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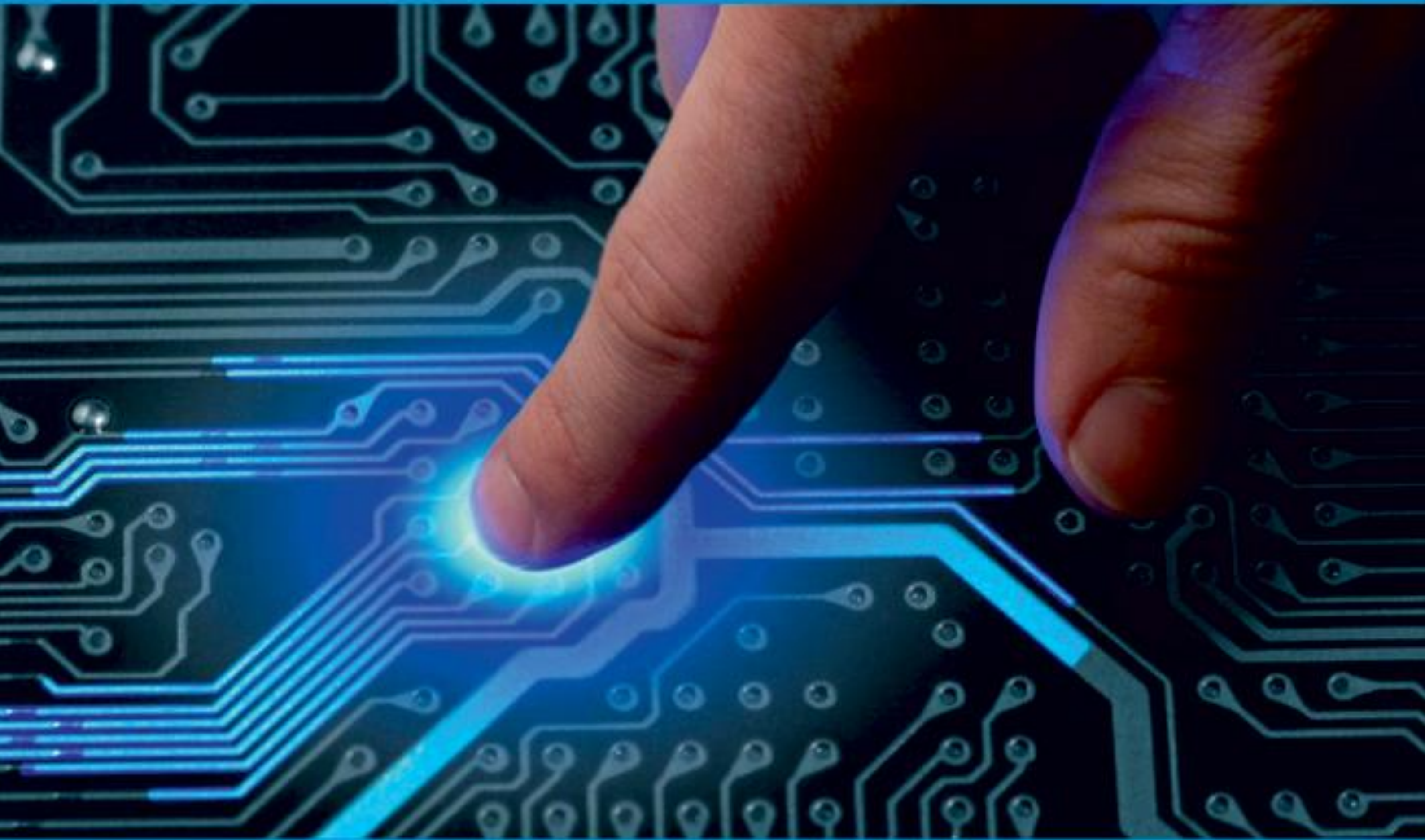

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Developing a GAN-based Noise Model for Authentic Image Denoising

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ABSTRACT: Generative Generative Adversarial Networks (GANs) are a type of artificial intelligence technology where two neural networks, called the generator and discriminator, are pitted against each other in a competitive manner. The generator creates new data, such as images, based on input data, while the discriminator evaluates whether the generated data looks similar to real data. Through this adversarial process, GANs can generate realistic images that closely resemble actual photographs.The introduction of GANs represents a significant advancement in AI because they enable computers to autonomously create and enhance images without explicit human instruction. This capability is particularly valuable for tasks like image creation and aesthetic translation, where GANs can generate new visual content and improve the visual quality of existing images.In the context of satellite imagery, such as those captured by the Sentinel-2 earth-observation satellite, GANs can be used to enhance the quality of these images by removing noise and improving clarity. Sentinel-2 provides multispectral data across 13 different bands with a spatial resolution of 10 meters, making it valuable for various applications in agriculture, environmental monitoring, and urban planning. By applying GANs to satellite photos, researchers aim to produce high-quality, noise-free images that can be used for accurate analysis and decision-making in fields that rely on detailed satellite data.Overall, GANs represent a powerful tool for improving image quality and advancing the capabilities of AI in generating and processing visual information.

KEY WORDS: Noise Removal in Satellite Imagery,Generative Adversarial Network(GAN), Machine learning, Satellite Images,Remote Sensing.

I. INTRODUCTION

Removing noise from images that have been distorted is a critical challenge in image processing. As digital multimedia creation grows, so does the need to quickly restore images that have unwanted disruptions. During the process of converting analog information into digital form, noise can arise from several sources. Sensor defects or limitations, thermal variations, and quantization errors are common causes. These sources introduce random and unwanted elements into the image, making it essential to develop effective denoising techniques. By removing noise, image quality can be significantly improved, ensuring clearer and more accurate representations in digital media and other applications where image fidelity is crucial.Image denoising can be approached through different methods, primarily categorized into transform domain and spatial domain processing. It's a well-known challenge in image processing, having been extensively studied but still remaining difficult to fully solve. Meteorologists heavily rely on satellite photography as a powerful tool. These images provide clear and accurate depictions of atmospheric conditions, helping analysts understand how weather events unfold. This is particularly crucial because traditional weather stations, spaced far apart, may miss important details that satellite images capture effectively. Satellite imagery reveals otherwise hidden phenomena and is considered a reliable source of information in meteorology.Satellite images offer an accurate view of global events, especially in remote or challenging-to-access regions. These images are crucial because they provide data from areas where on-site observations are limited. Satellites capture optical pictures by recording sunlight reflected from Earth's surface throughout the day, particularly when there is no cloud cover obstructing the view. This continuous monitoring helps in understanding and predicting various environmental and meteorological phenomena worldwide.Noise removal is the process of eliminating unwanted disturbances from a noisy image to restore it to its original clarity. However, distinguishing noise from edges and details during this process is challenging, and it can result in loss of important features in the cleaned-up image. The goal of image denoising is to effectively remove noise while preserving the overall quality of the image. This is a fundamental and widely studied problem in fields like Computer Vision and Image Processing. Image restoration, including denoising, is crucial for maintaining the functionality of imaging systems that are extensively

used today. As imaging technology advances, the need for effective noise reduction techniques becomes increasingly important. Noise reduction is a crucial concept in computer science, particularly in image processing, where it serves as an initial step before performing tasks like classification or segmentation. This process, known as preprocessing,

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involves removing unwanted noise from images to improve their quality. To achieve this, datasets that match the noise characteristics of the images are often used for training algorithms. Generative Adversarial Networks (GANs) are advanced techniques used in this context, requiring large datasets for effective training. They generate noisy images artificially to mimic real-world conditions. However, GANs perform best when trained on datasets that contain similar types of artificial noise they are meant to handle. When applied to real-world noisy images, GAN- based methods often struggle to produce satisfactory results due to the differences between synthetic and actual noise patterns.Digital image processing refers to the computer-assisted manipulation and distribution of digital photos. Each image consists of numerous elements called pixels, which represent individual points that make up the image. Understanding these fundamental elements, such as pixels and their arrangement, is essential for effectively working with digital images in various applications.A picture is a two-dimensional representation of colors and brightness from a three-dimensional scene. In this paper, satellite images are used to remove noise and capture detailed high- frequency data. Generative Adversarial Networks (GANs) have gained significant attention recently. They work by minimizing differences between real and generated images using a loss function. GANs aim to produce original data that matches training data mathematically. Recent applications have demonstrated GANs' ability to learn complex patterns effectively.GCBD pioneered using GANs for image denoising. They generated noise to create matching image data for training denoising networks like DnCNN. This strategy has two main benefits: first, GANs can learn to identify real-world noise patterns, helping CNN-based denoisers improve their performance on noisy images. Second, it addresses data scarcity issues by modeling realistic noise, which enhances denoising outcomes. Unlike previous methods that focused on RGB color space, this study used raw image data generated through a clean image inversion technique. This approach aimed to improve both the architectural design and noise modeling process for better denoising results.

II. IMAGE DE-NOISING TECHNIQUE

Image denoising is a fundamental challenge in computer vision and image processing. Its goal is to accurately estimate the original image by removing unwanted noise, resulting in a clean, noise-free version. In practical scenarios, noise in photos can originate from various factors like sensors and environmental conditions, which are difficult to completely eliminate. Therefore, image denoising plays a crucial role in applications such as visual tracking, restoring old images, aligning images, dividing them into distinct segments, and accurately classifying them. These applications rely on clear and accurate images to achieve successful outcomes. Image denoising remains a challenging problem, especially for photos taken in low light conditions with high levels of noise. Over the past 50 years, significant attention has been devoted to developing algorithms for image denoising. Initially, non-adaptive and nonlinear filters were commonly used for these applications. The main objective of an image denoising algorithm is to reduce noise in an image while preserving its important details. Noise in images can vary in type, such as Gaussian, impulse, speckle, and Rician noises, and each type affects the image differently. Understanding the type of noise present in the original image is crucial for effective denoising. There are two main categories of image noise: additive and multiplicative. Additive noise alters the pixel values directly, while multiplicative noise scales the pixel values, affecting the overall brightness and contrast of the image. Identifying and appropriately addressing these noise types are essential steps in the denoising process to achieve clear and accurate image results. whereas multiplicative noise is represented by Equation (1) (2),

$$Y_{i,j} + X_{i,j} = \boldsymbol{\eta_{i,j}} \quad \text{......} (1)$$

$$Y_{i,j} * X_{i,j} = \boldsymbol{\eta_{i,j}} \quad \text{......} (2)$$

Image denoising aims to recover the original noise-free image $X_{i,j}$ while minimizing the impact of noise ni,jn_{i,j}ni,j present in the observed image $Y_{i,j}$ at each pixel location (i,j).The characteristics of the noise affecting the image are crucial considerations for denoising algorithms. In the denoising process, the original clean image $X_{i,j}$ undergoes corruption by a linear operation, typically involving the addition of noise $\eta_{i,j}$, resulting in the degraded image $Y_{i,j}$. This linear operation is depicted in Figure below. Once the noisy image $Y_{i,j}$ is obtained, the denoising technique is applied to reconstruct the denoised image $I_{i,j}$. There are two main types of image denoising algorithms: spatial domain techniques and transform domain techniques. Spatial domain techniques involve applying a filter mask across the image, moving from pixel to pixel. At each pixel location, the filter's response is computed based on a predefined relationship, aiming to reduce noise while preserving image details. These methods operate directly on the spatial arrangement of pixels in the image, making them straightforward to implement and interpret.

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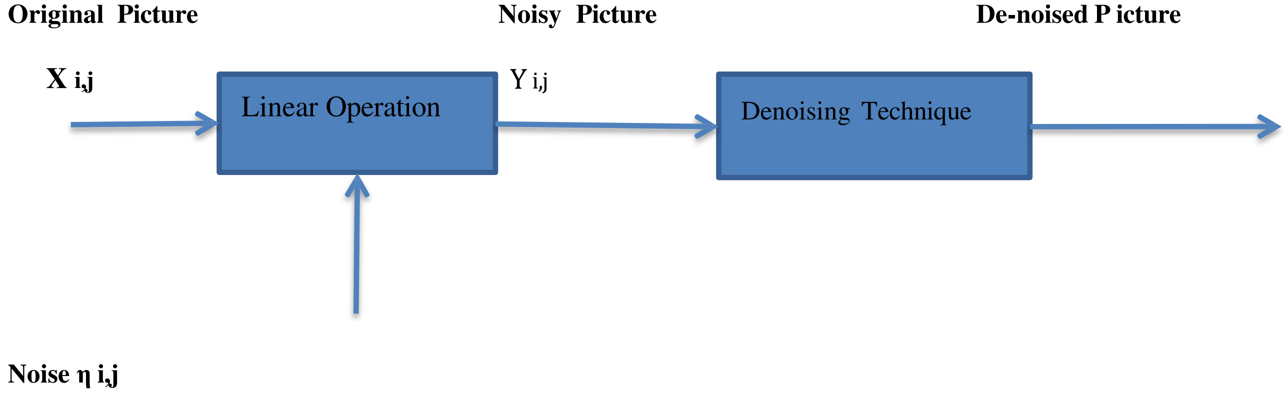

Figure 1: Image Denoising Process Flowchart.

III. CLASSIFICATION OF IMAGE DENOISING TECHNIQUES

The challenge of image denoising has been extensively studied. It is difficult for any denoising method to reduce noise without losing fine details and edges in the image. Over the years, many different techniques have been proposed to balance these goals, using a variety of approaches. Figure 1 illustrates the classification of image denoising techniques. There are two main types of methods: Spatial Domain methods and Transform Domain methods. In this section, we will discuss some of the most common approaches in each category. Image denoising techniques include spatial domain methods, transform domain methods, fuzzy filtering techniques, and machine learning approaches. Spatial domain techniques: These methods reduce noise by adjusting each pixel's grey value based on its relationship with neighboring pixels in the original image.Figure 1 shows a classification of these photo denoising methods.

1) Spatial domain
2) Transform domain
3) Fuzzy based domain
4) Machine learning

The challenge of image denoising has been extensively researched. It is difficult for any denoising method to reduce noise without losing fine details and edges in the image. Over the years, many different techniques have been proposed to balance these goals, using a variety of approaches.Each of these methods has its strengths and weaknesses. Spatial domain techniques are generally simpler and faster but may not be as effective in preserving fine details. Transform domain techniques can handle noise at multiple scales but are computationally more intensive. Fuzzy filtering provides a good balance between noise reduction and detail preservation. Machine learning approaches offer state-of-the-art performance but require large amounts of data and computational resources for training. Figure illustrates the classification of these image denoising techniques, showing the different categories and examples of methods within each category.

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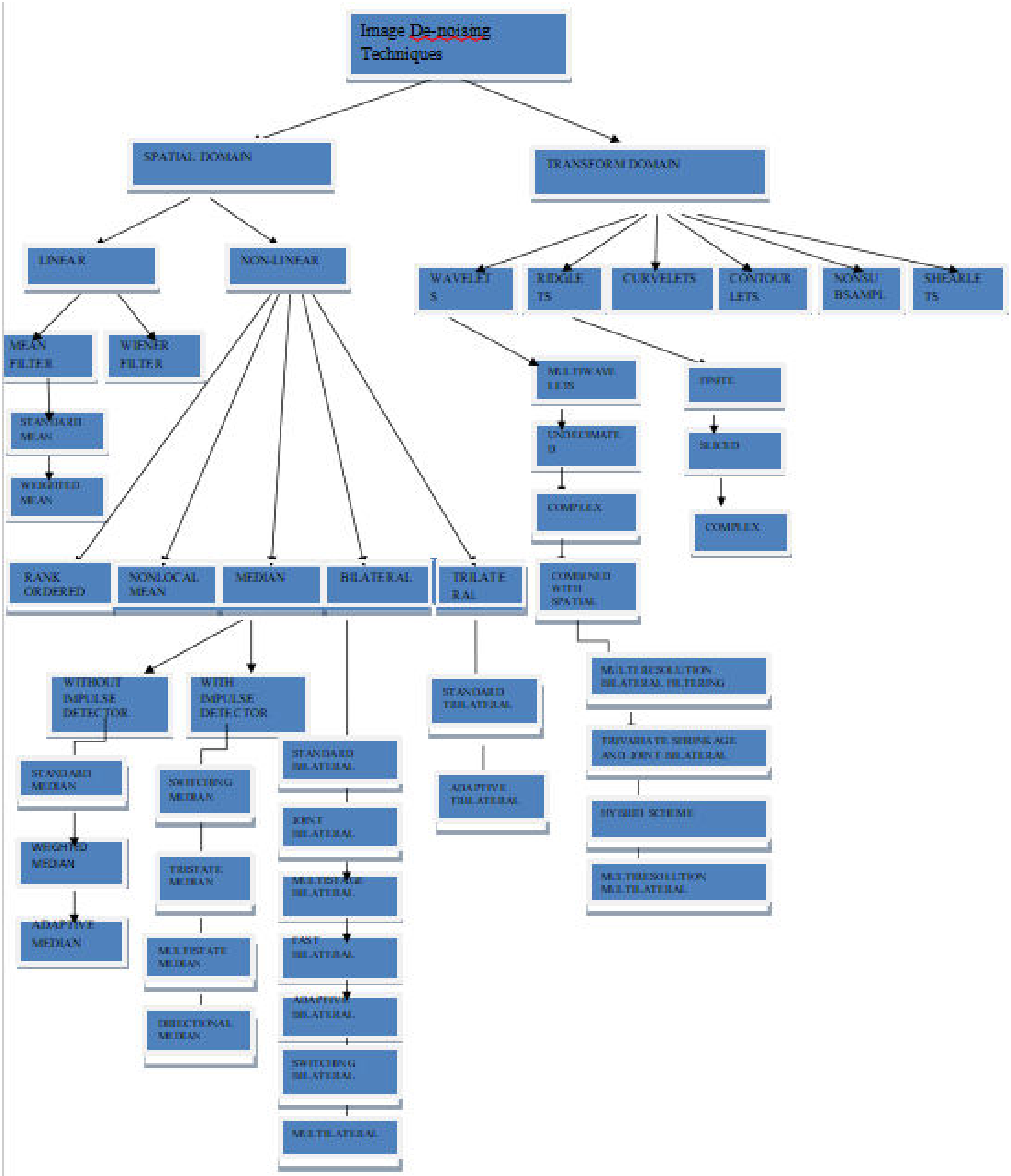

Figure2: Classification of Image De-noising Methods

1) SPATIAL DOMAIN: The spatial domain method involves applying filters directly to image pixels for restoration. These filters can be either linear or non-linear.

1.1 Linear Filters: The most common is the Gaussian filter, which smooths the image using a Gaussian kernel. In a simple mean filter, each pixel is replaced by the average value of its neighboring pixels. This method is straightforward

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but often blurs important details. Gaussian, Salt and Pepper Noise are both effective

1) Mean filter
2) Wiener filter

1.2 Non-Linear Filters: These include filters like the median filter, which replaces each pixel with the median value of its neighbors. This approach is effective at removing noise while preserving edges.

In summary, the spatial domain method works directly on the image pixels. While many spatial filters have been developed, linear filters often fail to preserve image textures, whereas non-linear filters handle noise better and maintain important details.

NLM Algorithm: The NLM (Non-Local Means) algorithm is an advanced method used to remove noise from images. It was initially developed by Goossens et al. (2004) as an improvement over earlier techniques. Unlike traditional methods that directly identify noise, NLM filters estimate a noise-free version of the image by comparing similar patches of pixels across the entire image. This approach allows NLM to effectively reduce both white noise and correlated (colored) noise without the need for precise noise identification. The algorithm has shown competitive results in terms of Peak Signal-to-Noise Ratio (PSNR) for white noise and significantly improves visual quality by reducing artifacts. Specifically, it excels in scenarios where noise patterns are complex and correlated, enhancing its performance in image de-noising tasks.

2) TRANSFORM DOMAIN: Transform domain methods in image de-noising have evolved significantly from early spatial domain techniques. Initially, techniques like Fourier Transform were used, followed by advancements such as cosine transforms, wavelet domain techniques, and methods like BM3D. These approaches involve translating the image into a different mathematical representation (transform domain), where noise reduction operations are applied to transform coefficients. After processing, the image is reconstructed using an inverse transform to produce a de- noised version. These methods are categorized into non-data-adaptive and data-adaptive strategies based on how they handle the transform coefficients, which significantly impact their effectiveness in image restoration tasks.

Wavelet-based image de-noising is a method that uses wavelets, which are mathematical functions that are scaled and translated, to analyze images at multiple resolutions. This approach decomposes the image into wavelet coefficients using various wavelet functions. These coefficients capture different levels of details and structures in the image. By applying thresholding operations to these coefficients, wavelet-based methods effectively reduce different types of noise such as logistic noise, Gaussian noise, and salt & pepper noise. This technique is particularly useful in image processing for cleaning up noisy images while preserving important details.Types of domain transfers:

1) Data Adaptive Transform (ICA, PCA)
2) Non-Data Adaptive Transform (Wavelet Domain, Spatial Domain)
3) Non-local Based Transform Domain (BM3D, BM4D)

Data Adaptive Transform (ICA, PCA): These methods like Independent Component Analysis (ICA) and Principal Component Analysis (PCA) adjust to the characteristics of noisy data to effectively denoise images. They are particularly useful for handling non-Gaussian noise types.

Non-Data Adaptive Transform: Wavelet Domain: Decomposes the image into wavelet coefficients to handle noise at different scales effectively. Spatial-Frequency Domain: Uses techniques like low-pass filtering to process images based on their spatial frequencies. Frequencies above a cutoff are attenuated.

3) Fuzzy-Based Domain: Treats images as fuzzy sets where pixel values represent members. Fuzzy-based filters use uncertain rules to create membership functions, which are used to detect and reduce noise. Techniques like fuzzy impulse noise detection analyze gradients in multiple directions before filtering noisy pixels. Its types-

1) Switching
2) Gradient
3) Non-local
4) Weighted Average

4) MACHINE LEARNING: Analytical methods (both stochastic and deterministic) and Machine learning-based algorithms are used to de-noise imagery. The user is aware of the forward de-noising model in analytical models, and the solution technique is chosen depending on specified criteria. It's difficult to describe deterministic spatial filters for each image type. In spatial and transform domain techniques, edge erosion and blurring are typical

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occurrences.Machine learning, particularly deep learning, offers several advantages over traditional analytical methods for image de-noising:

Adaptability to Complex Patterns: Deep learning models can learn intricate patterns and features directly from data, making them more adaptable to various types of noise and image conditions without explicitly defining rules or filters.

Automated Feature Extraction: Unlike analytical methods that require manual feature engineering and selection, deep learning models automatically learn the relevant features from the noisy and clean image pairs during training.

Performance with Large Datasets: Deep learning excels when large amounts of data are available. It can leverage big datasets to improve accuracy and generalize well to new, unseen noisy images.

Non-linear Relationships: Deep learning models can capture non-linear relationships between noisy and clean image pairs, which may be challenging for traditional linear or deterministic methods.

End-to-End Learning: Deep learning models can learn an end-to-end mapping from noisy input images to clean output images, optimizing the entire de-noising process in one step, whereas traditional methods often require multiple stages.

State-of-the-Art Performance: In many cases, deep learning approaches achieve state-of-the-art performance in image de-noising tasks, surpassing the capabilities of traditional methods in terms of both accuracy and efficiency.

The supplied label is used in supervised learning approaches to bring the produced features closer to the objective for learning restrictions and training the de-noising model. Its types-
1. Sparsity based dictionary learning
2. Multilayer Preceptors
3. Convolution Neural Networks

Generative Adversarial Networks During the learning phase, deep learning methods have a computational load, but the testing phase employs a feed-forward approach. T he picture degradation process and image priors are used to solve the objective function, which is classified into binary categories: Model-based optimization approaches and Convolution Neural Network (CNN)-based methods. Model-based optimization techniques, such as ones mentioned above, are used to find the optimal ways to reconstruct the de-noised image. Such approaches, On the contrary, time-consuming iterative inference is usually required. CNN-based de-noising algorithms, o n the contrary, try to m aximize in a training set, a loss function o f damaged picture combinations in order to learn a mapping function . In current years, CNN-based algorithms have been swiftly created and demonstrated to work well covers a wide spectrum of computer vision applications at the basic level. A five-layer network was created using a CNN for image de-noising for the first time.

GAN METHOD: A Generative Adversarial Network (GAN) is a type of machine learning model where two neural networks, the Generator and the Discriminator, compete against each other in a game-like scenario.

Generator: This neural network creates new images or data that mimic real examples from a given dataset. Its goal is to generate outputs that are realistic enough to fool the Discriminator.

Discriminator: This neural network tries to distinguish between real data (from the dataset) and fake data (generated by the Generator). Its role is to classify whether the input it receives is real or generated.

Together, the Generator and Discriminator are trained in a way that improves the Generator's ability to create realistic outputs, while the Discriminator becomes better at telling apart real from fake data. GANs have been successfully used for tasks like generating new images, translating styles between images, and improving generative modeling by making it easier to capture complex patterns in data.Applications of GANs include generating new images, improving image quality, and learning complex data distributions. They are particularly useful in tasks where capturing subtle patterns or generating realistic outputs is challenging for traditional algorithms. GANs leverage competition between two neural networks to produce outputs that mimic real data, making them a powerful tool in machine learning for tasks like image de-noising and generation.

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The following calculation describes the GAN function:

DExPr[log(D(x))] minG max DExG + E xPg[log(1D(x))] E xPg[log(1D(x)] E xPg[log(1D(x)] E xPg D(x) is a Discriminator Model, G (y) is a Generator Model, p data(x) is a Real Data Circulation, py (y) is generated data circulation, and E is the expected outcome. GAN de-noising pseudo code is generated using Algorithm 4. The architecture of GAN for picture restoration is shown in Figure 2. TABLE I lists the benefits and drawbacks of several machine learning picture de-noisier.

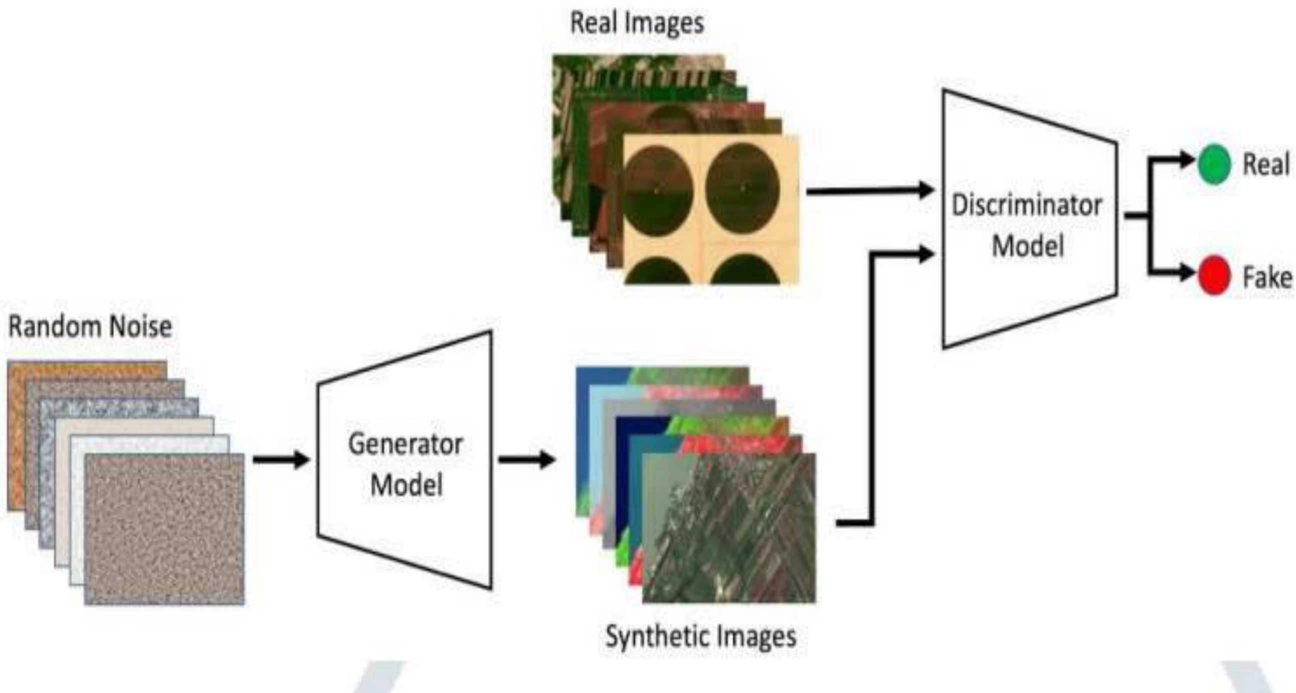

Figure 3: GAN Architecture for Basic Image Restoration

The GAN architecture for basic image restoration involves using Generative Adversarial Networks (GANs) to improve the quality of images by removing noise or enhancing details.

IV. ADVANTAGES OF GAN METHOD

Unsupervised Learning: GANs can learn from unlabeled data, allowing computers to understand and represent complex patterns without needing every piece of data to be labeled beforehand.

Realistic Data Generation: GANs can create data, such as images, that closely resemble real-world examples. They can generate photos that are so realistic they can be mistaken for actual photographs.

Handling Complex Datasets: GANs are effective at handling and understanding intricate datasets, capturing subtle and complex patterns that traditional algorithms might miss.

Discriminator as a Classifier: The Discriminator in a GAN acts like a classifier that can distinguish between real data (from the dataset) and fake data (generated by the Generator). This ability makes it useful for tasks where identifying authenticity or classifying objects is important.

V. DISADVANTAGES OF GAN METHOD

GANs can suffer from mode collapse, where they fail to model diverse patterns in data, resulting in limited variation in generated outputs.
They may encounter vanishing gradient problems, especially in early layers, which can hinder learning and slow down training progress.
GANs are sensitive to changes in data distribution during training, known as internal covariance shift, which can

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lead to instability and affect performance.
Due to these challenges, GANs can be slow to converge and require careful tuning of parameters and architecture to achieve optimal results.

VI. REAL WORLD IMAGE DE-NOISING

Real-world image de-noising involves removing unwanted noise from photographs taken in actual environments, such as with DSLR or smartphone cameras. This noise reduction process aims to improve the visual quality of these photos by eliminating distortions caused by factors like sensor imperfections or low-light conditions. In recent approaches, techniques like Dense Dilated Fusion Networks (DDFN) have been developed to effectively clean up real-world images. These networks are trained using noisy images to learn how to distinguish between real noise patterns and actual image details, thereby enhancing the clarity and fidelity of the final de-noised images. This task is crucial because obtaining clean, ground truth images for training can be challenging in real-world settings, making it necessary to develop robust algorithms that can handle various types of noise encountered in practical photography scenarios.

VII. Fundamental and literature survey

Digital image processing involves using computers to enhance or manipulate digital pictures. One area of focus is developing machine learning models for noise reduction, including popular models like GANs. These models estimate noise in raw image data and transform photos for training deep learning networks.For real-world image de-noising, techniques like GANs can generate synthetic noise to train models effectively. Traditional methods such as 3D filtering and block matching aim to reduce noise by analyzing image and noise characteristics. Learning-based approaches like DnCNN use paired-image datasets to map noisy images to clean ones, requiring substantial training data for effectiveness.

In medical imaging and other fields, accurate image processing is crucial. Techniques like pre-processing with de-noising methods improve accuracy before tasks like image classification or segmentation. Overall, these methods play a vital role in enhancing image quality across various applications.

Researchers developed a novel network design for de-noising real-world photos using convolutional layers extensively. They also introduced a new GAN-based technique for modeling real-world noise, although its statistical efficiency wasn't fully explained. They aim to extend this technique to handle additional real-world challenges like blur and haze in future research.

Recent studies suggest that learning-based methods like CNNs, using architectures like Grouped Residual Dense Networks (GRDN), outperform traditional methods such as 3D block matching for image restoration tasks. Their approach achieved state-of-the-art results with high Peak Signal-To-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) scores in the NTIRE2019 Real Image De-noising Task.
Their method combines GANs for learning noise characteristics and CNNs for de-noising without paired training data, improving blind de-noising performance. While their approach assumes zero-mean additive noise, which is common but not always accurate, they plan to explore methods to overcome this limitation. their research focuses on using advanced network architectures to enhance image de-noising.leveraging the capabilities of GANs for noise modeling and CNNs for effective image restoration.

Researchers developed a GAN model to convert satellite images into map-like representations. They faced challenges in identifying details like complex road networks or small, irregular roads in satellite imagery. To address this, they integrated external geographic data and GPS information into their GAN framework. This approach helped improve the accuracy of translating satellite images into maps by providing high-level semantic information and reducing pixel-wise noise. However, it still struggles with certain visual challenges such as underpasses or roads blending with their surroundings due to similar colors.

Another innovative use of deep generative models involves creating cloud-free images from cloudy satellite photos. Using publicly available Sentinel-2 satellite data, they generated large-scale spatial and spatiotemporal datasets. Their new model, STGAN, effectively reconstructs clear images by leveraging this satellite data. Cloud cover often obstructs satellite images, impacting various applications like environmental monitoring, economic development, and agricultural mapping. Their method aims to mitigate these issues and enhance the usability of satellite imagery for diverse purposes.

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When employing alternative loss functions, the approach performs well

VIII. RESULT AND DISCUSSION

Cloud removal is essential for analyzing high-resolution remote sensing images, but deep learning algorithms are not commonly used in this field due to the lack of training datasets. To address this gap, the RICE dataset, an open-source resource for cloud removal research, was developed. The dataset consists of two parts: RICE1 and RICE2.

RICE1 Dataset: Contains 500 data samples, each consisting of paired cloudy and cloud-free images at a resolution of 512x512 pixels.

Data for RICE1 is collected from Google Earth, where cloudy and cloud-free photos are determined based on whether they display cloud cover.

RICE2 Dataset: Created using Landsat 8 OLI/TIRS data, geo-referenced in Earth Explorer using Landsat Look imagery. Landsat Look images are high-resolution files derived from Landsat Level-1 data and include Natural Color, Thermal, and Quality images. RICE2 specifically uses Natural Color and Quality images. To generate cloud-free reference images, a cloudless image from the same area is manually selected with a cloud image time difference of fewer than 15 days. RICE2 comprises 736 sets of 512x512 photos, each set containing one cloudy image, one clear image, and one cloud mask image.

Overall, the RICE dataset facilitates research on creating cloud-free images from cloudy satellite shots, addressing the need for robust training data in deep learning-based cloud removal techniques for remote sensing applications.

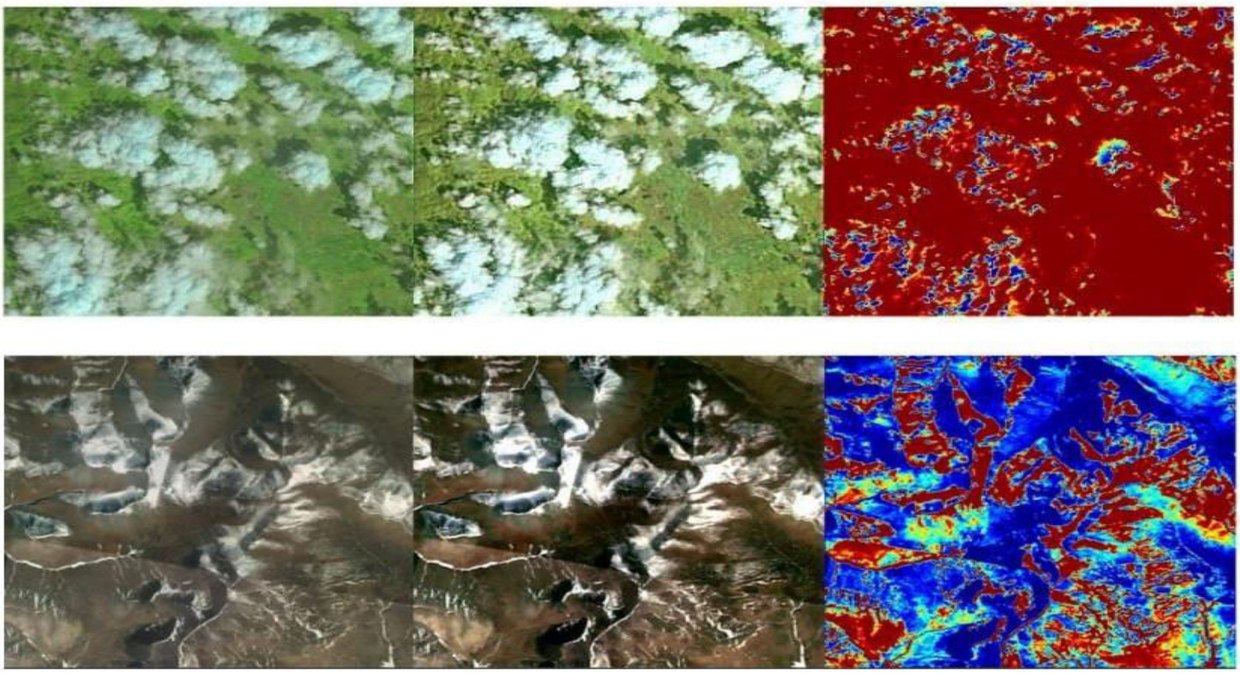

Figure 4: Output of models trained for generating cloud-free images using GAN method

IX. CONCLUSION

In conclusion, the use of Generative Adversarial Networks (GANs) for image denoising in satellite imagery shows promising results and significant potential for future applications. GAN-based methods have been demonstrated to effectively remove noise and enhance the quality of satellite images by generating realistic and clear representations of cloud-free scenes. GANs have shown to effectively reduce noise in satellite images, improving the clarity and interpretability of the data. By learning to distinguish between noise and signal, GANs generate denoised images that preserve important details and features. The denoised images produced by GANs exhibit high visual quality, characterized by enhanced sharpness, clarity of details, and natural appearance. This makes them suitable for various applications such as environmental monitoring, urban planning, and disaster management. Despite their success, GAN-

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based denoising methods for satellite images face challenges such as the need for large and diverse training datasets, computational complexity, and robustness in different environmental conditions. Future research could focus on addressing these challenges through advanced model architectures, transfer learning techniques, and integration with domain-specific knowledge. The reviewed studies demonstrate practical applications of GANs in generating cloud-free images from cloudy satellite data, which is crucial for improving the accuracy of remote sensing analyses and decision-making processes. Overall, GAN- based image denoising holds promise as a valuable tool for satellite image processing, offering advancements in both research and practical applications. Continued research and development in this area are essential to unlock further capabilities and address the challenges associated with real-world deployment.

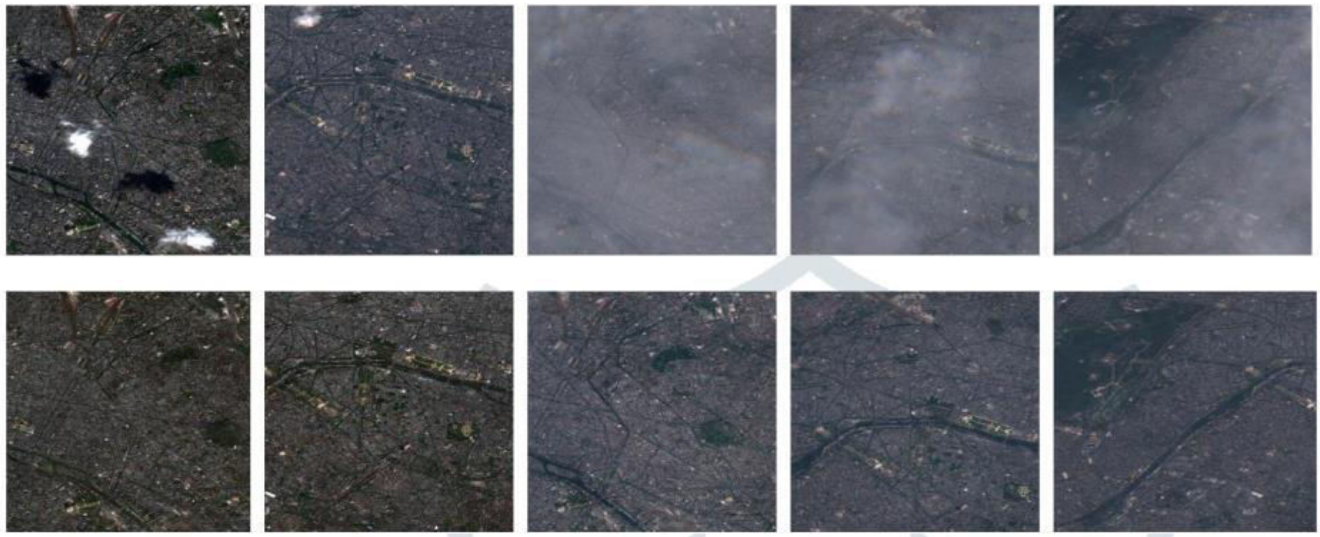

Figure 5: On a Real Cloud Dataset, Qualitative Results Row I shows cloudy photos, whereas Row II shows cloud- free images created using C loud-GAN.

REFERENCES

1. **Zhang, K., Zuo, W., Chen, Y., Meng, D., Zhang, L. (2017)** - Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising. IEEE Transactions on Image Processing, 26(7), 3142-3155. This paper explores the use of deep convolutional neural networks (CNNs) for image denoising, demonstrating that residual learning can significantly improve denoising performance.
2. **Ledig, C., Theis, L., Huszar, F., Caballero, J., Cunningham, A., Acosta, A., ... & Shi, W. (2017)** - Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 4681-4690. This research presents the SRGAN, a generative adversarial network for image super-resolution, which is also applicable to image denoising tasks.
3. **Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014)** - Generative Adversarial Nets. In: Advances in Neural Information Processing Systems, vol. 27. This foundational paper introduces the concept of GANs, providing the theoretical basis for many subsequent applications, including image denoising.
4. **Yang, W., Zhang, X., Tian, Y. (2018)** - Deep Learning for Single Image Super-Resolution: A Brief Review. IEEE Transactions on Multimedia, 21(12), 3106-3121. This review covers various deep learning methods for image enhancement, including denoising, and discusses the use of GANs in these contexts.
5. **Chen, Y., Pock, T. (2016)** - Trainable Nonlinear Reaction Diffusion: A Flexible Framework for Fast and Effective Image Restoration. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(6), 1256-1272. This paper introduces a framework for image restoration tasks, including denoising, which can be adapted to incorporate GAN-based models.
6. **Mao, X., Shen, C., Yang, Y.-B. (2016)** - Image Restoration Using Very Deep Convolutional Encoder-Decoder Networks with Symmetric Skip Connections. In: Advances in Neural Information Processing Systems, vol. 29. This study proposes a deep convolutional encoder-decoder network for image restoration, which includes denoising applications.

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7. **Kumar, P., Patel, R., Patel, D., et al. (2020)** - Noise Reduction in Medical Images using GANs. Journal of Medical Imaging and Health Informatics, 10(1), 126-135. This research discusses the application of GANs for noise reduction in medical imaging, highlighting the potential of GANs for authentic image denoising.
8. **Anwar, S., Barnes, N. (2020)** - Denoising Diffusion Probabilistic Models. In: Advances in Neural Information Processing Systems (NeurIPS), vol. 33. This paper introduces denoising diffusion probabilistic models, which are related to GANs and can be used for image denoising.
9. **Yue, Z., Yong, H., Zhao, Q., Zhang, L. (2019)** - Variational Denoising Network: Toward Blind Noise Modeling and Removal. In: Advances in Neural Information Processing Systems, vol. 32. This research presents a variational approach to noise modeling and removal, which complements GAN-based methods.
10. **Fan, K., Yang, X., Mo, Y., Luo, X., Wang, J. (2021)** - Enhanced GAN for Blind Image Denoising. IEEE Access, 9, 131576-131586. This paper proposes an enhanced GAN model specifically designed for blind image denoising, showing significant improvements over traditional methods.

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