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A Survey on Single Image Super-Resolution Using Deep Learning Techniques for SAR

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Abstract— This survey paper discusses different image super resolution techniques. In the current generation super image resolution is one of the most important topic among various researchers. There are many challenges take place in this area. In the last decade there are many research work purposed in the single image super-resolution techniques. Single image super-resolution is a classical image restoration problem which aims to recover a high-resolution (HR) image from the corresponding low- resolution (LR) image. In SISR problems, the given image is usually assumed to be a low-pass filtered and down- sampled version of an HR image. In this review paper discuss the various aspect of super image resolution. Machine learning play an important role in super image resolution. There are different machine learning approach presented by different researchers. These method are discuss in this survey also give a comprehensive analysis of those method.

Keywords —Super Resolution, Deep Neural Network, Image Super Resolution, Convolution Neural Network, Remote Sensing Image, Up Sampling, Residual.

I. INTRODUCTION

The Single image super-resolution (SISR) has been a key topic among scientists in the last few years. Single-image super-resolution and other methods have been created to identify various high-resolution images. These solutions seem to be very reliant on a variety of circumstances as well as unique datasets and observations. Single-image super resolution is shown in the following fig.1."Super-resolution" is the process of converting low-resolution images into high-resolution images (SR). Therefore, to put it differently, LR stands for a single image input, high-resolution for the real data, and SR for the predicted high-resolution.

Fig. 1. Shows the Single Image Super Resolution (SISR) [12]

Image super resolution is well know problem for satellite image as well as synthetic aperture radar images (SAR). The main objective of proposed research work to improve the visual quality of satellite and SAR images. [27]. The research and technique of receiving information about an item, region, or phenomena by processing results collected by a machine that is not in communication with the subject, place, or activity being researched is known as "remote sensing" [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]. High-resolution satellite images have been shown to serve a vital function. But compared to synthetic photographs, remote sensing photography has less resolution and geographic clarity because of things like long-distance imaging, unstable weather, broadcast distortion, and mobility distortion.. 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].

A. Explanation Takeaways

Artificial intelligence refers to the simulation of human intelligence in machines. The goals of artificial intelligence include learning, reasoning, and perception.AI is being used across different industries including finance and healthcare. Simple or single-task centred is what weak AI is, whereas jobs that are more sophisticated as well as human-like are done by strong AI.

B. 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 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].

II. LITERATURE REVIEW

Yu, Fanghua, Xintao et.al. **(2023)."OSRT: Omni directional image super-resolution with distortion-aware transformer"** , In this research work , authors find that the previous down sampling process in the ODISR task harms the intrinsic distribution of pixel density in ODIs, which leads to poor generalization ability in real-world scenarios. To tackle this issue, we propose Fisheye down sampling, which mimics the real-world imaging process to preserve the realistic density distribution. After refining the down sampling process, we design a distortion-aware Transformer (OSRT) to modulate distortions continuously and self-adaptively. OSRT learns offsets from the distortion-related condition and rectifies distortion by feature-level warping. Moreover, to alleviate the over fitting problem of large networks, we propose to synthesize additional ERP training data from the plain images. Extensive experiments have demonstrated the state-of-the-art performance of our OSRT [1].

***Zhang, et.al. (2022),*"Single-Image Super Resolution of Remote Sensing Images with Real-World Degradation Modeling"**, In this article, a real-world degradation modeling framework and a residual balanced attention network with modified UNet discriminator (RBAN-UNet) have been presented for remote sensing image super resolution. The quality of real RSIs is affected by a series of factors, such as illumination, atmosphere, imaging sensor responses, and signal processing, resulting in a gap in the performance of previous methods between laboratory conditions and actual conditions. To model the real-world degradation of RSIs, researcher presented to estimate the blur kernels and noise patches in the dataset separately. Then, the blur kernels and noise patches Researcher used to construct a realistic dataset that follows the desired mapping function from realistic LR images to clean HR images. Moreover, researcher develop a novel CNN model to perform the SR reconstruction for RSIs. Researcher use a residual in residual architecture as the backbone and embed balanced attention modules (BAM) to improve the performance. To generate more realistic results, a modified UNet pixel-wise discriminator is employed. Detailed experiments were carried out to compare the presented model with classic SISR networks. Referenced experiments, non-referenced experiments, and ablation studies validate that the degradation modeling framework improves the performance of models dealing with real RSIs and the presented RBAN UNet model achieves a state-of-the- art performance in the real-world SISR problem for RSIs **[2].**

***Zili, et.al. (2022),*"Unsupervised Remote Sensing Image Super- Resolution Guided by Visible Images",**In this research work presented a novel cross-domain super-resolution method called UVRSR, which allowed training to be conducted with unpaired HR visible images and LR remote sensing images. It enhanced the capability for HR visible images to assist in the reconstruction of remote sensing images. It is the first work to apply visible images to assist remote sensing domain SR, and is also the first to perform cross-domain SR without HR/LR training pairs. It combines the advantages of HR visible images and remote sensing images, or, in other words, the advantages of visible realistic details and remote sensing structural information. In UVRSR, to learn more detailed images without domain shift in the reconstruction, researcher presented a novel two-branch training strategy and a domain ruled discriminator. The two-branch training, which included the visible image-guided branch (VIG) and the remote image-guided branch (RIG), has different functions for the SR network. VIG is designed to explore sufficient high frequency information from the HR visible target, while RIG is meant to learn the inner relationship in the remote sensing domain [3].

Wang, et.al, (2022)"**Remote sensing image super-resolution and object detection: Benchmark and state of the art."** The object localization and detection task in RS images is a topic of continuous research; thus, developing state-of-the-art object detectors for remote sensing of the environment is of utmost . In this research work presented a new benchmark RSSOD dataset for remote sensing object detectors with a high overlap of classes and complex settings, emphasizing small-sized

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objects. Researcher also presented an RFA-based MCGR network that achieved state-of-the- art image SR quality and object detection tasks. The current detection accuracy for the classes like vehicle, airplane, and ship Researcher satisfactory, while there needs further exploration to learn the complex features of the tree and low-vegetation classes. Extensive experiments show that using an image SR network before the object detection task helps in improving the map for object detection, and the presented MCGR outperforms the state-of-the-art YOLOv5 for map by 5% and 13% for scale factors of 2 and 4, respectively [4].

Jia, S., et.al, (2022).In this research, researcher present a GAN-based SR network named the multi-attention-GAN that correctly learns the mapping from LR to HR images to generate perceptually pleasing HR images. Specifically, researcher first designed a GAN-based framework for the image SR task. The key to accomplishing the SR task is the image generator with post-up-sampling that researcher designed. The main body of the generator contains two blocks; one is the PCRDB block, and the other is the AUP block. The AttPConv in the PCRDB block is a module that combines multi-scale convolution and channel attention to automatically learn and adjust the scaling of the residuals for better results. The AUP block is a module that combines pixel attention to perform arbitrary multiples of up-sampling. These two blocks work together to help generate better quality images. For the loss function, researcher design a loss function based on pixel loss and introduce both adversarial loss and feature loss to guide the generator learning. Finally, it is demonstrated by researcher experiments that researcher presented MA-GAN can perform better than some state-of-the-art SR methods [5].

Zhang, et.al, (2020), “Remote sensing image super-resolution via mixed high- order attention network”, In this article, researcher presented a novel network for remote sensing image SR named MHAN to fully exploit hierarchical features by applying different order HOA modules to feature maps with different frequency bands. Compared with commonly use CA, the presented HOA module is capable of modeling complex and high-order statistics. Due to the weighted channel wise concatenation (WCC), CG and CB can adaptively adjust the ratio between the nonlinear and identity mapping branches, hence extending the model representational capacity. Moreover, FAC is also presented to connect the feature extraction and feature refinement networks effectively. The comprehensive experimental results have demonstrated that researcher MHAN could provide the better performance in comparison with the state-of-the-art methods by using less running time and GPU cost [6].

***Li, et.al. (2019*)**,**"Feedback network for image super-resolution",** In this research, researcher a novel network for image SR called super-resolution feedback network (SRFBN) to faithfully reconstruct a SR image by enhancing low-level representations with high-level ones. The feedback block (FB) in the network can effectively handle the feedback information flow as well as the feature reuse. In addition, a curriculum learning strategy is presented to enable the network to well suitable for more complicated tasks, where the low-resolution images are corrupted by complex degradation models. The comprehensive experimental results have demonstrated that the presented SRFBN could deliver the comparative or better performance in comparison with the state-of-the-art methods by using very fewer parameters [7].

Dai, et.al. (2019),**"Second-order attention network for single image super- resolution."** Researcher presented a deep second-order attention network(SAN) for accurate image SR. Specifically, the non-locally enhanced residual group (NLRG) structure allows SAN to capture the long-distance dependencies and structural information by embedding non-local operations in the network. Meanwhile, NLRG allows abundant low-frequency information from the LR images to be bypassed through share source skip connections. In addition to exploiting the spatial feature correlations, Researcher presented second-order channel attention (SOCA) module to learn feature interdependencies by global covariance pooling for more discriminative representations. Extensive experiments on SR with BI and BD degradation models show the effectiveness of researcher SAN in terms of quantitative and visual results [8].

Zhao, et.al, (2019), "FC2N: Fully Channel-Concatenated Network for Single Image Super-Resolution."In this research, Researcher present a novel and simple network structure aimed at effective image SR tasks, i.e., FC2N. Compared with previous advanced models, a major technical novelty of researcher FC2N is the introduction of WCC as all skip connections in the network, and the avoidance to use residual learning. Through WCC, the model can not only adaptively select effective inter layer skips and make full use of hierarchical features, but also pay joint attention to the linear and nonlinear features. The CIC structure with CGs and CBs can also ease local representation learning and allow the model to fuse features from a fine to coarse level. Extensive experiments show that researcher FC2N model outperforms most advanced models in both lightweight and large scale implementations, verifying its effective mining of model representational capacity [9].

Hou, et.al (2017), "***Adaptive super-resolution for remote sensing images based on sparse representation with global joint dictionary model",*** In this research, Researcher presented an adaptive SR for remote sensing images based on sparse representation in conjunction with a GJDM. In order to make the reconstructed HR images more natural and their edges clearer, the NL feature was introduced into the SR model. First, researcher selected the suitable image feature with which to train the joint dictionary to better represent the image textures and edges. Second, researcher used a global restriction to make the reconstructed HR image look more real. Finally, researcher obtained the optimal result by using Algorithm[10].

Chang, et.al (2018), ***"Single image super-resolution using collaborative representation and non-local self-similarity",*** This research considers a competitive reconstruction-based frame work which simultaneously utilizes both the external and internal priors of natural images. First, the suitable local neighbors are collected from external data so as to establish the CRR prior. After that, to yield a better SR result, the NLR prior which exploits NLSS of natural images is also incorporated. The effectiveness of the presented CRNS algorithm is demonstrated by the experimental results with comparisons against different SR methods. Particularly, the average improvement of CRNS over NCSR (which provides the second best results among all the tested methods) is 0.40 dB in terms of PSNR, 0.0068 in terms of SSIM and 0.0059 in terms of FSIM. [11].

Table I. Comparative Study Of Different Super Image Resolution Techniques and Methods Algorithms

Year /Ref	Journal	Adopted Methodology	Remark/ Data Set	Outcomes / Result
2023/[1]	IEEE./ CVPR	Distortion-aware convolution block	SUN 360 Panorama and ODI SR	PSNR - 30.77 SSIM - 0.8846
2022/[2]	MDPI	Novel residual balanced attention network	RSIs-CB256	PSNR - 27.43 SSIM - 0.8034
2022/[3]	MDPI	Remote Sensing SR Method	NWPU- RESISC45	PSNR-31.16 NIQE- 2.03 PI-2.02
2022/[4]	ELSEVIER	NLSN	RSSOD	PSRN-34.68 SSIM- 0.93
2021/[5]	IEEE	interpolation- based methods	NWPU- RESISC45	PRNR- 31.98 SSIM-0.9102
2020/[6]	IEEE	reconstruction- based methods	RSSCN7	PSNR- 34.28 SSIM- 0.953
2019/[8]	IEEE	CNN-based methods	DIV2K	PSNR- 39.72 SSIM- 0.9797
2019/[9]	ECE	Convolutional Neural Networks (CNNs)	DIV2K	PSNR- 39.68 SSIM- 0.9792
2018/[10]	IEEE	Learning Based Methods	USC_SIPI	GJDM (TD1) -37.O7 GJDM (TD2) -37.013 GJDM (TD3) -36.962
2018/[11]	ELSEVIER	Collaborative Representation Based	BSD100	PSNR- 27.54 SSIM- 0.8479

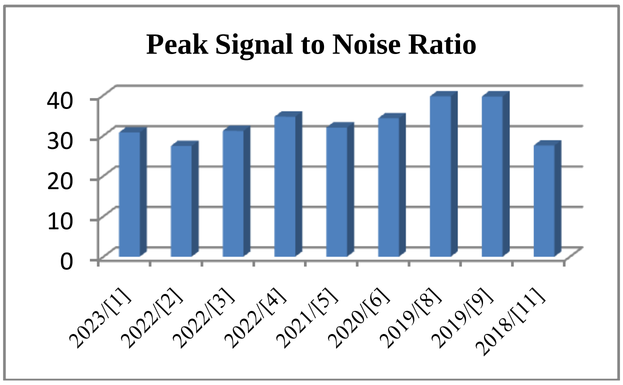

Fig. 2: PSNR comparison of previous Method

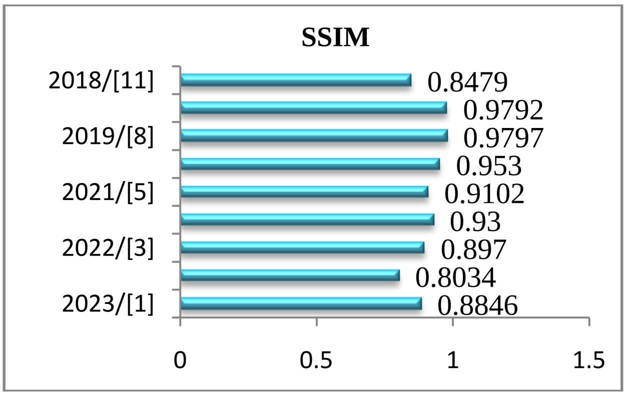

Fig. 3: SSIM comparison of previous Method

In the above Fig. 2 and Fig.3 shows the comparison of previous methods in terms of peak signal to noise ratio and structural similarity index measurement.

III. DEEP LEARNING AND MACHINE LEARNING

Deep learning is an artificial intelligence (AI) activity essentially simulates human mind's analysis input information as well as structure formulation through order to make a decision. Usually called the deep learning model or deep convolution neural network. Deep learning, also every linear response to convert the incoming data it into increasingly as well as model is an appropriate. The information inside a computer vision implementation can be a structure of images; a first truly representative layer might subjective the pixel density as well as convert seams; the middle level can really build or transmit side accommodations; the core layer can generate an eyes and mouth; and its fourth layer could represent however that image proposed recognition. Significantly, Neural network is a type of learning algorithms primarily teaches the machine understand common sense. In machine learning, a software program comes to understand to function trained dataset on difficult and complicated information in the form of pics, word, or noise. The above methods could also fulfill state-of-the-art (SOTA) precision, and often achieving individual intelligence. Algorithms usually developed employing great selection data classified input and mixed human brain specifications. Similarly Expert Systems is a greatest platform under the computer technologies like voice assistants, skin evaluation, fully electric cars, etc.

Similarly Expert Systems are a greatest platform under the computer technologies like voice assistants, skin evaluation, fully electric cars, etc. Deep learning's performance requires continuous preparation about the body. Deep teaching is based on that same learning of material as well as the understanding about situations. The learning method is regarded named 'Deep,' that's because the artificial neural network quickly create levels of information from each passing decade. When time information becomes studied, an objective is to improve outcomes. Since it is commonly accepted by personal information expert, that skill presentations as well as depths skill training were significantly improved because as quality of the information is risen.

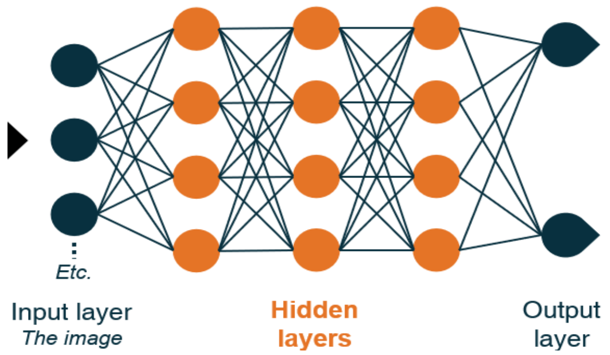

Fig .4: Deep Learning[24]

Advantages of Deep Learning

Capacity to produce additional features out from reduced train data present. Applying unsecured algorithms to include practical as well as predictable objective solutions seems to be a benefit. It decreases shorten the time necessary of classification techniques, and also one of the greatest time-consuming topics of cognitive computing. Its structure it became responsive to new but also hardworking on a number of difficulties as a result of successful practices.

IV. TECHNICAL BACKGROUND

The concept of super-resolution is predicated on the assumption that a series of low-resolution (noisy) photographs of a scene may be combined to create a high-resolution image or sequence of photos. Reduced-quality photographs from a collection are utilized to create a new, higher-resolution snapshot of the scene. This idea proposes that low-resolution images are just down sampled representations of their full-resolution counterparts. The final goal is to resample based on the input photographs and the imaging model to get the high-resolution picture from the low-resolution recorded photos. Therefore, an accurate imaging system is crucial for super-resolution, and incorrect modeling, such as that of motion, may actually damage the image. The observed pictures might be stills from a video sequence or the output of many cameras. The photos must be transformed into a standard coordinate system.

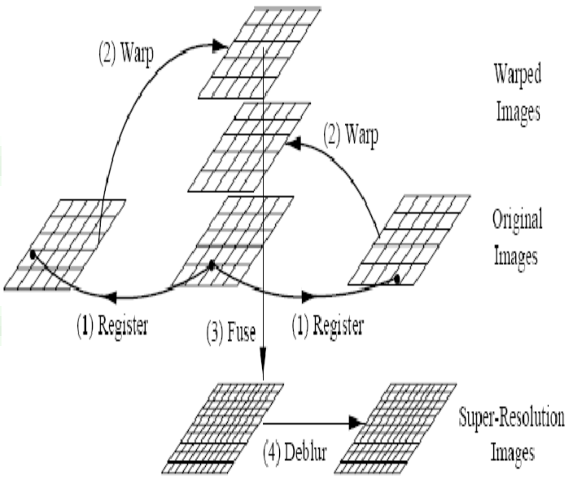

Fig 5: The Super-Resolution Process and Its Steps

A. Image Registration

Image registration is the process of translating data from several low-resolution photographs into a single coordinate system so that it may be used to accurately depict the original scene. For picture identification, affine changes, bi-quadratic transformations, and planar homographic evolutions may all be necessary. This alignment involves geometric component as well as photometric component [25].

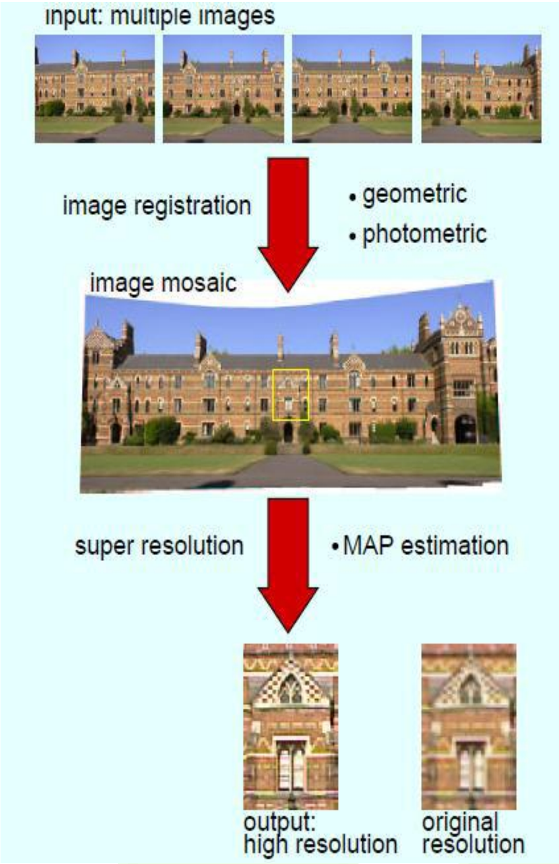

Fig 6: Super Resolution

B. Photometric Registration

Images may undergo both geometric and photometric alterations. Estimating these photometric shifts owing to variations in light levels, contrast, etc. is the focus of a process called photometric registration. These effects may be modeled using a simple parametric model, and the model's parameters can be estimated from the data we already have in the form of photographs. We have an illustration employing an affine transformation (contrast and brightness) model. Super Resolution is a method for restoring a high-resolution (HR) image from a lower-resolution (LR) one (SR). Reduced spatial resolution (smaller size) or picture deterioration may both contribute to an impression of "reduced resolution" in an image (such as blurring). The following equation describes the relationship between the high-resolution and low-resolution images: Degradation equals LR (HR)

A low resolution image kept besides its high resolution version. Clearly, on applying a degradation function, we obtain the LR image from the HR image. In the ideal case, yes! If we know the exact degradation function, by applying its inverse to the LR image, we can recover the HR image. In the last decade the world has seen an immense global advancement in technology, both in hardware and software. Advances in technology allowed enterprises to make electronic technologies such as computers, cell phones, as well as PDAs for a lower cost than before. Digital cameras with high resolution (HR) can only be made using sensors that are as sophisticated as the ones used in the cameras themselves. Although, HR digital cameras are available, many computer vision applications such as satellite imaging, target detection, medical imaging and many more still had a pressing need for higher-resolution images, which current HR digital cameras were unable to provide. These applications looked to image-processing methods for a way to create high-resolution HR imaging in order to meet the increasing demand.

As a potential digital imaging technology, resolution image reconstruction (RIR) seeks to recreate high-resolution (HR) imagery by merging limited details obtained from a collection of low-resolution (LR) images of the same scene (LR). Up sampling under sampled pictures for super-resolution image reconstruction eliminates artifacts like noise as well as blur. In comparison to various image enhancement techniques, super-resolution image reconstruction technique not only improves the quality of under-sampled, low-resolution images by increasing their spatial resolution but also attempts to filter out distortions.

V. CONCLUSION

In this survey paper discuss on different image super resolution techniques. In the literature review discuss various super image resolution techniques presented in the last decade. Also compare the previous methods.Single image super-resolution (SISR) is a classical image restoration problem which aims to recover a high-resolution (HR) image from the corresponding low-resolution (LR) image. In SISR problems, the given image is usually assumed to be a low-pass filtered and down-sampled version of an HR image. In this review paper discuss the various aspect of super image resolution . Also discuss the various machine learning approach play an important role in super image resolution. In future present a robust technique for image super resolution that is preserve the fine details of image and also improve the quality of the images.

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