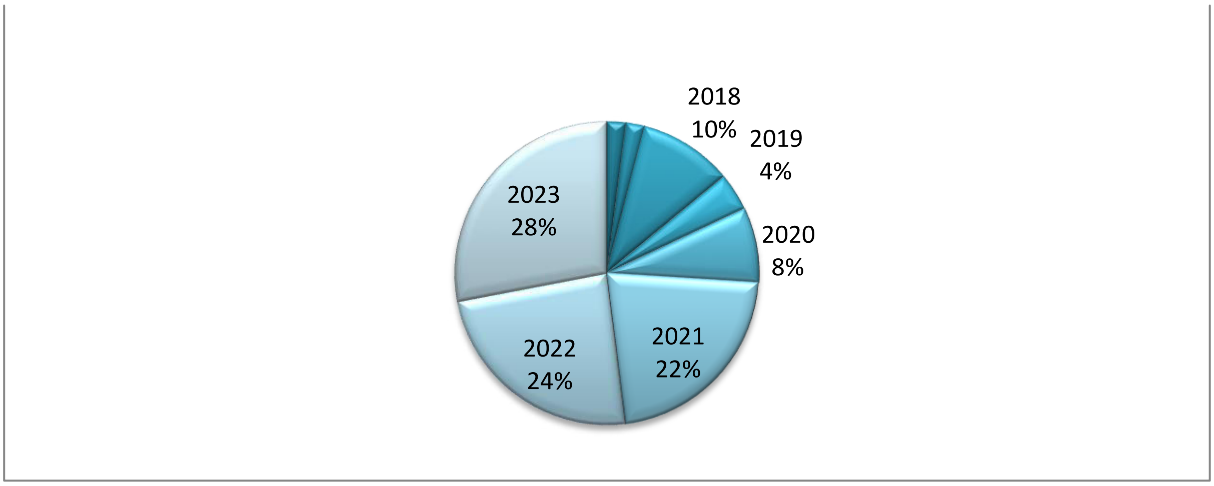


Figure 6 number of publication contributions

A recent study evaluated the scope of research in this area by analyzing a variety of academic sources, investigating the influence of artificial intelligence (AI) on the educational system. The research looked at a wide variety of publications, such as those published by MDPI, Elsevier, Springer, and Wiley, as well as documents from conference proceedings. With a total of twenty publications, MDPI was the source that supplied the most papers among these sources. Elsevier and Springer came in a close second with ten papers apiece that they donated. The number of papers contributed by Wiley was slightly fewer, with five, but the number of papers contributed by conference proceedings was five more. Synthesizing insights from a variety of sources in order to provide a thorough grasp of the subject matter, the review's objective was to conduct an exhaustive investigation into the applications, benefits, and difficulties that artificial intelligence (AI) presents in educational contexts.



2005 2%

Volume of Research Papers 2017 2%

Figure 7 Volumes of Research Papers

Over the course of several years, there has been a discernible shift in the number of research publications that document the influence that artificial intelligence (AI) has had on the field of education. The fact that only one paper was written about this subject in 2005 is indicative of the relatively young interest that existed at that time in the intersection of artificial intelligence and education. However, in 2017, this interest began to surge, leading to the addition of a single new publication to the existing body of knowledge. There was a considerable increase to five papers in 2018, which indicates that there is a growing awareness of the possible applications of artificial intelligence in educational settings. This signified the acceleration of momentum. This pattern repeated the following year, in 2019, with two more publications contributing to the ongoing discussion that was taking place. A further increase occurred in 2020, with four papers investigating various aspects of the impact that artificial intelligence has had on education. Following that, the field experienced a significant surge in 2021, with the publication of eleven papers, indicating a heightened concentration on this subject spanning multiple disciplines. In 2022, twelve publications continued to investigate the problems and opportunities presented by artificial intelligence in education. This enthusiasm continued into the year 2022. In 2023, the pattern peaked with the publication of a record fourteen papers. This exemplifies the growing interest and investment in comprehending and utilizing the potential of artificial intelligence to alter educational practices and outcomes.

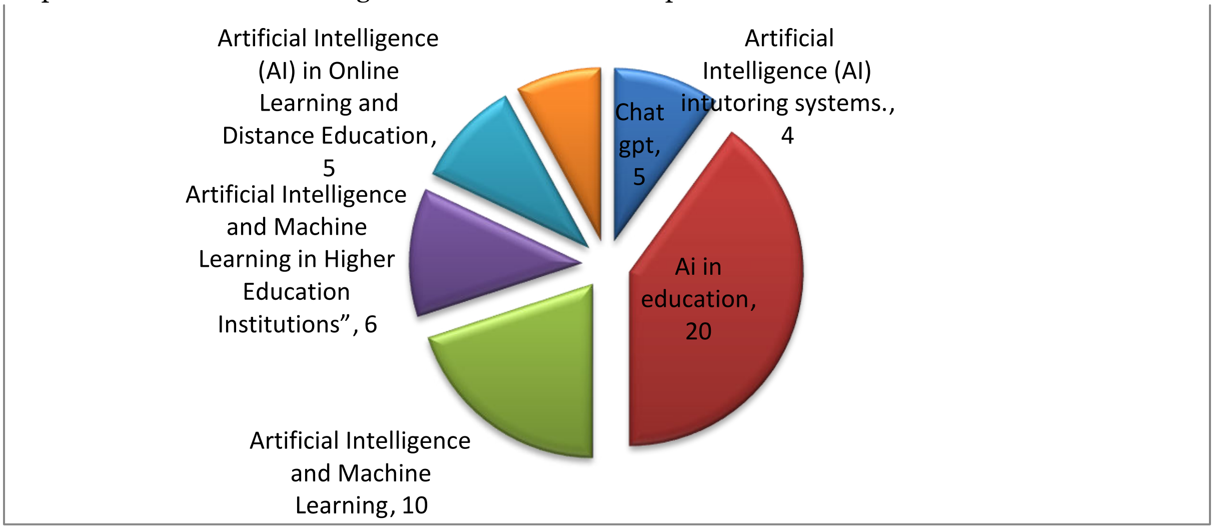


Figure 8 number of publication contributions in artificial intelligence (AI)

During the process of doing a literature review on AI in education, a wide variety of subjects came to light, each of which received a different amount of attention from academics. Underscoring the significance of artificial intelligence in education as a rapidly developing field of study, the majority of the research, which amounted to twenty articles, concentrated specifically on the overarching topic of AI in education. The topic "Artificial Intelligence and Machine Learning" received ten papers because of the interdisciplinary nature of the impact that artificial intelligence has on educational practices and systems. Six publications dedicated themselves to the analysis of artificial intelligence's role in higher education institutions, indicating a more detailed exploration. Five articles investigating the implications and uses of the convergence of artificial intelligence with online learning and remote education have garnered significant interest. Last but not least, the field of artificial intelligence in tutoring systems has emerged as a specialized area of research, with four publications devoted to gaining an understanding of its benefits and difficulties. These studies collectively underscored the diverse impact of artificial intelligence on education, spanning various contexts and applications.

Image Quality Assessment

Measuring the performance of the model requires the use of suitable picture evaluation measures because it is a visual task. The image's visual effect is often where the HSI quality assessment begins. The next step is to conduct an impartial evaluation of the observables' structure and spectral fidelity. When it comes to reviewing photos, researchers typically opt for objective assessment as their primary method of choice because, in comparison to subjective evaluation, objective evaluation is a quicker and less time-consuming form of evaluation. However, the commonly used objective evaluation criteria at this stage often don't align with the real human visual perception. This section introduces several commonly used objective evaluation measures. Image Quality Assessment (IQA) metrics accomplish a quantitative measurement of an image's quality in relation to a reference image. These metrics allow for the evaluation of a picture's fidelity after applying a variety of image processing techniques or compression. We commonly employ the following IQA measures:

PSNR (Peak Signal-to-Noise Ratio): The signal-to-noise ratio (PSNR) is a metric for evaluating a picture's quality that takes into account the signal-to-noise proportion relative to a reference image. The formula for calculating the PSNR is as follows:

PSNR=10*log10((MAX^2)/MSE)(1) Here, MAX represents the maximum pixel value that can be used (for example, 255 for an 8-bit image), and MSE represents the average squared difference between the original and distorted images of matching pixels.

RMSE (Root Mean Square Error): A measure called root-mean-squared error (RMSE) is used to determine how much of a change occurred between the original and distorted images' pixels. It is calculated as: RMSE = sqrt(MSE) (2)

SSIM (Structural Similarity Index): The SSIM algorithm compares the luminance, contrast, and structure of the original image with the deformed image in order to determine the degree of structural similarity between the two. A value between -1 and 1 is returned by it, with 1 indicating that there is no difference between the two. There are terms for brightness, contrast, and structural comparisons included in the calculation, which itself is somewhat complicated.

MAE (Mean Absolute Error): MAE measures the average absolute difference between corresponding pixels in the original and distorted images. It is calculated as:

MAE = (1 / N) * Σ|I_original - I_distorted| (3) Where N is the total number of pixels in the image.

Deep Architectures for Super-Resolution Network Design

This section will not only explain and demonstrate basic deep learning approaches, but also present and investigate a variety of common design ideas and network models used in the super-resolution domain. Also included in this section is the fact that network design is an essential component of the deep learning process. At long last, we will talk about a few design approaches that are worthy of investigation further.

Learning That Is Circular It is usual practice to improve the performance of the network by increasing the depth and width of the model; however, doing so might result in a significant increase in the number of computational parameters, as illustrated in Figure 4. Recursive learning controls the number of model parameters and achieves the goal of sharing parameters between recursive modules. For the sake of simplicity, recursive learning refers to the process of repeatedly utilizing the same module. Within the realm of super-resolution issues, the recursive unit in DRCN [23] is a single convolutional layer, which allows it to use recursive learning. Additionally, by activating 16 recursions, the perceptual field expands to approximately 41 without adding unnecessary parameters. The layered usage of recursive modules, on the other hand, can result in a number of disadvantages, including the absence or explosion of gradients. Therefore, DRRN implements global and local residual learning to address the gradient problem [57]. We use ResBlock as the recursive unit to reduce the complexity of the training process. (24) [24] These modifications have improved ResBlock's recursive application. To further accelerate network training and make the information transfer process more effective, they proposed a connection structure that included both global and local cascade connectivity. Furthermore, [25]'s EBRN utilizes recursive learning to distinguish information with varying frequencies. To achieve this distinction, the network designs shallow modules to process low-frequency information and deep modules to handle high-frequency information. Recent studies have extensively utilized recursive learning. For example, [26] proposed the SRRFN, A series of fractal modules with shared weights. This allows for the reuse of model parameters.

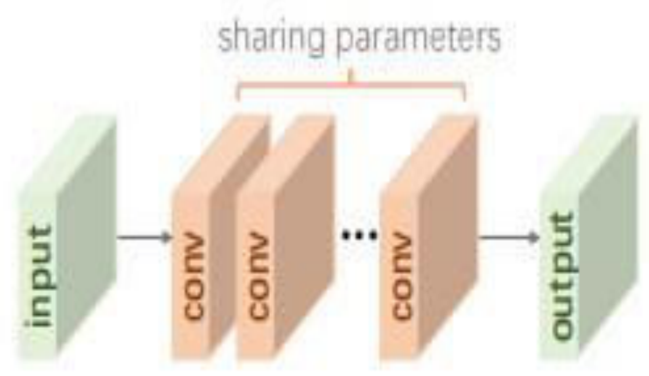


Figure 4. The structure of recursive learning

Residual Learning

Although recursive learning allows models to achieve a higher level of performance with the fewest parameters available, it also introduces the challenge of bursting or vanishing gradients at the same time. Residual learning is a commonly used strategy to address these challenges. (27) [27] (27) [27] ResNet proposed the use of residual learning as a potential application. Using layer-hopping connections to generate constant mappings aims to solve the problem of gradients that are either inflating or disappearing. This is intended to ensure that the network front-end can receive backpropagation gradients directly through shortcuts, as shown in Figure 5. Image super-resolution tasks typically require low-resolution input photos and high-resolution rebuilt images, which contain a lot of the key feature information. Therefore, learning only the residuals between the two sets of images is necessary to recover the lost information. This framework encompasses a significant number of models based on residual learning. [28] introduced the VDSR, a comprehensive super-resolution residual network based on VGG-16. This network, comprising twenty layers, uses an interpolated low-resolution image as its input image. When the network has learned all the leftover information and added it to the initial image, that's its output. This is the network's final product. Reference [29] states that other methods exist for creating this structure. The residual branch's conventional elements include three convolution layers, BN layers, and the relu activation function. So we can't do super-resolution operations on the residual module's BN layer, says EDSR [68]. The document clearly states this. The reason for this is that once the BN layer is processed, it normalizes the color distribution of any given image. This is the reason why it is the case. This leads to the loss of contrast information from the original image, negatively impacting the network's image quality. This leads to the frequent removal of the BN layer during the residual module generation process for super-resolution projects. This is due to the rationale stated above. RDN proposes the residual dense block (RDB), which preserves all the properties present in the output of each convolution layer. This is what makes the residual dense block (RDB) so effective. Today's world widely employs residual learning as a technique for building super-resolution networks and incorporates it into a wide range of models [30].

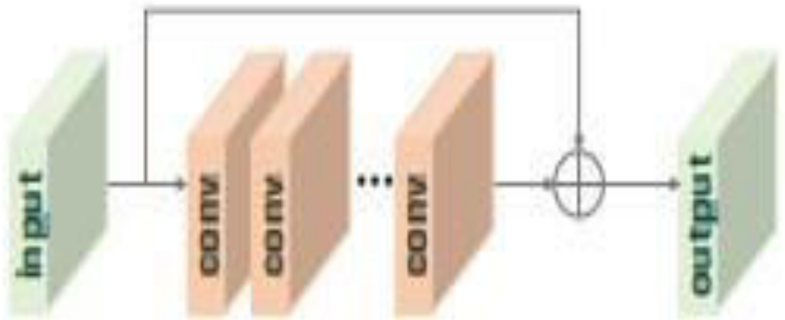


Figure 5. The structure of residual learning.

The term "global residual learning" refers to the jump connection that builds from the input to the output, even though this technique for global residual learning manages to produce satisfactory results. This is due to the inability of global residual learning to recover a significant amount of lost information at increasingly complex network levels. As a result, researchers recommend using local residual learning, which aids in detail preservation and is located in every few stacked layers. Models that use a technique that blends global and local residual learning to carry out their operations. People have noticed that photographs of varying sizes exhibit a variety of characteristics, and these diverse characteristics will contribute to the generation of superior quality reconstructed images. We have presented multi-scale learning as a technique that enables models to fully exploit characteristics at many sizes, concurrently applying it to a large number of SR models. This is due to the effective demonstration of multi-scale learning. Since [31] concluded that earlier models were less scalable and robust to scale, multi-scale learning has been applied to strategic planning. As a result, multi-scale learning was utilized. In his presentation, he used a 1xC7>1 convolution kernel, along with 3xC7>3 and 5xC7>5 convolution kernels, to gather data at several scales, introducing a multi-scale residual module (MSRB). This can be seen in Figure 6. Additionally, the implementation of local residual learning aimed to enhance the efficiency of network training. For the purpose of extracting and fusing picture features that are present at many scales, the authors of [32] presented a multi-scale feature fusion residual block, also known as MSFFRB. The combination of multi-scale learning and residual learning was an effective method for achieving this goal. To extract information about variable frequencies, the multi-scale feature extraction and attention module (MSFEAAB) described in [33] used convolution kernels with varying sizes within the same layer. We did this to achieve the goal of extracting information. The extraction of low-frequency components is mostly the responsibility of convolution kernels of a smaller size, whereas the extraction of highfrequency components is primarily the responsibility of convolution kernels of a bigger size. Despite collecting rich image features, the algorithm's complexity remains unchanged. An increasing number of SR network models have incorporated multi-scale learning in recent times to enhance their performance. In the paper ELAN [34], the authors presented the grouped multi-scale self-attention (GMSA) module as a method for establishing long-range dependencies. This module computes self-attention by using windows of varying widths on a set of non-overlapping feature maps.

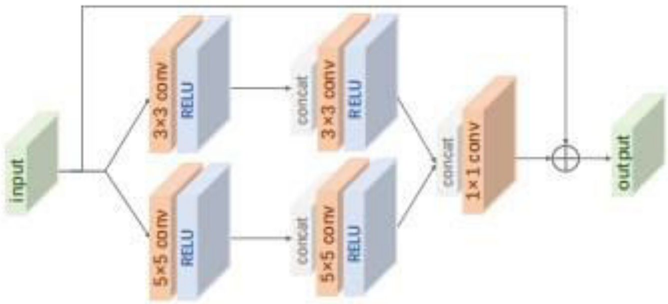


Figure 6. The structure of multi-scale residual block (MSRB)

Attention Mechanism

With convolutional neural networks, local knowledge is more important than global features. We created the attention mechanism to address this issue. A wide variety of computer vision activities make extensive use of the attention mechanism, which is frequently incorporated as a component into the backbone network. This mechanism's primary goal is to distribute computational resources to more significant jobs with limited processing capacity. In summary, the attention mechanism allows the network to ignore irrelevant information and focus on important ones. In the past, numerous works have been offered with the intention of facilitating the progress of attention processes. For instance, in [35], they introduced a novel "squeeze and excite" (SE) block. According to Figure 7, this block can change how channel feature replies work in a way that adapts to how channels depend on each other. The attention mechanism has started to focus on picture super-resolution tasks due to ongoing research and advancements in this field

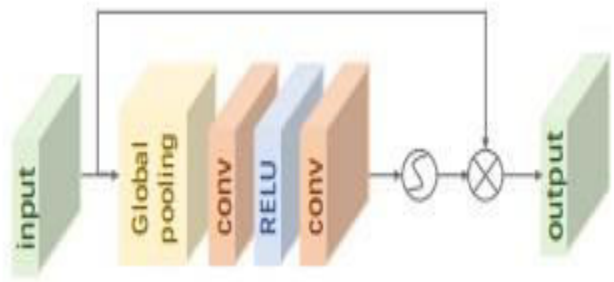


Figure 7. The structure of channel attention mechanism [80].

Channel Attention

In RCAN [36], a residual channel attention block (RCAB) was presented as a means of achieving improved accuracy through the process of learning the connection between channels in order to change individual channel attributes. Liu et al. [37] added an enhanced spatial attention (ESA) block to make the network focus more on the important spatial elements, which are part of the residual features. Every residual block may be smaller and easier to insert because this block used a 1/1 convolution to decrease the number of channels. Additionally, we utilize three of the three-by-three convolution combinations to broaden the scope of the perceptual field. Using this technique will result in the loss of several intermediate features during the image reconstruction process. This is because channel attention treats each convolution layer independently, without considering the correlation between the various levels. Based on this understanding, the authors of [38] A layer attention module (LAM) and a CSAM make up the holistic attention network (HAN). By gathering how features at different depths rely on each other, the LAM can offer different levels of attention to different layers of features. This will then allow the CSAM to learn about the relationships at different points in each feature map. This will make it easier for the LAM to find global features. The second-order channel attention (SOCA) function in SAN learns the relationship between the features on different channels. We use the second-order averages of the features to achieve this result. Before training the channel attention, the MMCA module changed the picture characteristics to the frequency domain using the discrete cosine transform (DCT). We took this action to accurately reconstruct the SOTA results.

Non-Local Attention

Most of the time, image super-resolution networks can only effectively extract local information from images. They don't notice the link between long-range properties in pictures because their perceptual field size is too small. However, the information that this may provide is critical for image reconstruction. This has led to suggestions for certain studies about the association of non-local features. For example, in SAN, the region non-local RLNL module aims to segment the input image into its component parts and apply non-local operations to each of those parts independently. The tally comes to 39. In order to understand the relationships between deep features in one place and those in other places, someone proposed employing a non-local recurrent network (NLRN). A few examples of applications for this network are image recovery and recurrent neural networks (RNN) that incorporate non-local operations. Research demonstrated that a cross-scale non-local (CS-NL) attention module could aid in the non-local focus of CSNLN. Using this module, one can determine the degree to which their image's LR feature blocks resemble their HR target feature blocks. This makes the SR model work better.

Other Attention

In addition to the typical attention mechanisms discussed earlier, there are a few attention mechanisms that were constructed from a specific perspective. The contextual reasoning attention network, for instance, is responsible for the generation of attention masks by utilizing global contextual information. This enables the constant adjustment of the convolutional kernel size to adapt to changes in visual features. 40.0] Because it shares attention across windows of varying sizes and performs attention calculations more quickly, a module named grouped multi-scale self-attention (GMSA) was proposed. Some processes are superfluous for tasks with extremely high resolution, and the transformer's self-attention computation is too large, according to the reasoning. The GMSA module was therefore suggested. [Forty] The non-local self-attention system made use of sparse representation to improve attention mechanism performance and reduce operation count.

Feedback Mechanism

A key distinction between the feedback system and the input-to-target object mapping is the inclusion of a self-correcting phase in the model's learning process. Transferring data from the system's back end to its front end is the main focus of this section. Feedback and recursive learning are quite similar in operation. Recursive learning shares parameters between modules, whereas feedback allows the parameters to self-correct. Over the past few years, computer vision tasks have gradually incorporated feedback systems. People also frequently use feedback systems in SR models because they can send a lot of detailed information to the network's front end. It's easier to turn LR images back into HR images because they help handle shallow information. 42. 42. The suggested depth inverse projection network for super-resolution uses a stage structure that switches between upsampling and downsampling to get each level of error feedback. We built it on top of DBPN [42], a feedback mechanism for super-resolution video jobs. RBPN uses an encoder-decoder method to combine singleframe input and multi-frame input into a single image. DBPN also adds a response system. The SFRBN suggests using a feedback module (FB). The preceding module's output serves as an input for the subsequent module. This process enhances low-level knowledge.

Transformer-Based Models

As of late, transformer's prominence in NLP has prompted its use in computer vision tasks. Experts have successively offered image categorization [43], picture segmentation [44], and numerous other transformer-based algorithms. If your goal is to recover the textural features of your photographs, a transformer should be used because it can model long-term dependencies in images [45] and retrieve high-frequency information. Transformers have the same benefit. [45] [46] One possible option for improving the resolution of images is to employ a texture transformer network. As the technique's texture transformer fuses several feature levels in a cross-scale fashion, it transfers texture information extracted from the reference image to the high-resolution image. The final result would be superior to more modern approaches. In its 47th year, an attention transformer that combines channel attention with the traditional transformer was suggested as a hybrid. This transformer improves the capacity to examine pixel data. Furthermore, we suggested OCAB, an overlapping crossattention module, to enhance feature fusion across multiple windows. (48) A lightweight and efficient super-resolution CNN with a transformer (ESRT) was suggested for the purpose of deep feature extraction. One aspect of the extraction process is the CNN portion's ability to dynamically resize the feature map. On the other hand, the efficient multithreaded attention (EMHA) and efficient transformer (ET) methods capture the long-term associations between comparable patches in an image. To put it another way, this improves model performance while reducing the demand on computational resources. Combining the transformer with CNN for SwinIR allows for super-resolution reconstruction, which in turn allows for the determination of long-term picture dependencies using a shifted window approach. in section 49. They suggested a hierarchical patch transformer to gradually restore high-resolution images. This transformer allows for the hierarchical partitioning of an image's patches for distinct regions. Images with a lot of texture, for example, might have smaller patches applied to them.

Reference-Based Models

The suggested reference-based SR approach mitigates the inherent pathological difficulty of SR. This method enables the acquisition of an LR image by degrading a large number of HR photos. In order to improve data diversity, RefSR used external images from various sources, such as cameras, video frames, and network images as a reference. We then used these images to reconstruct LR images and provide additional information. According to [50], one problem with the previous RefSR is that it relies on reference images with similar content to the LR images, which can affect the reconstruction results if not taken into account. After matching the features of the reference image and the LR image, SRNTT borrowed the concept of neural texture migration for semantically relevant features to address previously discussed challenges. The reference image served as the foundation for the texture transformer that TTSR proposed. This transformer's job was to take the reference image's texture data and paste it into the high-resolution version.

Remote Sensing Applications

High-resolution remote sensing images that include a tremendous deal of detail are among the most important characteristics that contribute to the success of remote sensing applications. These applications include recognition of scenes and detection of targets. Consequently, the effort to develop super-resolution methods for remote sensing has significantly increased. In an effort to tackle the features of remote sensing photos from different angles, many academics have suggested super-resolution algorithms in recent years. This section will examine two primary methods: supervised remote sensing image super resolution and unsupervised remote sensing image super resolution. We will also provide a concise overview of their respective attributes.

Supervised Remote Sensing Image Super-Resolution

When training models to map between the two categories of remote sensing data, it is common to pair low-resolution and high-resolution photos. According to the preponderance of the current remote sensing image super-resolution approaches, supervised learning is the preferred method. In [51], a multiscale convolution network (MSCNN) is developed to extract features from remote sensing images. This network employs various diameters of convolution kernels to acquire more detailed and comprehensive features. Pan et al. devised the RDBPN, which is a reverse model of the DBPN and ResNet. The projection units of RDBPN incorporate a dense residual connection to generate global and local residuals. In addition, it achieves feature reuse, providing more comprehensive features for superresolution large-scale remote sensing images. it is [52] We introduced the coupleddiscriminate GAN (CDGAN) to focus on remote sensing images with more low-frequency characteristics and flat regions. We provide the discriminator in CDGAN with inputs from both real HR images and SR images to enhance the network's ability to distinguish between low-frequency portions of remote sensing photographs. We further optimize the network with the help of a linked adversarial loss function. In [53], the authors propose the MHAN, a hybrid higher-order attention network. It comprises two networks: one for feature extraction and the other for feature refining. We employ the High-order attention mechanism (HOA) as one such process to reconstruct the high-frequency features of remote sensing photos. We further improve the layered features by incorporating frequency awareness. Although EDBPN is an enhanced variant of DBPN, the generator network's foundation is DBPN. The integration of an enhanced residual channel attention module (ERCAM) enhances the performance of E-DBPN by maintaining the original features of the input image and training the network to focus on the most critical regions of remote sensing images. This module is capable of extracting features that are beneficial for super-resolution extraction. E-DBPN introduces a sequential feature fusion module, or SFFM, to process the feature output from various projection units in a progressive manner. Common characteristics of remote sensing images include a wide range of scene dimensions and objects with significantly different sizes. Using remote sensing images, we can resolve this issue.

Unsupervised Remote Sensing Image Super-Resolution

Although there has been progress using the supervised learning super-resolution approach, problems with LR-HR remote sensing picture matching persist. Firstly, both existing technology and environmental factors fail to meet the demand for high-resolution remote sensing images. Secondly, the ideal degradation modes (e.g., double triple down sampling, Gaussian blur, etc.) used to acquire these images don't even come close to replicating the degradation of realistic low-resolution images.

We acquire high-resolution remote sensing pictures through recurrent rounds by rebuilding the image using a generator network. It is necessary to project the produced noise to the target resolution in order to guarantee that the reconstruction constraint is met on the LR input image; this step is described in detail in [54]. The article [55] proposes a distant sensing super-resolution network based on CycleGAN. This training setup involves feeding the output of the degradation network into the super resolution network, and vice versa. They may optimize the network's performance by creating a cyclic loss function. Reference 56 presents the theory of the unsupervised network UGAN. In order to augment the unsupervised super-resolution process with additional data, the network directly supplies the generator network with low-resolution remote sensing images. It then uses convolution kernels of varying sizes to extract features. We use the difference between the degraded model image and the original low-resolution image from the remote sensing network to construct a loss function [60]. To do this, one must follow the steps outlined in [57–58], which include training with a mountain of synthetic data and culminate in creating a model that faithfully mimics real degradation.

CONCLUSIONS

This research aims to examine deep learning-based picture superresolution algorithms in detail. Included in these methods are common datasets, procedures for evaluating picture quality, methods for reconstructing models, deep learning techniques, and optimization of network metrics. A comprehensive presentation on image super-resolution techniques and their application to remote sensing images is also part of the package. And lastly, although there has been much progress in the field of study regarding picture super-resolution technologies, particularly with regard to the generation of super-resolution remote sensing images, there are still many issues that need remediation. Problems include poor model inference efficiency, a lack of a standardized method for evaluating picture quality, and unsatisfactory reconstruction of real-world images. More efficient and lightweight model design techniques, more flexible approaches to remote sensing picture super-resolution, and more accurate and diverse image evaluation metrics are some of the promising avenues for further research and development that we highlight. All parties involved believe that this review will be useful for researchers interested in remote sensing image processing and image super-resolution techniques. As a result, knowledge of these procedures might grow within the area.

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