

## Research Article

# Security Protection Mechanism in Cloud Computing Authorization Model Using Machine Learning Techniques

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Because of the vast number of applications and the ambiguity in application methods, handwritten character recognition has garnered widespread recognition and increased prominence in the community of pattern recognition researchers ever since it was first developed. This is due to the fact that application methods can be quite ambiguous. Computer in the cloud, on the other hand, allows for suitable network access on demand to a shared pool of customizable computing resources and digital devices. According to those knowledgeable in the subject, the standard filtering techniques are not enough when it comes to the process of denoising images. In many different approaches to machine learning, information is lost not just during the filtering process itself but also at other points during the process. When a convolutional neural network is going through its pooling operation, the internal data representation either becomes misaligned or entirely vanishes (CNN). The reconstruction of low-intensity digital photographs, which takes place during repetitive filtering, breaks away the artefacts that remain after each filtering function, which results in an image that is more uniform. The multilayer wavelet transform, or MLWT, is a method for processing features that comprises of many filter bands and is used in cloud computing authorization that is protected securely. In this scenario, a significant quantity of information gets obliterated from digital photographs during the process of feature extraction and processing. These issues are investigated by the deep learning algorithms that make use of autoencoder, and the methods also handle the novel windowing blocks that are being introduced to the layers. In this section, the magnitude and phase information is considered in order to construct a deep learning framework that will provide good denoising of digital images. The proposed architecture is equipped with the capability of accurately identifying, in real time, the noise level and type that was employed in the training of the network. The method that we have proposed, which is centred on the distribution of noise, may be used to determine the kind of noise. In order to categorise the various types of noise, we investigated nine distinct noise distributions. Dilated convolutional filtering will be used as the method of choice in order to ascertain the specific nature of the noise that can be found in the digital images. An autoencoder-based deep learning algorithm is able to accomplish numerous experimental results in digital image denoising operations that are superior to those achieved by a typical deep learning algorithm even when the intensity of the scenario is low. The performance of the method that is produced by combining the autoencoder and the dilated convolutional filtering techniques is enhanced over the performance of the technology that is currently in use. Using the method that we have outlined in this study, it is possible to recreate the low-intensity images in their entirety. We were able to show that our proposed method beat other existing algorithms for low-density digital photos by comparing several metrics, such as the peak signal-to-noise ratio (PSNR), the structural similarity index, and others (SSIM).

## 1. Introduction

Recently, a machine learning method has been developed to determine the best practices for image denoising development. The following are examples of varied noise distributions dependent on the surrounding characteristics and parameters: Gaussian, log-normal, uniform, exponential, Poisson, salt and pepper, Rayleigh, speckle, and Erlang are all types of probability distributions.

Figure 1 shows the denoising structure. The machine learning-based denoising technique is able to produce a high peak signal-to-noise ratio (PSNR) value when contrasted with more conventional methods of processing. It is important to extract features from images in order to specify the aim for learning parameters, and supervised learning is the method by which this may be performed. This parameter is essential for preparing the denoising model for feature categorization before beginning training [1]. In order to train the supplied samples and provide patches for use in the matching process, which is essential to fulfil the specific tasks at hand, unsupervised learning methods are used. Unsupervised learning techniques are applied. A cycle in cycle GAN approach for image denoising was reported not too long ago, and its intended use is in the process of training the super determination model. In the semisupervised learning model, one phase in the labelling process is to design a data distribution system to label unlabeled models. This is one of the components of the model. The sinogram restoration network, which is also utilised for feature distribution and the distribution of sinograms, is employed in the instruction of this topic. A wide range of techniques, including feature classification and high-fidelity sinograms [2, 3], may be used to acquire these paired sinograms. The plug-and-play network structure has allowed the convolution neural network to demonstrate outstanding performance in image denoising [3]. These convolutional kernels include a wide array of visual properties that may be used in various classification tasks. The convergence of these kernels occurs at a quite modest rate as a result of the activation utility it has. It is possible for the graphics processing unit to determine whether or not there are any artefacts present in the photographs that are currently being processed. In this particular scenario, the problem of machine learning with overfitting is solved by using this method. When dealing with overfitting problems in machine learning, the data augmentation method may also be employed as a strategy. The residual learning unit approach [4], which is used in combination with gradient descent, which allows for the possibility of speeding up the process, may be used to do so.

The AlexNet technique, which is capable of supporting a broad range of algorithms [5, 6], is used to organise the spaces that utilise the least memory during the process since it is handling massive convolutional kernels [7]. This strategy is used to organise the spaces. Figure 1 displays low-intensity digital images that were captured at low resolution and include both noisy and clear photographs.

Figure 2 depicts the traditional approach's fundamental block architecture, which is used in the context of the image denoising application. The traditional approach to image

denoising is used here with the intention of reducing the amount of noise that is present in the original images. When combined with the process of deep learning, this approach generates better results in the final product. The wavelet techniques are included into the U-Net method, which is developed for the purpose of image denoising [5]. CNN and the Gaussian image denoising technique are efficient and useful for the process of picture denoising. It operates on a large pixel domain.

*1.1. Motivation.* The quality of the damaged images has been reduced due to the presence of a variety of noise spectra, the likes of which are impossible to anticipate in real-world scenarios. In order to get a better degree of image quality, it is not sufficient to obtain a clear picture by using traditional or classical methods such as filtering technique in order to remove the noise from the spectrum. When considering the process of image denoising from a more long-term perspective, the feature extraction mode of the deep learning approach will become rather significant. The noisy spectrum ensemble has recently been subjected to an application of the multidimensional degrading technique [6]. When extending digital pictures, it is essential to eliminate the appearance of gridding in the images as much as possible so as not to detract from the expanded photographs. Figure 3 is an illustration showing how an autoencoder is used in the process of image denoising.

## 2. Organization of the Research

The following is the structure of this research article: Section 3 provides an overview of contemporary strategies for picture denoising, including preliminary results. Section 4 outlines a process for proposing filtering approaches for digital photos, which may be found here. Section 5 outlines the findings of the study. Section 6 summarises the work completed to date and outlines next responsibilities.

## 3. Preliminaries

In the field of image processing, the wavelet filtering approach for the purpose of picture denoising has been in use for a considerable amount of time. The process of restoring images is essential in a broad variety of study fields [8, 9]. In this instance, the PSNR value is used in order to provide an explanation of the overall performance of the method. Dictionary-based approaches have shown a potentially useful performance in the context of image denoising with superresolution [9]. As an extension of the image denoising approach, recent developments have resulted in the creation of prior knowledge-based regularisation algorithms [10]. In a fast and effective way, the standard regularisation approaches are capable of eliminating artefacts from noisy photographs. Within the realm of image processing, the modelling of picture denoising that is done on the basis of many sparse representations is especially widespread. After using the sparse representation model to locate the data points in the images, the images are linearly reconstructed utilising a strategy that is based on a dictionary in order to

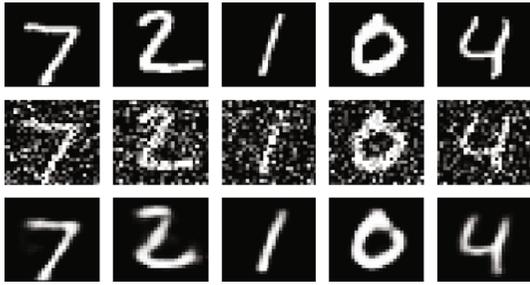


FIGURE 1: Example image for denoising in cloud environment.

locate the data points in the images. There will be a significant number of parameter coefficients that are not different from zero [11], [12]. Within the context of an application for image denoising, Chen et al. offer a deep learning strategy for picture denoising. They researched and tested a large number of neural networks that produce excellent results for feature extraction in circumstances when there is a lot of noise [13]. They achieved this by stacking the neural networks one on top of the other. When it comes to techniques for image denoising, Ahirwar et al. provide a CNN that is completely linked and is able to extract features from images despite the presence of background noise [14].

Mao and his colleagues provide a deep CNN design for the photo denoising process. This design includes a recurrent neural network architecture in addition to 30 layers of convolutional and deconvolutional layers. The connected approaches make use of an unbalanced skip through the layers, which enables them to be carried out more quickly. As a direct consequence of using this tactic, they were successful in overcoming two obstacles by utilising deep CNN. The first reason is that the issue has been fixed, and the second is that the issue prevents efficient backpropagation. The gradient problem, which may be traced back to a variety of sources, is a significant factor that contributes to inadequate backpropagation. Increasing the total number of layers in the network is the solution that may be used to correct or get rid of the gradient problem. As the number of layers in a network grows, there is a better chance that the quantity of mistakes that are made will be cut down to a manageable level. Their network connection has been built up in such a manner that it enables the gradient kernels to reverse broadcast. This is accomplished by upsampling and downsampling through convolutional and deconvolutional layers, respectively. The second issue is that there was a loss that occurred all the way through the process of downsampling layer sampling. This information leak may be rectified or totally eradicated by training the upper layers in the appropriate way [15], which involves the use of coefficients. These days, with the help of feature extraction and machine learning, it is feasible to store all of the information pertaining to the whole image in a single location [16, 17]. Deep learning does not give any promises in this respect due to the absence of a choice of features from photos in the deep learning framework [18]. The extracted features ought to be resilient; nevertheless, deep learning does not provide any guarantees in this regard. The vast majority of studies on machine learning methodology approaches are conducted within the

context of photo denoising applications. This CNN approach image denoising ensemble is paired with the embedding of strong feature extraction from the photos. Both of these processes are carried out in conjunction with one another. The CNN method, which consists of numerous connected layers [5], is able to handle images well even when the edges are blurry and the intensity is low.

A combination of wavelet and U-Net approaches is used in order to achieve the goal of reconstructing the images without resorting to the use of gridding. Machine learning systems are able to handle nonlinear, noisy images and rebuild them in a form that is useable. This is one of the capabilities of these systems. When it comes to dealing with nonlinear, noisy photos, the CNN that is paired with kernel-based techniques is highly successful [19]. For the goal of image denoising, Chetlur et al. [20], Bengio et al. [21], and S. Kaur et al. [22] reported in their respective studies a mix of multilevel wavelet filtering (MLWT) approaches and CNN. They were unable to cope with nonlinear and low-intensity digital images as a consequence of this, which is why they failed in the denoising sector.

**3.1. Research Gap.** It is possible to rebuild digital pictures from a noisy domain using a CNN-based method, which is one of the several options. Images with weak edges and noise are difficult to process, and dealing with them is a difficult problem in image processing. The issue was handled using a dual U-Net deep learning technique, as described above. However, despite having a high PSNR and SSIM value, it was not successful. Low-intensity digital pictures are particularly affected by the gridding effects of dilated convolutions, which occur when high-dimensional images are enlarged and reduced in size. As a result of the nonlinearity function of the noisy pictures, many deep learning algorithms fail when it comes to selecting the suitable kernel for a CNN.

**3.1.1. Maintaining Strict Secrecy.** Restrictions are placed on the availability of information and the dissemination of that information or the protection of the data from being seen or accessed in an unauthorised manner.

**3.1.2. Moral Rectitude.** Protecting data from being altered or deleted by other parties who are not authorised or data is sent from the sender, it is expected that the recipient will get the identical data.

**3.1.3. Availability.** It ensures that the necessary information or resources are accessible at the appropriate time. This assures that services will always be accessible when they are required.

**3.1.4. Key Management.** Because of this, negotiating, preserving, and setting up keys for communication between parties are possible entities.

**3.1.5. The Policy of Nonrepudiation.** It offers protection in the event that one of the companies engaged in a transaction decides to deny to have taken part in the communication in its whole or in part to have taken part in the communication.

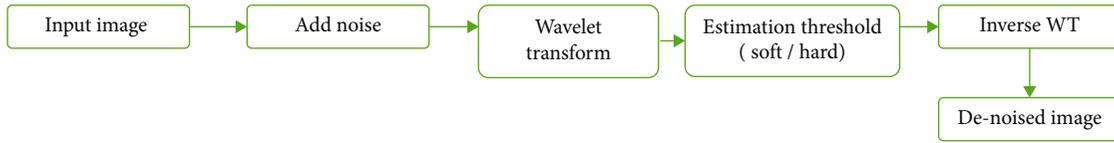


FIGURE 2: Block diagram of classical approach for image denoising.

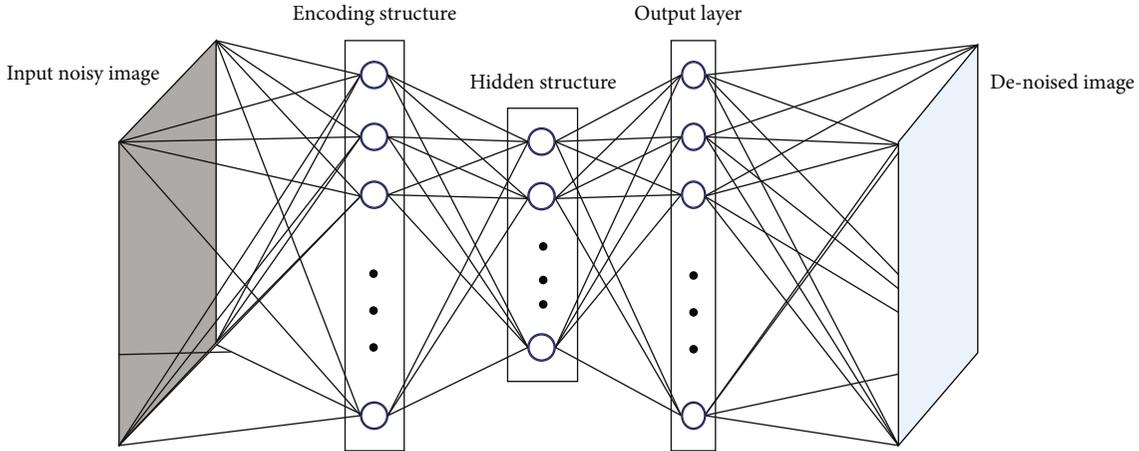


FIGURE 3: Simplified flow diagram of autoencoder technique in image denoising.

Platform as a service, often known as PaaS, refers to the method of using and accessing the service of software without the need to download it on the user's premises or even install it on a local system for any user, whether they are the product's creator or an end user. It offers significant degree of platform/integration for multitenant systems. Platform as a service is chosen by users when they are unable to handle the underlying infrastructure, including the network, servers, operating systems, and storage. <http://Force.com>, Google App Engine, and Microsoft Azure are a few examples of platforms offered as a service (PaaS).

Infrastructure as a service (IaaS) is the act of sharing various physical resources across a network. IAAS stands for "infrastructure as a service." The primary objective of IAAS is to facilitate the quick access of operating systems and applications to servers, storage, and networks. As a result, it is able to provide basic infrastructure services on demand by using application programming interface (API). Within the cloud architecture, the user is not responsible for managing the core hardware; nevertheless, they do have control over the server, applications, and operating system. IaaS is shown by services such as Amazon elastic cloud computing (EC2). Database as a service (DaaS) allows customers to store essential document files and other information in a centralised location. DaaS is also known as "cloud computing." Additionally, this offers services associated with the storage of a vast quantity of data, any of which may be mined for information that is pertinent. The database is also an essential component of these services, since it is responsible for storing user-related data such as personal information and credential information.

**3.2. Problem Statement.** The removal of the gridding effect of dilated convolutions in an output layer of CNN during

image reconstruction will depend on the number of layers in CNN. Besides, the investigating kernel functions with CNN can provide good results in image restoration.

**3.3. Proposed Solution.** Construction of the CNN model is fused with the autoencoder approach. The extracting features from the images should be robust and multilayered from input to output information flow in autoencoders. During enlarging, the images at receptive fields can be improved through a convolutional dilated filtering approach.

## 4. Methodologies

The existing network architecture should be changed in an effective way to reconstruct the images from noisy ones. The multi-layer-based knowledge procedure is preferable for better image denoising [23]. The CNN is comprised of convolution and learning knowledge of the magnitude and phase features. This construction should be facilitated for a low-intensity image denoising model. During extending, the region of interest of resultant images facing blurred and false image artifact problems is not addressed with the existing procedures [22].

**4.1. Wavelet Filtering-Based Simplified Denoising Approach.** Figure 3 shows the procedure steps of wavelet filtering approach in feature extraction. Here, WT stands for wavelet transform. Feature processing is denoted by FP.

In a cloud environment, one of the primary concerns is ensuring the safety of the users' information. Data protection encompasses a wide range of concerns, including the management of confidentiality and integrity, the provision of authentication, and the accomplishment of availability,

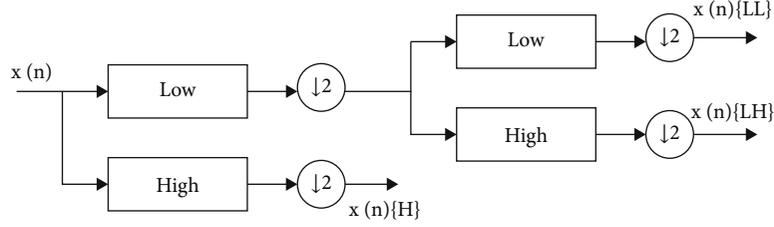


FIGURE 4: Filters at wavelet domain.

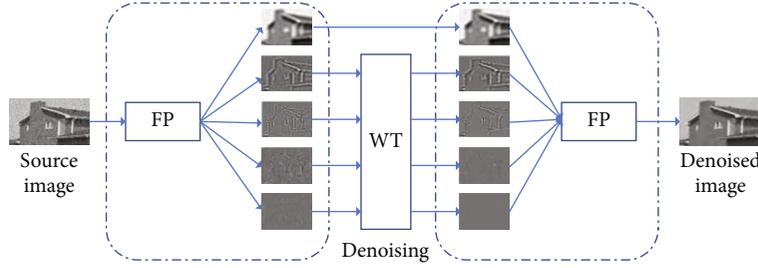


FIGURE 5: Wavelet filtering approach in feature extraction.

amongst many others. In order to maintain data confidentiality, only users who have been successfully authenticated may access the data. Maintaining data integrity implies ensuring that the information is unaltered whether it is being stored on a distant system or a local system.

Authentication is the process of verifying the identity of a user in order to determine whether or not the information they requested should be granted access to. The capacity to access data at any time and for any purpose is referred to as its availability.

Confidentiality is normally accomplished by the use of encryption methods; however, in the cloud environment, where user data and user personal information are kept separate from one another, confidentiality may be maintained. Only when we consider the security of user-maintained documents is encryption relevant; however, when personal information is at risk of being compromised by an adversary, encryption is needed to protect the confidentiality of databases stored on cloud servers.

The encryption method may be used in this setting, but it is quite time-consuming for both encryption and decryption due to the fact that thousands of processes are carried out all at once. Therefore, in order to accomplish both speed and security, a framework was necessary that addresses issues relating to users and cloud servers by making use of the techniques outlined.

Various cloud researchers, each using their own strategy to address the issue of accurate data storage, have found and addressed the problems that arose as a result of their work. Their phenomenon may also point out additional expenses incurred in the cloud or additional burdens on the client side.

Database security does not have this option supplied.

It is pricey to share documents with others.

Users are not provided with a broad array of security solutions by them.

The majority of the efforts are either focused on the server side or on the client side. The client is not supplied with file versioning.

*Step 1.* Let us consider for the subband images named as  $x_1(n)$ ,  $x_2(n)$ ,  $x_3(n)$ , and  $x_4(n)$ ,

$$\begin{aligned} x(n)\{LL\} &= \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}, \\ x(n)\{LH\} &= \begin{bmatrix} -1 & -1 \\ 1 & 1 \end{bmatrix}. \end{aligned} \quad (1)$$

Subband separation in the images through wavelet low pass and high filtering approach is shown in Figure 4.

*Step 2.* For subband images up to  $x_k(n)$ , here,  $\{k \text{ is } 1, 2, 3 \dots\}$ , based on the levels.

Here, Daubechies (DB2) wavelets are taken, and it is incorporated with CNN that provides related network output based on wavelet filtering function is defined as  $F(y; \Xi)$ ; let  $\{(y_k, x_k)\}$  with an interval from  $k = 1$  to  $N$  for our training set. It denotes the comparison of inputs and ground truth images. Feature extraction and processing are done with wavelet transform and inverse wavelet transform, respectively [24]. Figure 5 shows outline of the feature processing with an aid of wavelet transform details [25].

*Step 3.* Finally, the network parameter for wavelet function in CNN domain is defined as

$$L(\Xi) = \frac{1}{2N} \sum_{k=1}^N \|F(y_k; \Xi) - x_k\|_F^2, \quad (2)$$

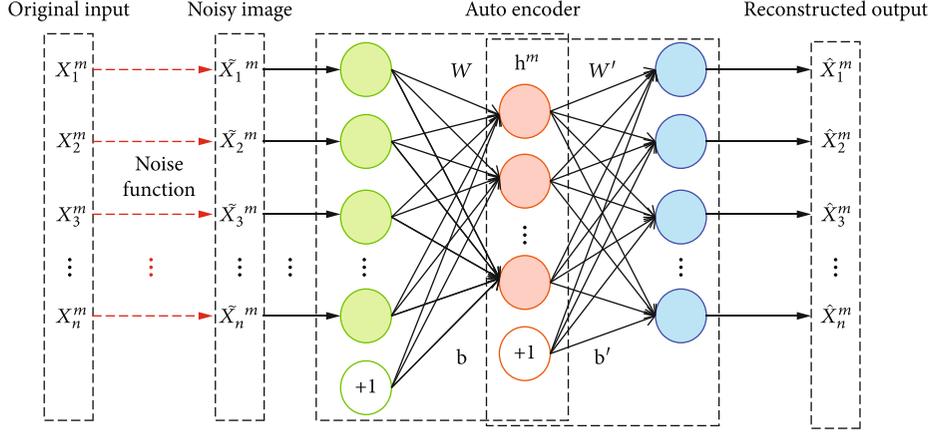


FIGURE 6: Proposed structure of autoencoder type deep Learning process.

where parameter is denoted as  $\Xi$  and  $F$  is denoted as objective learning function.

**4.2. Proposed Deep Learning-Based Denoising Algorithm.** Our proposed algorithm comprises of autoencoder techniques in the deep learning method and dilated convolution filter during our reconstruction section for real noisy images [26]. This new approach provided better PSNR and SSIM values compared to the existing methods [27]. The proposed algorithm is the succeeding step-by-step procedure as follows.

*Step 1.* For fundamental framework, let us consider

$$y = x + \sigma, \quad (3)$$

where  $x$  and  $y$  are the reference image and noisy image and  $\sigma$  is the standard deviation of the additive white Gaussian noise (AWGN).

The function of clean and corrupted image is

$$x_k = f(y_k, \theta, l), \quad (4)$$

where  $\theta$  is the parameter and  $l$  indicates the noise level.

*Step 2.* Training the algorithm with stochastic gradient variation Bayes estimator, the graphical model is

$$g_m = \sum_{k=1}^N p_{\theta}(x_k | y_k). \quad (5)$$

The learning approximation is

$$l_a = \sum_{k=1}^N q_{\phi}(y_k | x_k), \quad (6)$$

where  $\theta, \phi$  are denoted as the estimation parameters of the encoders.

*Step 3.* The probability of latent vector distribution in terms of divergence function is defined as

$$L(\theta, \phi, x_k) = \text{div} \left( q_{\phi}(y_k | x_k) \| p_{\theta}(y_k) \right) - E_{q_{\phi}(y_k | x_k)} \left( \log_{p_{\theta}}(x_k | y_k) \right). \quad (7)$$

*Step 4.* The shape of the variation factorized Gaussian function is

$$\begin{aligned} q_{\phi}(y_k | x_k) &= N(\rho(x_k), w^2(x_k)I), \\ p_{\theta}(x_k | y_k) &= N(\mu(y_k), \sigma^2(y_k)I), \end{aligned} \quad (8)$$

where  $\rho(x_k)$  and  $w^2(x_k)$  are the encoder output, while  $(\mu(y_k)$  and  $\sigma^2(y_k)$  are the decoder outputs.

*Step 5.* In reconstructing images,

$$y_k = f_{\theta}(\hat{x}_k) = s(\omega_{\hat{x}} + b), \quad (9)$$

where  $\hat{x} \sim q_D(\hat{x}_k | x_k)$  is named as the stochastic mapping.

*Step 6.* The general framework of deep learning based model is

$$\min_{\Xi} \text{loss}(\hat{x}, x). \text{ s.t. } \hat{x} = f(y, \sigma) \quad (10)$$

Finally, loss function can be calculated as

$$L_m = \frac{1}{N} \sum_{k=1}^N (x_k - y_{k-1})^2. \quad (11)$$

*Remark 1.* Calculating loss function can be minimizing blurry impact in resultant images from a noisy domain. Stochastic mapping provides a better reconstruction of the images [28]. Finally, our proposed algorithm is constructed with the incorporation of the loss function measuring formula [26]. Figure 6 shows our proposed framework construction with autoencoder type.

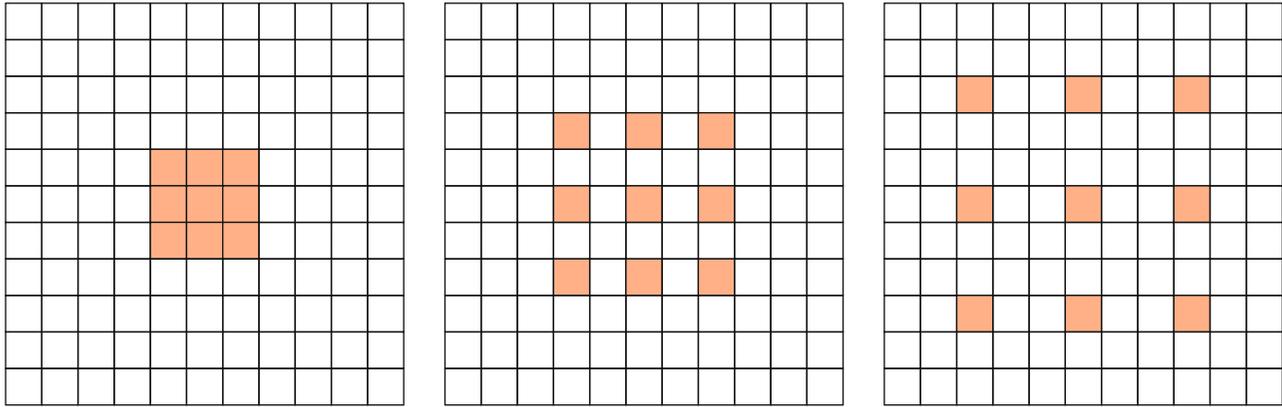


FIGURE 7: Dilation convolutional at spatial resolution.



FIGURE 8: Test images in datasets.

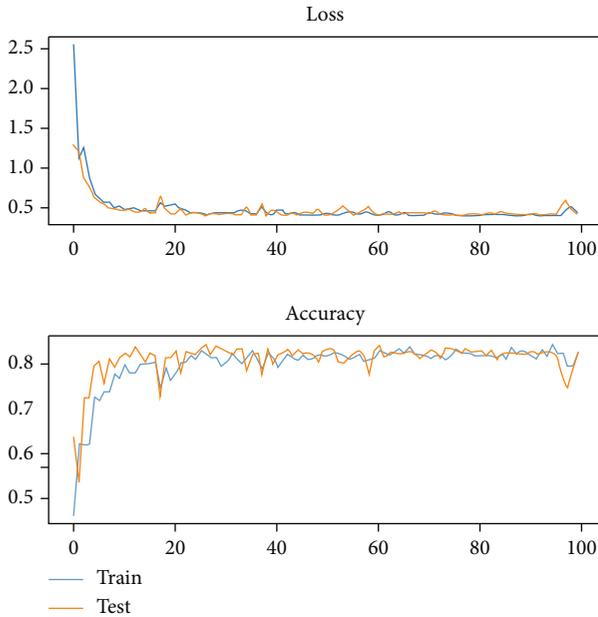


FIGURE 9: Loss and accuracy measures for training and testing dataset.

### 5. Results and Discussion

We examined our algorithm with 12 test images for our experimental results [29]. The public datasets for image denoising procedures are DND, SIDD, Nam, and CC for our experiments. Simplified wavelet filtering methods are designed and tested with dataset [23]. Due to the unavailability of ground truth clean images, the NC12 dataset is not used in our experiment [30]. The multilevel wavelet methodology is functioning on digital images for denoising procedure with CNN-based approach [31]. The spatial resolution of dilated convolutional filters is shown in Figure 7.

We strongly believe that the readers can understand our proposed method in a better manner. We examined our algorithm with ground truth images as well as real noisy images and it gives the best results of reconstruction. The extracted features from CNN can be utilised with the kernel method that it is used to convert to linearity features [32–34].

The wavelet filtering approach is struggling with reconstructing the denoised output images after decomposition in analysis filter bank. The DnCNN, MLWT, and WNNM methods are affecting the blurring details in the denoised images with sharp edges [35]. In our case, the MLWT is a very potent tool to reconstruct the edges from a noisy spectrum [36]. Figure 8 shows the dilation rates in every pixel-wise that produce gridding artifacts due to dilated

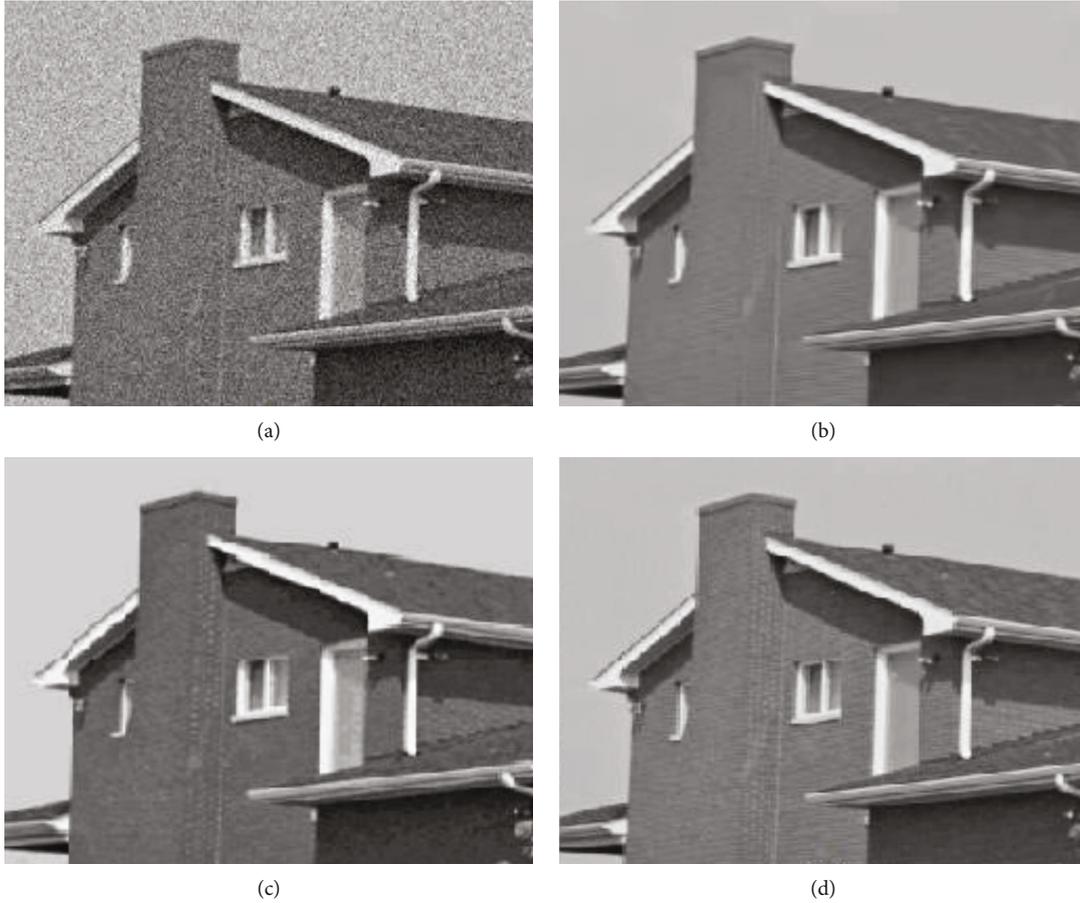


FIGURE 10: Result obtained for house images.

TABLE 1: Results obtained through learning network.

S. no	Test images	Methods	Metric	
			PSNR	SSIM
1	Lena image	DnCNN	27.1	0.71
		WNNM	26.5	0.601
		MLWT	21.74	0.316
		Proposed method	31.31	0.855
2	House image	DnCNN	22.05	0.46
		WNNM	25.41	0.621
		MLWT	26.65	0.685
		Proposed method	27.98	0.721
3	Number image	DnCNN	21.875	0.585
		WNNM	25.955	0.611
		MLWT	24.195	0.5
		Proposed method	29.14	0.789

convolutions operation. Our validated dilated convolution 2D kernel is of the size  $3 \times 3$ , and its approximated rate is from unity, 2 and 3, respectively [37–39]. Our computation is different from the actual receptive fields with separate sets of units in the inputs. Figure 9 shows some test images for our experiments to denoising procedure [40].

Our proposed algorithm can be evaluated for those test images in dataset with performance metrics of PSNR and SSIM and computation time between multilayers. The visual quality is not dependent on quantitative measurement [41]. Therefore, the visual quality comparison is provided in Figure 10. We tabulated the obtain results with various deep learning algorithm [42] about PSNR and SSIM in Table 1.

The set of test images can be tested, removing the noises from the real noisy images and artifacts and unwanted texture [43]. The loss and accuracy of the dataset during the training and testing process are shown in Figure 9. When we handle low-intensity and nonlinear images, MLWT approach provides low visual quality measures [44]. Figure 10(c) image is cleaned from noisy spectrum images by MLWT method. When enlarging region of interest in an image, more scrap of artifact problems with blurry detail occurred in digital image.

Figure 10 shows denoised output of house images. Figure 10(d) image shows the clean image from the noisy image by our proposed method. Figure 10(b) images contain very less artifacts in the image during enlarging function [45]. The detailed PSNR and SSIM performance measures for MLWT, our proposed algorithm, DnCNN, and FFDNet are shown in Figure 11.

Our proposed algorithm performs well in removing unwanted details from the noisy [46] spectrum which is

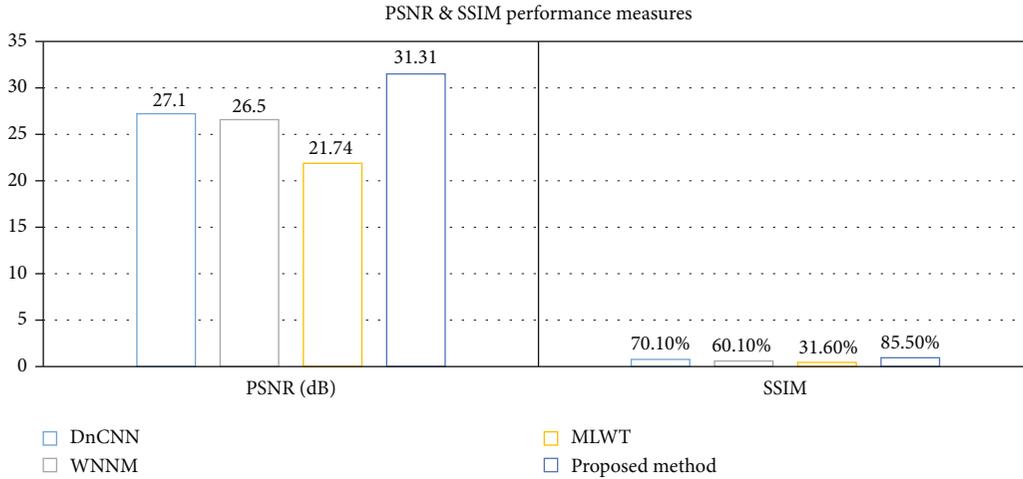


FIGURE 11: Comparison chart between the proposed and existing algorithm.

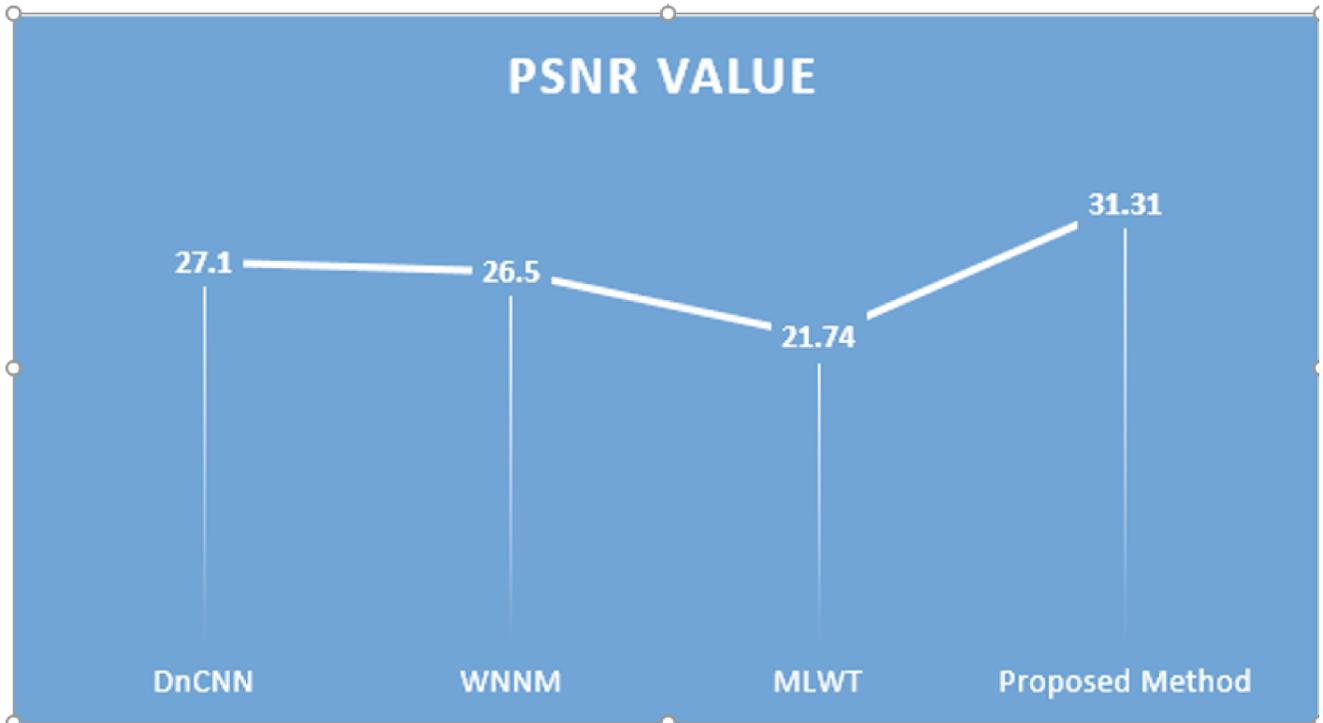


FIGURE 12: Comparison of MLWT vs. proposed method by PSNR.

shown in Figure 12 in terms of PSNR value. Therefore, our proposed algorithm is suitable for very high-dimensional noisy images and low-intensity digital images to do denoising procedures [47]. The convolution operation in our proposed algorithm is used to extract the features from the images.

Encoder techniques are reducing the dimension of the obtained images which can be stored in the memory with less memory space [48], but our algorithm is used to store data with more space range.

From Figure 13, our proposed algorithm is very stable and robust when it reached high visual quality with better

PSNR value compared to MLWT as well as other methods [49]. Finally, the deep learning method is fused with an autoencoder that is reconstructed clean images from the noisy spectrum [50]. The obtained resultant images are calculated by peak signal-to-noise ratio and structural similarity index to identify the visual quality measures in the images. Denoising performance can be measured by following metrics:

$$PSNR(x, \hat{x}) = 10 \cdot \log_{10} \left( \frac{255^2}{\|x - \hat{x}\|_2^2} \right). \quad (12)$$

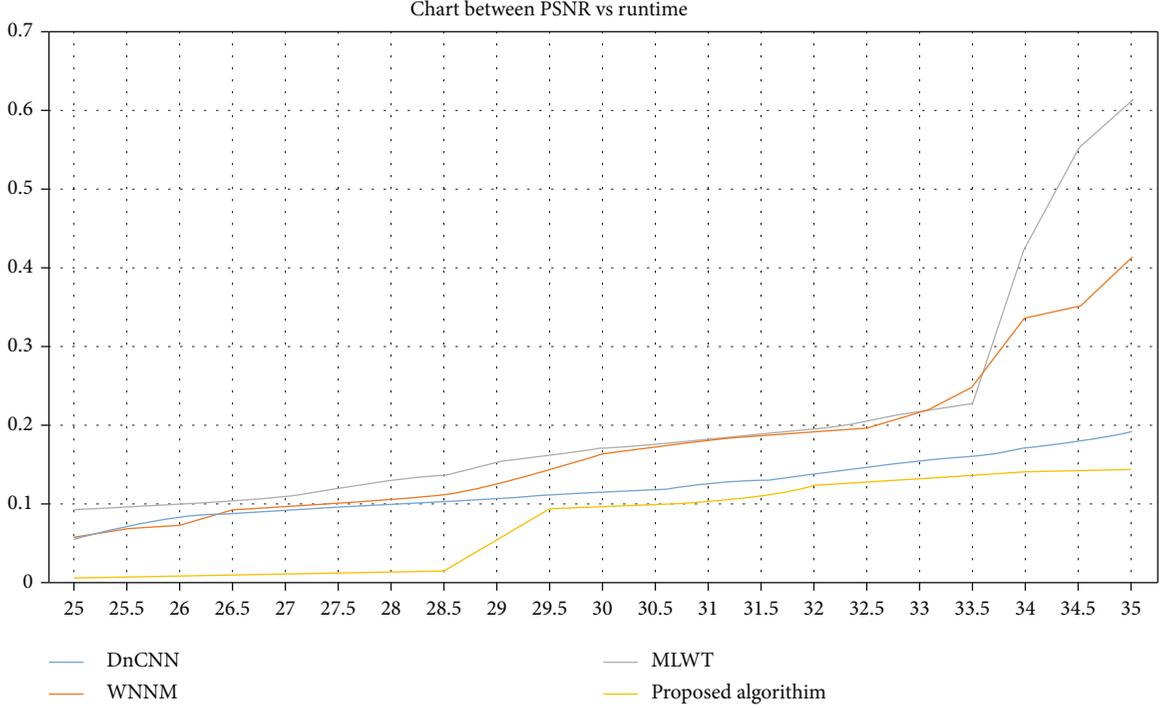


FIGURE 13: Proposed algorithm chart of PSNR vs. runtime in seconds.

In addition, the structural similarity index (SSIM) is calculated by

$$\text{SSIM}(x, \hat{x}) = \frac{(2\mu_x\mu_{\hat{x}} + C_1)(2\sigma_{x\hat{x}} + C_2)}{(\mu_x^2 + \mu_{\hat{x}}^2 + C_1)(\sigma_x^2 + \sigma_{\hat{x}}^2 + C_2)}, \quad (13)$$

where  $\mu_x$  and  $\mu_{\hat{x}}$  are the mean,  $\sigma_x$  and  $\sigma_{\hat{x}}$  are the variance,  $\sigma_{x\hat{x}}$  is the covariance, and,  $C_1$  and  $C_2$  are constants.

In our experiments, complete proposed algorithm is executed by Intel core i5-4570 CPU 3.2 GHz with 16 GB memory desktop PC.

**5.1. The Period of Data Obfuscation.** During phase 1, our goal is to manage sensitive data that is submitted by DO/DU and to safeguard that data from inappropriate usage. The user is responsible for providing any essential information at step 1, after which the CSP will obfuscate any incoming data and then store it in a database. This is the most general phase that is come into existing in many of the phases that have been mentioned above because all of the details of the client that may be related to personal, group policy, or document sharing are in the form of obfuscated data on the cloud server side. This phase can be found in many of the phases that have been mentioned above.

Step 1: send ((data))

Second stage: CSP uses obfuscation, and then, save the data in the database

Obfuscation, decryption, and file downloading phase: phases 8 and 9 are concerned with decrypting and downloading files from CSP. Additionally, obfuscation is often conducted to secure data stored on cloud computers. The user sends a request to check the file list, and the request is approved by the owner. In the next stage, the user will be

able to download the file from the cloud. Once this has been completed, the user may download the file and decrypt it locally. The obfuscation and deobfuscation processes are typically always conducted at certain stages of the database development life cycle during which data will be saved in and retrieved from the database.

## 6. Conclusions

As a consequence of this study, we have created a filtering approach that is fundamental but effective. This method has been examined on a digital image including the dilated convolution effect. In conclusion, the method that we have proposed handles and mitigates the issue of the gridding effect in the noisy spectrum, in contrast to the wavelet filtering denoising approach, which is unable to address and mitigate this problem. As an added benefit, the visual resolution of digital images is enhanced as a direct consequence of using the technique that we proposed. In order to handle low-intensity digital image denoising problems in a noisy domain, the autoencoder is functioning in combination with the convolutional dilated filtering approach. This strategy combines the two techniques in order to perform its function. When working with noisy photos taken in the real world, the dilated convolution approach is used to generate structural information about the digital image that is under consideration. As a result of this, when contrasted with other methods, the dilated convolutional filtering technique may obtain a higher PSNR value while also taking less time to process the data than the other methods. The output denoised image has been increased, which has resulted in a considerable improvement in the visual quality of the digital pictures. In order to show the visual quality of digital

photographs throughout the course of our extensive experiment, we are making use of a variety of datasets, each of which is explored in further depth in the section under “findings and discussion.”

**6.1. Future Enhancement.** Because our proposed framework makes use of the deep learning technique, it is important for it to need extra memory storage space in order for it to be saved. This space might be taken up on the computer’s hard drive. Because of the multidegradation process that it goes through, the autoencoder that we have proposed is ineffective when it comes to capturing genuine photographs that have noise in them. In addition, it is insufficient in order to reply to the unsupported denoising work that was done. For reasons that should be evident, it is not feasible to use the PSNR and SSIM metrics to determine whether or not digital photos have been too smoothed out. The process of blind deconvolution and image deburring are two examples of the kinds of applications that might benefit from an upgraded version of the method that we have proposed. In addition to this, it will be tested for high-level visualisation applications, and then, it will be integrated with deep learning image classification to offer a complete answer.

## Data Availability

The data that support the findings of this study are available on request from the corresponding author.

## Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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