Enhancing Leaf Image Quality Using Deep Learning Denoising Techniques

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It might be difficult to eliminate noise from images in the area of research. Image Denoising is a strategy used to take out distracting noise from images while preserving the original image. Plant Diseases can cause great harm to the agricultural industry. Denoising of the collected images can improve the accuracy of the identification process. Noise in images can be caused by a variety of factors such as dust, variations in light intensity, scratches, or camera artifacts. This noise can obscure the features of the plant that are used to identify the disease. Denoising can help to remove this noise and reveal the true features of the plant, which can lead to more accurate identification. There are a number of denoising approaches used to remove unwanted noise from images. In our paper, deep learning methods are used to denoise an image. We present a comparative analysis of deep image denoising approaches. In our paper, we propose four deep learning models, REDNet, MWCNN, PRIDNet, and CBDNet to identify noises in the plant leaf images. The PSNR and MSE value for these four methods is calculated and compared to the results. The greatest PSNR value is discovered to be in CBDNet. In contemporary image processing systems, image denoising is crucial. We have taken the PlantVillage dataset which comprises of 54303 diseased and normal leaf images and real images. Images of noisy leaves are given as input to the four denoising algorithms.

Keywords: Denoising, Deep Learning, Signal to noise ratio, REDNet, MWCNN, PRIDNet, CBDNet.

1. Introduction

Image noise is a term used to describe certain redundant data pertaining to digital picture disturbance. Excessive interference information can cause hazy images and impede viewers. The image noise typically uses the probability distribution function to explain its random process since, theoretically, the image noise cannot be predicted and probability statistics should be used to analyze its random error. In our paper, we put forward a comparative study to detect noises in an image using various deep-learning models.Four models-REDNet, MWCNN, PRIDNet, and CBDNet are used to denoise images and calculated the MSE,PSNR and find the model with the highest PSNR. Denoising images is a method used to reduce or delete unwanted noise from digital images. Low light conditions, limitations of the sensor devices that are used to sense the images, errors in transmission, etc are some of the factors that cause noise in an image. Some of the approaches used for denoising are,

1. Spatial Filtering: This method applies a filter mask to each pixel in an image to reduce noise. Some examples are the Gaussian filter, bilateral filter, and median filter.

2. Wavelet-based methods: This method decomposes an image into different frequency bands. By applying these algorithms, noise can be removed from different frequency components.

3. Non-local means denoising: This method deals with redundancy in images by considering similar patches in the image to find the denoised pixel.

4. Deep learning-based methods: The best-known denoising method is Convolutional neural networks (CNN). Several pairs of clean and noisy images are used to train a neural network. Different architectures such as ResNet, RedNet, MWCNN, PRIDNet, CBDNet, etc. are used in this method.

In our paper, we put forward a comparative study to detect noises in an image using various deep-learning models Four models, MWCNN, PRIDNet, and CBDNet are used to denoise images and calculate the PSNR, and find the model with the highest PSNR.

2. Related Works

Xiao-Jiao Mao, Chunhua Shen, and Yu-Bin Yang Mao proposed an image restoration method by using a deep fully convolutional auto-encoder network. It is an encoding-decoding framework that consists of symmetric convolutional-deconvolution layers. Skip connections are used to recover clean images.

Another study by Yiyun Zhao, Zhuqing Jiang, and Aidong Men Guodong Ju was based on the Pyramid Real Image Denoising Network. They used this method to tackle the issue of blind denoising of real images. The proposed study contains three sections. This method has proven that it can be a better method for denoising.

Rina Komatsu and Tad Gonsalves used UNet models for denoising. They proposed a deep-learning model that handles five variants of noises-gaussian noise, clipped whites noise, clipped blacks noise, and camera shake noise. They used three variants of the U-Net model as Group Normalization, Residual U-Net, and Dense U-Net. The predicted image was assessed using PSNR and SSIM compared with the target image. Among these Residual U-Net and Dense U-Net are better at finding different kinds of noise.

Joon Hee Choi,Omar A.Elgendy, and Stanley H Chan in their work proposed a model for the reconstruction of the sensor. Sanjay Chakraborty,Soharab Hossain Shaikh,Amlan Chakrabarti and Ranjan Gosh, in their work, proposed the quantum image denoising technique. They calculated PSNR, MSE, and QIFM and found that quantum image denoising is better than other denoising methods. Network method for QIS picture reconstruction in this paper. Their deep neural network learns both the denoising and nonlinear transformation simultaneously using the binary bit stream from QIS as input. Their experimental results produced better results using this method when compared to other existing methods.

In their paper, Chunwei Tian,Lunke Fei, Wenxian Zheng, Yong Xu, Wangmeng Zuo and Chia-Wen Lin proposed a relative study of deep learning methods in image denoising. Four types of noisy photographs were taken into consideration: white noise, actual noise, blind denoising, and hybrid noise. They examined the theory and motivation of the denoising network for every segment of noisy photos. They compared the result of denoising on benchmark datasets.

In their work, Shuo-fei Wang, Wen-kai Yun, and Ya-xin Li invented the multi-wavelet convolutional neural network (MWCNN) for image denoising. They had taken MWCNN as the backbone. MWRDCNN has taken a shorter computation time when compared with RDN and MemNet. They calculated PSNR for different types of noises using this method.

In their study, Jianchao Lin, Jing Zheng, Dewei Li, and Zhixiang Wuxiang Wu suggested a denoising technique for surface microseismic monitoring based on CBDNet. A residual learning strategy is used in this method. This denoising method is evaluated by calculating the ratio of signal-to-noise and comparing it with other denoising methods. The proposed method showed good results.

Susheel George Joseph, Dr Vijay Pal Singh proposed deep convolutional neural networks for denoising images. They opted for CNN for blind denoising. They concluded that CNN is the best method for denoising.

3. Methods and Materials

Noise in image is an arbitrary variation in the information of color or brightness in the pictures that were taken. The image is deteriorating as a result of outside influences.. A mathematical representation of noise in an image is

$$A(x,y)=H(x,y)+B(x,y)$$

where $H(x,y)$ is the noise function and $B(x,y)$ is the function of the original image. The function of the noisy image is $A(x, y)$. Traditional image-denoising algorithms are not suitable for finding noises in real images. The noise in real images is called blind noise. Mean Square Error is calculated for the loss and it should be minimum. PSNR ratio is calculated to find the performance. The higher the ratio, better will be the result. The PSNR value ranges from 30 to 50.

The prescribed model is a comparative study of four deep learning architectures REDNet, MWCNN, PRIDNet, and CBDNet.

A. Dataset

The Dataset used here is a combined one, taken from Plantvillage and real images. The PlantVillage dataset is the largest dataset that gives a detailed study of plant diseases. The plantvillage dataset contains more than 54,000 leaf images. There are 38 classes corresponding to plant-disease pairs.

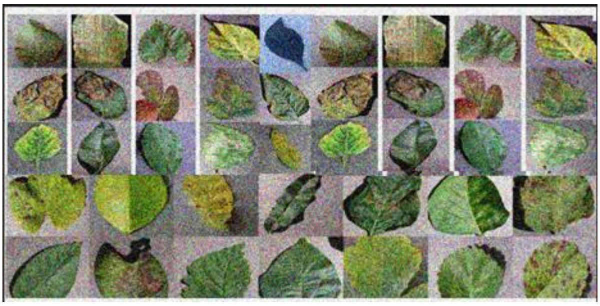

Fig 1. Dataset with noisy images

Fig 2.Clear images after denoising

B. REDNet

REDNet is a deep learning-based algorithm for denoising images. This auto-encoder architecture uses skip connections and is based on CNN.

1. Architecture: REDNet is similar to an auto encoder which consists of an encoder-decoder network structure. The encoder captures the noisy image, while the decoder constructs the denoised image.

2. Residual Learning: The concept of residual learning is employed in REDNet. The network learns to predict the residual between a clean image and a noisy image. After predicting the residual, capturing noises is the next focus which makes the denoising process more efficient.

3. Skip Connections: By using skip connections, one can link the output of one layer to the input of a different, non-adjacent layer. The skip connections are established between the layers of the encoder and decoder.

4. Loss Function: Loss is the penalty for a bad prediction. Rednet minimizes the loss function, which calculates the difference between the original image and the expected clean image.MSE or Mean Squared Error calculates the difference between actual and predicted image difference.

The architecture is as follows.

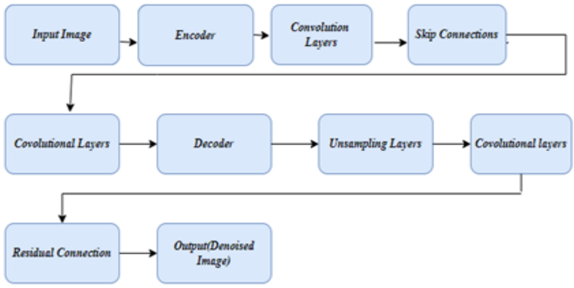

Fig 3. Architecture of REDNet

In this architecture, the noisy image serves as the input. The encoder consists of convolution layers that lower the supplied image's resolution while obtaining detailed characteristics. The encoder and decoder's matching layers are connected by skip connections to allow for information flow and maintain spatial features. We can observe that the REDNet architecture is working fairly well in image denoising. There is unquestionably some reduction in noise, and the picture is attempting to restore its natural colors for the damaged pixels. By contrasting the denoised and clean images, one may calculate the Peak Signal-to-Noise Ratio(PSNR) of a REDNet model. The steps are

1. Gather the clean and denoised images produced by the REDNet model.

2. Calculate the mean squared error (MSE) between the denoised image (D) and the clean image (C) first..Calculate the squared difference for each pixel position(i,j)

i.e. (C (i, j)-D (i, j)) ^2.

3. Take the average squared differences of all pixels in the image and calculate MSE.

MSE= (1/ (P*Q)*sum ((C(i,j)-D(i,j)) ^2))

Where P and Q are the image dimensions and sum () is the sum of the squared differences of all pixels.

4. The maximum pixel value (MAX) is calculated based on image bit depth.

5. Calculate the PSNR value using the MSE.

The formula is

PSNR=20*log 10(MAX)-10*LOG10 (MSE).

The quality of the denoised image produced by the REDNet model is determined by the final PSNR value. Greater PSNR values correspond to improved denoising performance. This architecture gave an MSE value of 1.14177 and a PSNR score of 31.5316.

C. MWCNN—Multi-level Wavelet CNN

Multi-Level Wavelet CNN, or MWCNN Convolutional neural networks and wavelet transform characteristics are combined to create CNN, a deep learning architecture. The architectural explanation is as follows.

1. Wavelet Transform: Using a wavelet transform, the input image is divided into several levels of wavelet coefficients. Sub bands that capture diverse frequency and spatial information at various resolutions are produced by this decomposition.

2. CNN Feature Extraction: In order to extract hierarchical features from each wavelet sub band, a set of CNN layers are applied individually and each wavelet sub band is treated as a separate input. As a result, the model can pick up on spatial dependencies and differentiating characteristics at various scales.

3. Fusion: In order to capture information across different resolutions, the extracted features from different sub bands are combined or fused. Fusion can be done using addition or concatenation.

4. CNN Reconstruction. The final output image is reconstructed by passing the fused features from the fusion method to additional CNN layers. Up-sampling and convolution processes are frequently used in these layers to improve the features and restore the image resolution.

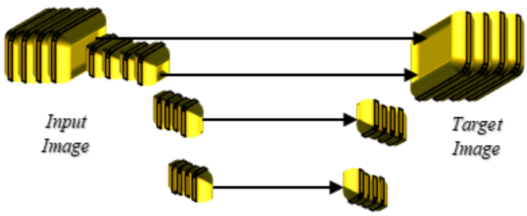

Fig 4. Architecture diagram of MWCNN—Multi-level Wavelet CNN

The PSNR calculation remains the same regardless of the denoising model used. So by applying the formula to calculate MSE and PSNR, gave an MSE value of 0.000451208 and a PSNR score of 33.45623. It can be observed that MWCNN architecture is showing a better result and we get a clearer image when comparted to REDNet.

D. Pyramid Real Image Denoising Network(PRIDNET)

PRIDNet is a deep learning architecture designed for real image denoising. There are more intricate noises, such as blind noise or real noise—noise on actual images. The architectural components of PRIDNet are as follows.

1. Pyramid Feature Extraction: To extract features at multiple scales, PRIDNet utilizes a pyramid structure. At each resolution level, the input image is down-sampled, and features are retrieved.

2. Dense Noise Attention Block: This block supports the learning of adaptive noise attenuation and estimation by PRIDNet. The pyramid features are taken as input and dense connections are applied to enhance feature reuse.

3. Residual Dense Block: Multiple densely connected convolutional layers are involved in

this block. It encourages feature reuse and increases the network's capacity for representation. The block's remaining connections enable the direct flow of information, assisting in gradient propagation and enhancing the denoising process

4. Feature Fusion: Feature fusion techniques are employed in PRIDNet to combine information from different pyramid levels. This fusion aids in gathering information from several scales and preserving consistency between them.

5. Reconstruction: Next step is to reconstruct the denoised image. The fused features are passed through sampling layers and convolutional layers. These layers reduce noise while improving the features and restoring the original resolution.

The MSE value obtained is 1.34867. This architecture gave a PSNR score of 34.453. It is evident that PRIDNet offers the best performance with the quickest denoise times for individual images.

E.CBDNet-Convolutional Blind Denoising Network

Convolutional Blind Denoising is an architecture created to deal with blind picture denoising. This architecture contains two subnetworks - one for noise estimation (CNNe) and the other for non-blind denoising (CNNd).. The architecture is shown below.

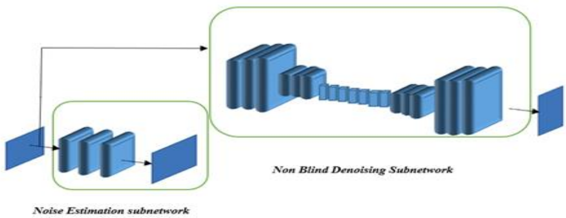

Fig 4. Architecture diagram of CBDNet

1. Input Layer: The noisy image is taken as the input to this layer. It is represented as a matrix of pixel values.

2. Convolutional Layers: CBDNet contains several convolutional layers. Features from the noisy input image are extracted by these layers.

3. Denoising Blocks: These are the core components of CBDNet. The denoising blocks contain multiple convolutional layers. These layers remove noise from the image. These are the layers that are trained to estimate the clean image from noisy images.

4. Skip Connections: In CBDNet, skip connections are frequently used to speed up the transfer of data. The corresponding layers in the encoder and decoder sections are connected by skip connections.

5. Residual Learning: Similar to residual networks, CBDNet uses a residual learning approach. The original noisy image is added to the output of the convolutional block and thereby getting a residual image. To capture the noise components accurately, this residual image is used.

6. Output Layer: The denoised image is generated by the output layer. This layer contains a

single convolution layer. Several activation functions are incorporated to make sure that the output image is within the desired range.

The MSE value obtained is 0.0002023. This model gave an average PSNR of 36.356 on test data.

4. Results and Discussion

Denoising is considered to be the most important part of identifying diseases in leaf images. After removing the noise from the plant leaves image dataset, we obtained clear images. Four different models are applied on the dataset. The corresponding MSE and PSNR values of various methods are shown below in the table. The method CBDNet has proven to be the better one.

Sl.No	Denoising Method	MSE	PSNR
1	RedNet	1.14177	31.5316.
2	MWCNN	0.000451208	33.45623
3	PRIDNet	1.34867	34.453
4	CBDNet	0.0002023	36.356

Table 1: Denoising values of four models

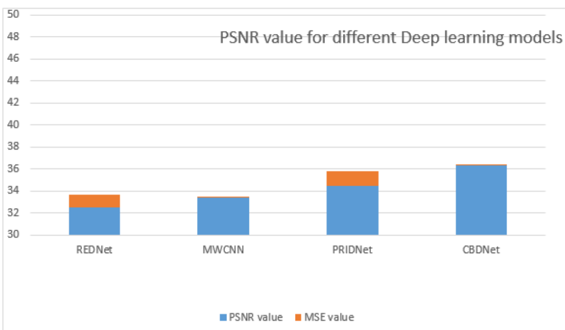

Fig 6. Graph showing PSNR and MSE value for four models

5. Conclusion

Image denoising is the process of eliminating noise to improve visual quality. Noise in an image can be caused due to low light conditions, transmission errors, limitations of sensors that are used to capture the images, compression artifacts, etc. Several algorithms and techniques are used for denoising of images. In our paper, we proposed four deep-learning approaches which are the most advanced methods used in denoising. The methods we used are REDNet, MWCNN, PRIDNet, and CBDNet. All four methods are producing very good results. The diseased leaf images are given as input and we got the clear images as output. For each of the four approaches, mean square error and peak signal to noise ratio are computed; the outcomes differ significantly. Of the four methods, CBDNet gives the highest PSNR value which can be used as the best method for denoising images. Hence we propose CBDNet as the best method for denoising images.Here we have taken images of diseased leaves from the plant village dataset and real images.

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