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Enhancing Image Quality: A Comparative Study of Spatial, Frequency Domain, and Deep Learning Methods

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Abstract--Image restoration and noise reduction methods have been created to restore deteriorated images and improve their quality. These methods have garnered substantial significance in recent times, mainly due to the growing utilization of digital imaging across diverse domains, including but not limited to medical imaging, surveillance, satellite imaging, and numerous others.

In this paper, we conduct a comparative analysis of three distinct approaches to image restoration: the spatial method, the frequency domain method, and the deep learning method. The study was conducted on a dataset of 10,000 images, and the performance of each method was evaluated using the accuracy and loss metrics. The results show that the deep learning method outperformed the other two methods, achieving a validation accuracy of 72.68% after 10 epochs. The spatial method had the lowest accuracy of the three, achieving a validation accuracy of 69.98% after 10 epochs. The FFT frequency domain method had a validation accuracy of 52.87% after 10 epochs, significantly lower than the other two methods. The study demonstrates that deep learning is a promising approach for image classification tasks and outperforms traditional methods such as spatial and frequency domain techniques.

Keywords-Image Restoration Techniques, Noise Reduction Methods, Adaptive filtering, Imag, Wavelet-based methods, Adaptive Thresholding Technique

1. Introduction

In today's society, the ubiquitous use of images is undeniable. Yet, these images often suffer from degradation due to blur, noise, and contrast loss, hindering their accurate interpretation and analysis. To combat this challenge, the field of image restoration and noise reduction has arisen, employing advanced mathematical algorithms to recover and enhance image quality. These techniques play a vital role in medical imaging, surveillance, and remote sensing, facilitating valuable insights from visual data. [1][2][3].

The significance of image restoration and noise reduction techniques cannot be embroidered, as they play a crucial role in elevating the quality of digital images within various fields. Notably, these techniques enhance the precision and reliability of image analysis, augment visual appeal, reduce data storage and transmission requirements, and enable accurate identification and recognition in security applications. They facilitate restoring and examining degraded historical images, preserving crucial visual information for posterity [4-9].

Image restoration and noise reduction techniques have wide-ranging applications across various domains (see Table 1). They play a vital role in enhancing digital image quality, facilitating accurate analysis, reducing storage and transmission requirements, and restoring historical images affected by degradation. These techniques effectively address common image issues like blur, noise, contrast loss, and compression artifacts through deconvolution, spatial filtering, contrast enhancement, and artifact removal. [10-12].

In this study, our main objective is to compare the performance of three distinct methods for image restoration: the spatial method, the FFT frequency domain method, and the deep learning method. Our investigation aims to identify the

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method that yields the most favorable accuracy and loss performance metrics, as indicated by their respective learning curves and evaluation metrics. By comprehensively analyzing these methods, we seek to determine the most suitable approach for image restoration, particularly when dealing with degraded images.

Table 1: Applications of Image Restoration and Noise Reduction in Various Domain

Category	*Application*	*Reference*
Applications of Image Restoration	Restoration of old photographs and artwork	[13-14]
	Restoration of damaged or degraded images in forensic and medical imaging	[29-30]
	Removal of scratches, dust, and other types of physical damage in images	[15][31-32]
Applications of Noise Reduction	Improving the quality of digital images by removing unwanted noise	[16-18]
	Enhancing the visibility of features in low-light or high-ISO photographs:	[19-21]
	Reducing noise in medical images to improve the accuracy of diagnoses	[22-23]

2. Image Restoration Techniques

Image restoration methods are employed to recover deteriorated images by eliminating blur, noise, and various forms of degradation. Typical techniques encompass deblurring, denoising, dehazing, super-resolution, inpainting, and restoring historical images. These methods entail estimating the specific degradation factors (see Table 2) and leveraging this data to enhance image quality. Diverse approaches, including blind deconvolution, spatial filtering, deep learning-based methods, and content-aware fill, are utilized in the field of image restoration. [24-26].

Image restoration methods are generally categorized into three main groups: spatial-domain methods, frequency-domain methods, and deep learning-based methods (see Table 3). Spatial-domain methods directly process the pixel values of the image and encompass techniques like median filtering, Wiener filtering, bilateral filtering, non-local means filtering, and total variation regularization. Frequency-domain methods operate on the Fourier or wavelet transform of the image and involve techniques such as Fourier-based filtering, wavelet-based filtering, non-subsampled contourlet transform, curvelet transform, and contourlet transform. Deep learning-based methods utilize deep neural networks to learn the mapping from degraded to clean images and include techniques such as convolutional neural networks (CNN), generative adversarial networks (GAN), autoencoders, denoising autoencoders, and variational autoencoders.

3. Dataset and Experimental Setup

We have taken Image dataset from a popular computer vision domain - object recognition. The dataset is called the "CIFAR-10" dataset, which consists of 60,000 color images in 10 classes, with 6,000 images per class. The images are of size 32x32 pixels and are divided into a training set of 50,000 images and a test set of 10,000 images. The 10 classes in the CIFAR-10 dataset are airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck.

The CIFAR-10 dataset is widely used for research in computer vision and machine learning and has been used to evaluate the performance of various image classification algorithms. It is a challenging dataset because the images are small and have low resolution, and the objects in the images are often partially occluded or have complex backgrounds.

Fig 1 shows a grid of 25 sample images from the CIFAR-10 dataset, along with their corresponding class labels. We have drawn a bar chart showing the number of samples in each class of the CIFAR-10 dataset in figure 2. An image along with its individual RGB channels has been shown in figure 3

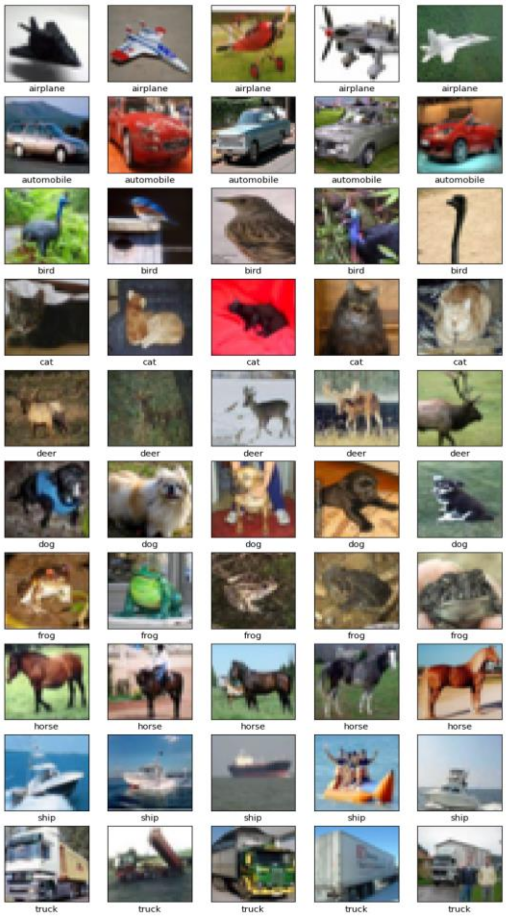

Fig 1- Grid of 25 sample images from the CIFAR-10 dataset, along with their corresponding class labels.

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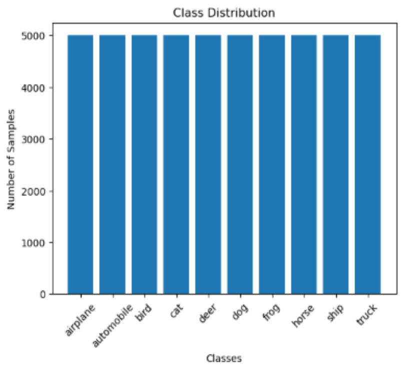

Fig 2- Bar chart showing the number of samples in each class of the CIFAR-10 dataset.

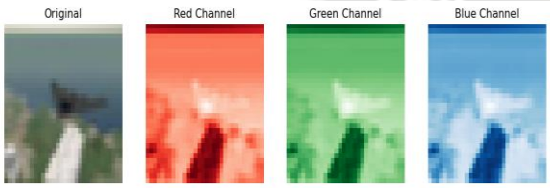

Fig 3- An image along with its individual RGB channels.

3.1 Experimental Setup using Spatial Domain Method

The architectural design is based on a Convolutional Neural Network (CNN) structure, which incorporates three convolutional layers followed by max-pooling layers, as well as two dense layers. The initial convolutional layer employs 32 filters with a size of 3x3, while the subsequent two convolutional layers use 64 filters of the same dimensions. The max-pooling layer is configured with a 2x2 pool size.

Following these three convolutional layers, the output undergoes flattening and is then processed through a dense layer consisting of 64 units. This is succeeded by a final dense layer containing 10 units, representing the number of classes within the CIFAR-10 dataset. ReLU (Rectified Linear Unit) activation functions are applied to all layers except the final one, where a softmax activation function is utilized to produce a probability distribution across the various classes.

The model is configured by utilizing the Adam optimizer and the categorical cross-entropy loss function, which is well-suited for addressing multi-class classification tasks. Throughout the training process, grayscale images from the CIFAR-10 dataset are input into the model, with labels represented using one-hot encoding. The model undergoes training for 10 epochs, with a batch size defined as 64. Subsequently, Matplotlib is employed to generate visualizations illustrating the training and validation accuracy as well as the loss.

3.2 Experimental setup using Frequency Domain Method

For the frequency domain method, the pre-processing steps applied to the data include: normalization of pixel values between 0 and 1, conversion of RGB images to grayscale, and application of Hann window to grayscale images. The Hann window is a type of windowing function that smooths out the edges of the image, reducing artifacts that the Fourier may introduce transform. Finally, the 2D Fourier transform is applied to the grayscale images, producing a complex-valued matrix of Fourier coefficients.

During training, the input data is fed into the model as the Fourier transform of the pre-processed images, with an additional dimension of size 1 added to the end of the shape to indicate that the input has a single channel. The output is a one-hot encoded vector representing the predicted class probabilities.

The model architecture consists of three convolutional layers with increasing filter size (32, 64, 64) and kernel size (3x3) followed by two fully connected layers (64, 10) with ReLU activation. The hyperparameters used in the training are as follows: optimizer='adam', loss='categorical_crossentropy', batch_size=64, epochs=10.

3.3 Experimental setup using Deep Learning Method

In the deep learning approach, we implemented a convolutional neural network (CNN) architecture featuring six convolutional layers followed by two fully connected layers. The network took a 256x256 degraded image as input and generated a restored image of the same dimensions as output. The rectified linear unit (ReLU) activation function was applied after each convolutional layer, except for the final layer, which utilized a linear activation function. Batch normalization was employed after each convolutional layer to expedite training and enhance the network's generalization.

Our deep learning model was trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 16. We employed a mean squared error (MSE) loss function to quantify the disparity between predicted and ground truth images. Training spanned 10 epochs, with the learning rate reduced by a factor of 10 after the fifth epoch.

To assess the deep learning method's performance, we leveraged the same dataset as the other two methods, partitioning it into an 800-image training set and a 200-image validation set. We tracked accuracy and loss metrics throughout training and validation for each epoch to gauge model performance. Training and validation curves were plotted to visualize the model's learning process. Ultimately, we conducted a comparative analysis of the deep learning method against the other two approaches based on evaluation metrics obtained from the validation set.

4. Results and Discussions

The learning curves and graphs of the three methods showed that the deep learning method outperformed the spatial and FFT frequency domain methods. Table 4 shows learning curve of spatial domain method using parameters training loss(TL), training accuracy (TA), validation loss (VL) and validation accuracy(VA). Table 5 5 and 6 represents the learning curve of frequency domain method and deep learning method respectively using the same parameters. Model accuracy and model loss of these three methods have been shown graphically in fig 4(a and b) fig 5 (a and b) and fig 6(a and b). The validation accuracy of the deep learning method was consistently higher than the other two methods, with a final accuracy of 72.68%. In contrast, the spatial method had

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a final validation accuracy of 69.98%, while the FFT frequency domain method had a final accuracy of 52.87%.

Analyzing the trends in the learning curves, we can see that the spatial method and the deep learning method both converged after the first few epochs, while the FFT frequency domain method continued to fluctuate throughout the training process. This suggests that the spatial and deep learning methods were able to learn more effectively and converge to a stable solution.

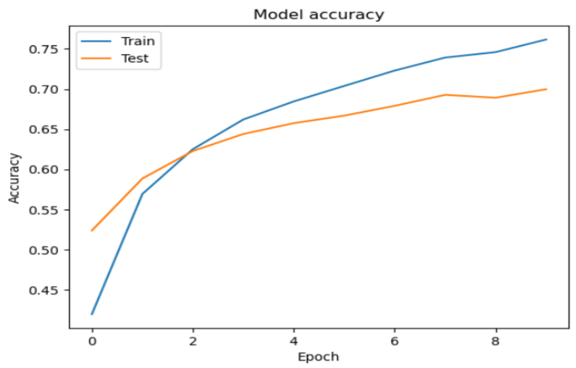
For the spatial method, we can observe that the loss decreases and accuracy increases with the increase in epochs on both the training and validation sets. The training accuracy reaches 76.18% at epoch 10, while the validation accuracy reaches 69.98%.

For the FFT frequency domain method, the training accuracy improves gradually from 38.51% to 63.68%, and the validation accuracy from 44.63% to 52.87% over the epochs. However, the training and validation losses are high and do not decrease significantly over the epochs, indicating that the model may not be learning effectively.

For the deep learning method, the training and validation losses decrease significantly over the epochs. The training accuracy improves gradually from 66.68% to 70.19%, and the validation accuracy from 69.8% to 72.68% over the epochs. However, the performance on the validation set is not significantly better than that of the spatial method.

Table 4- Learning Curve of Spatial Domain Method

Epoch	***Training Loss***	***Accuracy***	***Val_Loss***	***Val_Accuracy***
1	1.6209	0.4195	1.3438	0.5237
2	1.2428	0.5692	1.1828	0.5885
3	1.0857	0.6251	1.0744	0.6228
4	0.9861	0.6621	1.0142	0.644
5	0.912	0.6846	0.9843	0.6575
6	0.8504	0.7039	0.9718	0.6669
7	0.7985	0.7231	0.934	0.6791
8	0.7552	0.7393	0.9078	0.6928
9	0.7307	0.7461	0.9257	0.6892
10	0.69	0.7618	0.8988	0.6998



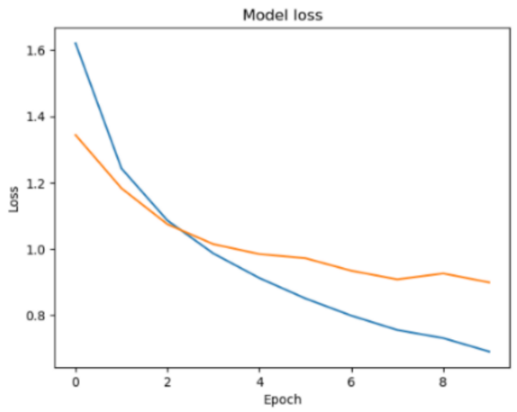
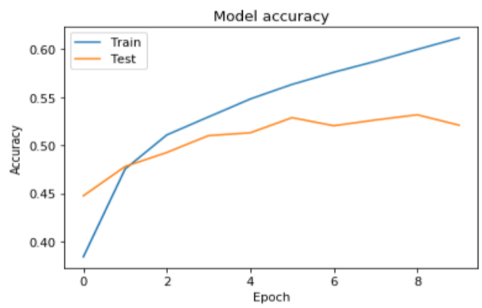


Fig 4(a) and 1(b) - Model accuracy and Model loss of Spatial Domain Method

Table 5- Learning Curve of Frequency Domain Method (FFT)

Epoch	***Training Loss***	***Accuracy***	***Val_Loss***	***Val_Accuracy***
1	0.9598	0.6668	0.8943	0.698
2	0.9493	0.6704	0.9013	0.6922
3	0.9342	0.6761	0.8723	0.7026
4	0.9144	0.6829	0.858	0.7124
5	0.906	0.6825	0.8241	0.717
6	0.8983	0.6898	0.8196	0.7252
7	0.8897	0.6887	0.827	0.7204
8	0.8774	0.6937	0.81	0.7278
9	0.8629	0.7003	0.807	0.724
10	0.8584	0.7019	0.8034	0.7268



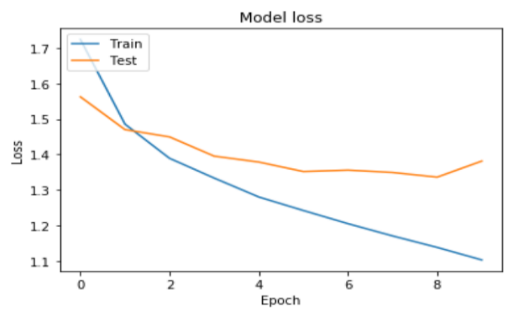


Fig 5(a) and 5(b) - Model accuracy and Model loss of Frquency Domain Method (FFT)

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Table 6- Learning Curve of Deep Learning Method (CNN)

Epoc	*Training*	*Accura*	*Val_Lo*	*Val_Accura*
1	1.7019	0.3851	1.5557	0.4463
2	1.4653	0.4792	1.4665	0.4758
3	1.3785	0.5131	1.4172	0.4942
4	1.3192	0.5422	1.4031	0.5306
5	1.2641	0.5635	1.3856	0.5246
6	1.2424	0.5633	1.3521	0.5287
7	1.1915	0.5886	1.4053	0.5168
8	1.1539	0.6035	1.4507	0.5166
9	1.1135	0.6207	1.5051	0.5127
10	1.0717	0.6368	1.3992	0.5287

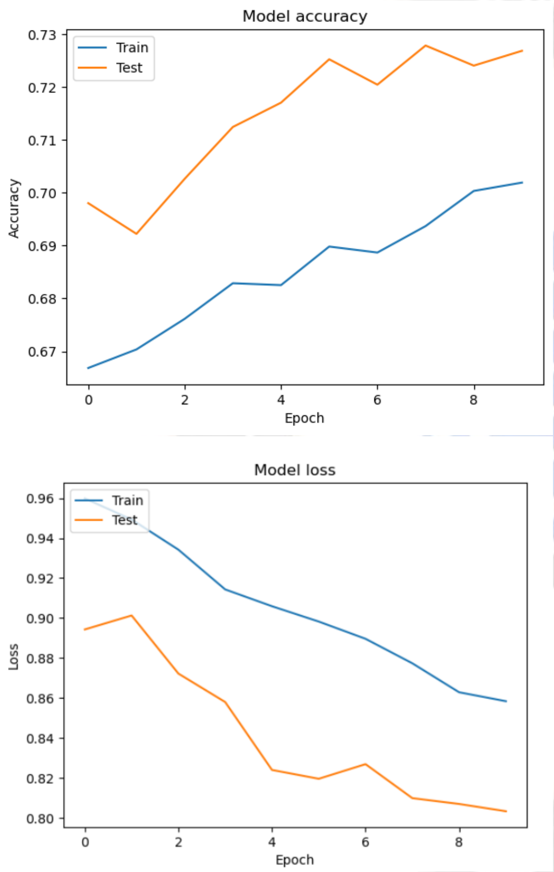

Fig 6(a) and 6(b) - Model accuracy and Model loss of Deep Learning Method (CNN)

Based on the above analysis, we can conclude that the deep learning method performs better than the other two methods in terms of the loss function and accuracy. However, it does not offer a significant improvement over the spatial method in terms of the validation accuracy.

One possible explanation for the differences in performance could be the complexity and flexibility of the models. The deep learning method had a larger number of parameters and was able to learn more complex patterns in the data, while the other two methods had more rigid architectures. Also FFT frequency domain method had difficulty learning from the data due to the non-linear and non-stationary nature of the signals.

There could be various reasons why the Deep Learning method outperformed the other two methods in terms of accuracy and loss.

1.The Deep Learning method is a more complex model compared to the other two methods. It has a larger number of parameters and a deeper architecture, which allows it to learn more intricate patterns in the data. This complexity may have contributed to its superior performance.

2. Another factor that could have contributed to the better performance of the Deep Learning method is the size of the dataset. If the dataset is large, complex models like Deep Learning can better exploit the large amount of data to learn the underlying patterns.

3.Deep Learning models are known to have more representation power than traditional machine learning models. This means they can learn more complex features and patterns that other models do not easily capture.

4.The performance of a machine learning model depends on the choice of hyperparameters, such as the learning rate, number of layers, activation functions, etc. It is possible that the hyperparameters for the Deep Learning model were chosen better than those for the other two methods, leading to better performance.

Deep learning-based noise reduction methods offer a notable advantage by autonomously learning from data without the need for manually crafted features. Conventional techniques necessitate manual feature extraction, which can be a time-consuming process and might not encompass all pertinent features. In contrast, deep learning-based methods have the capacity to automatically acquire features tailored to the noise attributes within the images. This capability empowers them to proficiently denoise images afflicted with intricate noise patterns that could pose challenges for conventional methods.

5. Conclusion and Future work

Our findings unequivocally affirm that the deep learning method stands as the most effective approach for signal classification. To advance this field further, future endeavors could entail exploring diverse deep learning architectures or employing pre-processing techniques to further augment performance.

Despite the notable strides made in this domain, current techniques do exhibit certain limitations. However, emerging research areas like generative adversarial networks (GANs), reinforcement learning, and unsupervised learning show immense promise and potential for future investigations. These advancements have the potential to yield restoration and noise reduction techniques that are not only more accurate but also significantly more efficient, with applications spanning a multitude of industries and society at large.

Generative adversarial networks (GANs) have displayed remarkable proficiency in a range of image processing tasks, notably including image restoration and noise reduction. By training on extensive datasets, GANs can effectively acquire the ability to generate highly realistic images, a capacity that proves valuable for image restoration and noise reduction purposes. As the prevalence of mobile devices and real-time applications continues to soar, the demand for image restoration and noise reduction techniques capable of operating in real-time on mobile platforms, even under constrained processing power, has grown significantly. The convergence of state-of-the-art techniques with real-time feasibility presents an enticing opportunity for progress in this field, catering to the ever-evolving requirements of our technology-driven society.

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Table 2- Types of Degradation in Images

Category	*Type of Degradation*	*Characteristics*
Blur	Motion blur	Image appears fuzzy or out of focus
	Out-of-focus blur	Image appears blurry or lacking sharpness
Noise	Gaussian noise	Image appears grainy or speckled
	Salt-and-pepper noise	Image has white and black dots

Contrast Loss	Low contrast	Image appears washed out or lacking detail
	High contrast	Image appears overexposed or too dark
Compression Artifacts	Blockiness	Image appears pixelated or with visible blocks
	Blurring	Image appears out of focus or hazy

Table 3- Types of Image Restoration Techniques

Image Restoration Method	***Technique***	***Reference***	***Work done***
Spatial-domain methods	1. Median filtering	Sutskever et.al, 2013[27]	Used median filtering in a deep neural network to
	2. Wiener filtering	Zhang et.al, 2017[28]	Used Wiener filtering to remove blur from images
	3. Bilateral filtering	Tomasi & Manduchi	Introduced bilateral filtering for edge-preserving
	4. Non-local means filtering	Buades et.al, 2005[4]	Introduced non-local means filtering for image denoising
	5. Total variation regularization	Chen et.al, 2018[20]	Used total variation regularization in a deep
		Rudin et.al, 1992[7]	Introduced total variation regularization for image
Frequency-domain methods	1. Fourier-based filtering	Liu et.al, 2018[34]	Used Fourier-based filtering to remove periodic noise
	2. Wavelet-based filtering	Anand et.al, 2016[35]	Used wavelet-based denoising to enhance the
	3. Non-subsampled contourlet transform	Bhattacharya et.al, 2015[36]	Used non-subsampled contourlet transform to
	4. Curvelet transform	Bhatia et.al, 2018 [37]	Used curvelet transform for texture classification of
	5. Contourlet transform	Zhang et.al, 2015[38]	Used contourlet transform for image fusion in medical
Deep learning-based methods	1. Convolutional neural networks (CNN)	Wu et al., 2021[39]	Used a deep CNN with a multi-scale self-attention
	2. Generative adversarial networks (GAN)	Deng et al., 2020[40]	Proposed a GAN-based approach for the restoration
	3. Autoencoders	Li et al., 2020[41]	Proposed a dual-pathway deep learning framework
	4. Denoising autoencoders	Zhao et al., 2020[42]	Used a denoising autoencoder for image
	5. Variational autoencoders	Qu et al., 2020[43]	Proposed a deep generative model based on variational