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De-Noising of Apple Fruit Images using Dilated Convolution Neural Network model with Mixed Activation Function

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Abstract

In the agricultural sector, fruit diseases contribute to substantial economic losses, emphasizing the need for effective disease detection methods. Image processing techniques play a crucial role in minimizing damage and financial losses. Pre-processing, a vital stage in image processing, involves noise elimination and quality enhancement, laying the groundwork for subsequent tasks such as segmentation, classification, and disease detection. This study focuses on, proposing a novel approach for denoising diseased apple fruit images using the Dilated Convolution Neural Network model with Mixed Activation Function (DCNMAF). Performance evaluation, utilizing metrics like PSNR and SSIM, highlights the superiority of the proposed model over existing methods. These advancements underscore the effectiveness of the proposed DCNMAF model, showcasing notable enhancements in both accuracy metrics.

Keywords: apple disease detection, de-noising, CNN, Dilation, Activation Function, PSNR (Peak-Signal-to Noise-Ratio), SSIM (Structural Similarity Index Method).

I. INTRODUCTION

Apple fruits are susceptible to various diseases, including apple scab, apple blotch, and apple rot. These diseases manifest as characteristic symptoms, causing spots, irregularities, and discoloration on the fruit's surface. The consequences of such diseases are not limited to individual fruits; they can lead to significant decreases in production, quality, and quantity, ultimately affecting the entire supply chain and leading to economic losses.

The proposed research focuses on de-noising diseased apple fruit images, a crucial preprocessing step to enhance the accuracy of subsequent processes, such as segmentation, classification, and disease detection. It is essential to eliminate unwanted noise and enhance image quality to achieve precise results. This study aims to introduce a novel approach using the Dilated Convolution Neural Network model with Mixed Activation Function (DCNMAF). The uniqueness of this approach lies in its ability to effectively remove noise while preserving the critical details of the image.

This research addresses the crucial role of pre-processing in disease detection from image data, emphasizing the need to lessen unwanted features introduced by external factors such as weather conditions and device alignment. The paper introduces a novel denoising model, the Dilated Convolution Neural Network model with Combined Activation Function (DCNMAF), designed to enhance image quality for disease detection in apple fruits. The proposed model leverages dilated convolution layers and various activation functions to effectively reduce noise and preserve important features. The study employs a dataset comprising diseased and healthy apple images, evaluating the DCNMAF model's performance against traditional methods such as Gaussian and Average filters, as well as the Denoising Convolutional Neural Network (DNCNN). The experimental results showcase the effectiveness of the DCNMAF model in improving image quality for disease detection applications.

The primary objective of this paper is to evaluate the performance of the proposed DCNMAF model in de-noising apple fruit images. This evaluation will be conducted using established metrics, including Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Method (SSIM). The results will demonstrate the effectiveness of the DCNMAF model in comparison to other existing methods. This research contributes to the advancement of agricultural technology and offers a promising solution to enhance the quality of diseased apple fruit images.

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Filtering and preprocessing are fundamental steps in agricultural data analysis to clean, enhance, and structure data for various applications in the agricultural sector. However, research in this area has identified certain gaps and challenges are discussed.

In our proposed method, we have achieved a notable improvement in the PSNR accuracy, reaching an impressive 34, whereas in the previous study [1], it was 33.37. Additionally, our work has substantially enhanced the Structural Similarity Index (SSIM) accuracy, achieving a commendable 0.94, compared to 0.88 in [1]. These advancements underscore the effectiveness of our proposed method, as both accuracy metrics have experienced significant enhancements.

Over the past few years, there has been a notable surge in the adoption of deep learning technologies in various research domains, encompassing areas such as agriculture and farming. These technologies include generative adversarial networks (GANs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs). However, it's worth noting that agricultural experts and researchers frequently employ diverse software systems without necessarily delving into the underlying mechanisms and concepts of these deep learning techniques, including GANs, RNNs, and CNNs, which are commonly utilized within deep learning algorithms[2].

The study focuses on image denoising and enhancement in computational ghost imaging (CGI) and single-pixel computational imaging. However, the effectiveness of the proposed method under various real-world conditions, such as different lighting conditions, noise sources, or complex scenes, are not be fully explored [3].

The authors [4] discusses different image filtering techniques for removing noise from aerial images. While the paper uses PSNR and RMSE for quality assessment, other objective image quality metrics like Structural Similarity Index (SSIM) or feature-based metrics could be considered to provide a more comprehensive evaluation of the denoising techniques [4].

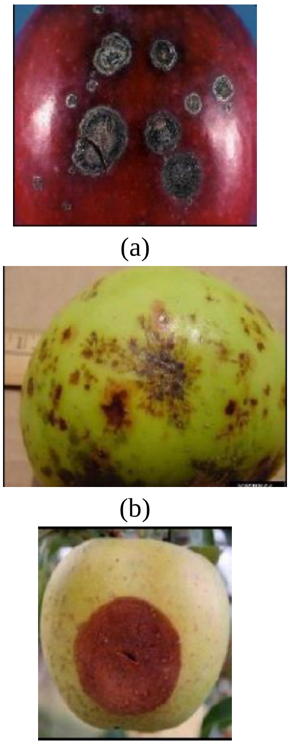
In real-world scenarios, images might contain various types of noise, such as blur, sensor noise, or other artifacts. There may be research gaps in developing robust preprocessing methods to denoise images effectively, ensuring that the model's performance is not adversely affected by these issues [5].

The apple, scientifically known as Malus domestica, was considered in this paper since it is the most significant fruit commercially and has the largest profit margin due to its extensive cultivation and several medicinal benefits. Among the many health benefits of apples include enhanced digestive health and lowered risk of stroke, high blood pressure, diabetes, heart disease, obesity, and some cancers. Apples are rich in fibre, vitamins and minerals and low in sodium, fat and cholesterol. Each apple disease has its own set of symptoms which is caused by fungi, bacteria, and viruses. Apple scab, apple blotch, and apple rot are few of the diseases that affect apple fruits which is depicted in Fig. 1.

Apple Scab: Black, circular spots on the upper surface of the apple fruit which may become distorted and crack that allow entry of secondary organisms.

Apple Blotch: Fungal diseases which appear on the surface of the apple fruit as dark, irregular or lobed edges.

Apple Rot: Small, purple specks on the upper surface of the apple fruit.



(a)

(b)

(c)

Fig. 1 Apple Diseases (a) Apple Scab (b) Apple Blotch (c) Apple Rot

These diseases can be identified by the unique symptoms of each one [3]. When normal fresh apple fruits are stored with diseased fruits, the quality and consumption of apple fruit are considerably decreased, which might result in a significant loss. It is extremely important to control its diseases to provide substantial profit. This formed a basis for the proposal of an effective technique for protecting other healthy apple fruits from a defective one.

Recent developments in computer vision and artificial intelligence have revolutionized the agricultural industry, enabling the development of accurate and efficient disease detection techniques.

The steps carried out in order to detect the disease of Apple fruit is shown in Fig. 2.

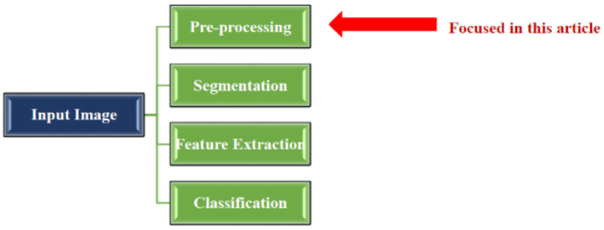


Fig. 2 Framework for Apple Fruit Disease Detection and Classification

Pre-processing is one of the most important steps in disease detection and classification. The captured images may have certain unwanted features due to factors like the weather, lighting, device alignment, etc. In order to make images fit for the purposes they are intended for, pre-processing is routinely used. Changing the colour space, expanding the contrast, scaling, rotating, smoothing, removing the background, and removing noise are a few pre-processing techniques.

In image processing, Noise is undesired information that degrades image quality and should be eliminated. Noise removal is the Pre-processing stage for many applications. Noise is one of the obstructions in automatic image understanding and noise reduction is very important to improve the results of further processing [4].

The biggest advantage of Deep Learning techniques is that they do not rely on hand-crafted features. Rather, these networks learn features while training without any human intervention [5]. The accuracy of disease detection and other classification category models has recently improved greatly because of recent developments.

CNN has proven excellent performance in the fields of robotics, automation, and agriculture as well as in audio, video, and image recognition. Numerous applications based on deep learning are being developed for smart agriculture [6].
This manuscript is structured as follows: Section II provides a concise overview of existing denoising techniques, Section III delineates the methodology employed, Section IV delves into the presentation and discussion of results, Section V conducts a thorough performance evaluation, and, ultimately, Section VI offers the conclusion.

II. LITERATURE REVIEW

A number of filtering techniques have been proposed to remove the noise in an image. Abhay Agarwal et al [7] proposed an automatic apple fruit disease detection method with three steps—Image Segmentation, Feature Extraction, and Classification. The SVM classifier has been used to detect the diseases namely Apple scab, black rot canker, and core rot as well as healthy apples. [8] summarized the various pitfalls in plant leaf disease detection before applying image processing techniques and revealed the complications of the diseased images and how they can be dealt and how a pre-processing stage is used to remove noise found in the image.

K.S. Archana [9] analyzed and compared four types of filtering techniques such as Gaussian filter, Wiener Filter, Mean and Median for noise removal in paddy leaf images and observed that among all the filtering process Wiener filter has better result.

Sangeetha Muthiah, A et.al [10] analysed the performance of various noises and different de-noising techniques on an infected coconut image. Noise reduction is accomplished through the application of various filters such as the Gaussian filter, Median filter, and Wiener filter. Through experimental analysis, it has been determined that the median filter yields superior results when dealing with salt and pepper noise. Additionally, the Gaussian filter exhibits effectiveness in mitigating Gaussian noise, and it is also proficient in addressing Poisson noise. The quality of noise reduction is quantified using metrics like Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE).

In [11] P.Srujana et.al have used CNN concept for Image Denoising and analyses its results with wavelet based method. They have taken an image and analysed at different noise variances values 1%, 5%, 10%. The results of CNN based image denoising method gives better and highest values when compared to wavelet-based method.

Hardeep Singh et.al [12] proposed a new technique, Applied Gaussian smoothing along with weighted kernel function within SVM for fruit disease detection in which both the pre-processing and segmentation phases have been covered. The results showed improved classification accuracy and reduced mean square error compared to the existing system.

Archana Tamizharasan et.al [13] proposed a new algorithm Mean Convolution Mass Filter (MCMF) to remove noise and improve the quality of the image. The MCMF computes neighbouring pixels with a predefined set of mass using a weight mask that is applied to every pixel in the image while preserving the edge information of the image. The MCMF achieves a PSNR value of 93% in comparison to alternative filters. Asmaa Ghazi Alharbi et.al [14] used CNN to classify healthy apples and apples with diseases namely apple blotch, apple scab and apple rot and showed the accuracy as 99.17% with 90% training data set and 10% testing data.

Ghose et al [15] used the pre trained denoising model because CNN model can be optimized continuously and the weights of convolutional kernel can be improved during training of the network. Authors also have analysed the results and compared them with Wiener filtering, Bilateral filtering, PCA, Wavelet based transform method and observed that CNN based denoising method shows best performance than all other compared methods.

C. Radhiya Devi et.al [16] proposed a novel approach, Dilated Convolution Neural Network model with Mixed Activation Functions (DCNMAF) for image denoising in image processing applications. The DCNMAF model combines dilated convolution, mixed activation functions, and deep learning techniques to efficiently eliminate noise in images. The preservation of image edges and the high PSNR and SSIM values make it a promising approach for image denoising.

From the above research works, it can be inferred that deep Convolutional Neural Network architecture can be applied for the denoising process of apple fruit image to enhance the quality of the result.

III. METHODS

A type of linear smoothing filters called Gaussian filter select their weights based on the characteristics of a Gaussian function. The Gaussian filter outputs a weighted average of each pixel's neighborhood, with the weighted average more towards the value of the central pixels.

Average Filter is applied for smoothing images by lowering the intensity values between adjacent pixels. In average filter the value of each pixel is replaced by the average of the intensity levels in the neighborhood defined by the filter mask which produces a weighted sum of a pixel's and its neighbor's values. This process is repeated for every pixel value in the image. The Average Filter has the limitation of blurring the image's object edges. Existing traditional filtering methods Gaussian Filter and Average Filter denoise the image by concentrating only on neighborhood pixels and it will not preserve the image edge details.

Deep Learning is a subset of Machine Learning research, which has gained popularity in recent past. A unique class of Artificial Neural Networks called Deep Learning models employs a hierarchy of multiple layers to learn multiple levels of representation. One of the primary strengths of Deep Learning techniques lies in their ability to automatically learn and extract relevant features from raw data, eliminating the need for manually crafted features. Rather, these networks learn features while training without any human intervention. Image de-noising has been accomplished through the use of a deep learning architecture known as Convolutional Neural Networks (CNN). A CNN architecture is designed with three layers, namely, the input layer, multiple hidden layers and an output layer. In a neural network, the input layer sets the specifications for the input data, determining its size and type. The hidden layers play a crucial role in shaping the fundamental architecture of the network. Finally, the output layers dictate the characteristics and format of the output data, completing the overall structure of the neural network. A Convolutional Neural Networks (CNN) is one of the most widely used deep neural network models. CNNs have gained popularity for image denoising problems. To complete a particular task using CNN model includes 2 steps. First is to design the corresponding network architecture and then learning the model using trained data.

One existing method using CNN is the denoising CNN, DnCNN proposed by Zhang et al [17]. The authors used the DnCNN for image denoising, super-resolution, and JPEG image blocking. The DnCNN proves to be a highly effective deep learning model designed for the task of generating a residual image by estimating the noise component from the input image corrupted with Gaussian noise. The difference between the noisy image and the residue image can be used to predict the noise-free image.

A. The Proposed DCNMAF Model

The method described in the paper[16] appears to be a novel approach for image denoising. Here are some reasons why it might be necessary or valuable to consider using this method.
Effective Noise Reduction: The DCNMAF method by [16] claims that the proposed DCNMAF model effectively reduces noise in images. Noise reduction is a crucial step in various image processing applications, as it enhances the quality of the images and makes them more suitable for subsequent processing or analysis.
Performance Improvement: The author [16] suggests that the DCNMAF model outperforms other denoising methods, as indicated by higher Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) values.
Deep Learning and CNNs: Deep learning techniques and Convolutional Neural Networks (CNNs) have gained popularity in image processing and denoising tasks due to their ability to learn complex patterns and features.

The basic concept of De-Noising algorithm is to maintain the edges and quality. The authors of this research in their previous work, developed a CNN model for denoising images called DCNMAF- Dilated Convolution Neural Network model with combined Activation Function. The objective of this study is to apply DCNMAF for denoising apple fruit images.

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DCNMAF model consists of multiple layers, including dilated convolution layers and activation functions such as Rectified Linear Unit (RELU) and Exponential Linear Unit (ELU). The model aims to enhance non-linearity and extract more features for image denoising. In the DCNMAF Model, the input images are of 40-by-40-by-1. A layer for image input is generated, matching the dimensions of the training images. Hidden layers perform the feature extraction and produce feature maps by the process of the convolution operation. To enhance the non-linearity of the network's modelling capabilities, an activation function has been added to the hidden layers. The Proposed DCNMAF model design is shown in Fig. 3.

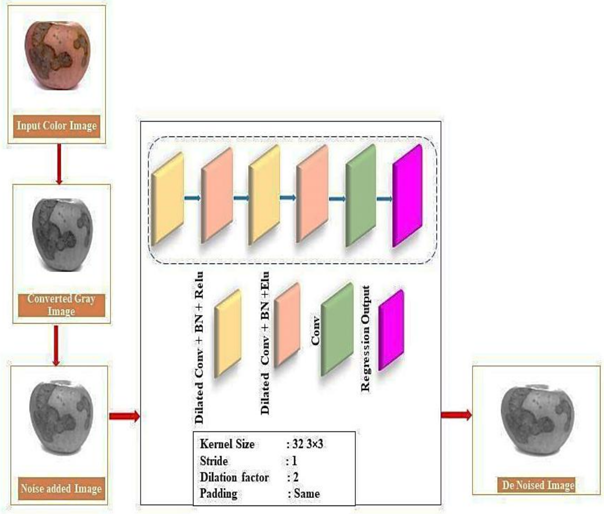


Fig. 3 Proposed DCNMAF Model

The proposed DCNMAF model consists of 15 layers including 4 dilated convolution layers. Dilated Conv refers to the dilated convolution with factor of 2. Dilated convolution increases the receptive field of the layer without adding more parameters or computation by using a dilated filter. The layer enlarges the filters by adding zeros between each filter component. Expanding the CNN's receptive field is a very effective way to extract more features for image denoising. The last convolutional layer uses regular convolution with dilation factor of 1, hence they are denoted by 'Conv'. The rectified linear unit (ReLU) activation operation executes a nonlinear threshold function, zeroing out any input values that fall below zero. Relu defined by $g(z) = \max\{0, z\}$. An Exponential Linear Unit (ELU) activation layer acts as an identity operation for positive inputs and introduces an exponential nonlinearity for negative inputs. Combining different activation functions like Relu and Elu for convolutional layers is the other important concept in this proposed DCNMAF model to make the model non-linear. To improve the problem of gradient disappearance, batch normalization is added between convolutional layers and Activation functions. The final output layer is the Regression Layer.

B. Dataset

To remove the noise and preserve the original information in the apple fruit images, DCNMAF model proposed by the authors [16] was trained with 382 apple images of diseased and healthy apple fruits with four classes namely Normal_Apple, Blotch_Apple, Scab_Apple and Rot_Apple and tested with randomly selected images from the dataset. The dataset is composed of RGB images with JPEG format and was taken from https://www.kaggle.com/datasets/kaivalyashah/apple-disease-detection. Dataset used by the proposed model is shown in Table 1.

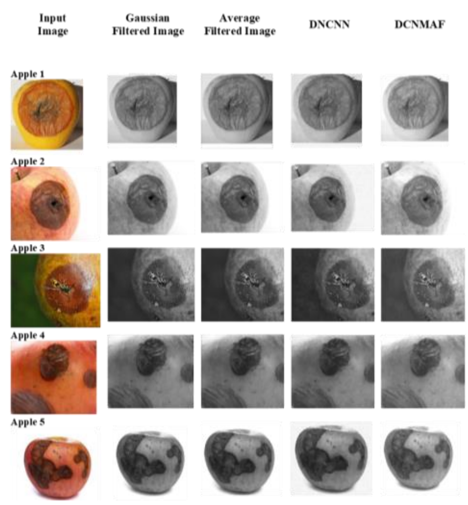
TABLE 1- CHARACTERISTICS OF DATASET IMAGES

S. No.	Class	Image Count
1	Normal_Apple	67
2	Blotch_Apple	116
3	Rot_Apple	114
4	Scab_Apple	85
	Total	382

IV. RESULTS

In this section, the experimental outcomes achieved by employing four distinct image processing models Gaussian, Average, DNCNN, and our novel DCNMAF model are described. These models were applied to images depicting the presence of Apple rot, scab, and blotch diseases.

The training of proposed model uses the Adam optimizer, a widely used optimization algorithm, and employed a mini-batch size of 128 images was processed simultaneously during each iteration of training. The training process was executed with two epochs and initiated with an initial learning rate of 0.0001. The experiments consisted of applying these models to images of Apple rot, scab, and blotch diseases. Fig. 4 shows the experimental result of Gaussian, Average, DNCNN and proposed DCNMAF model.



(a)

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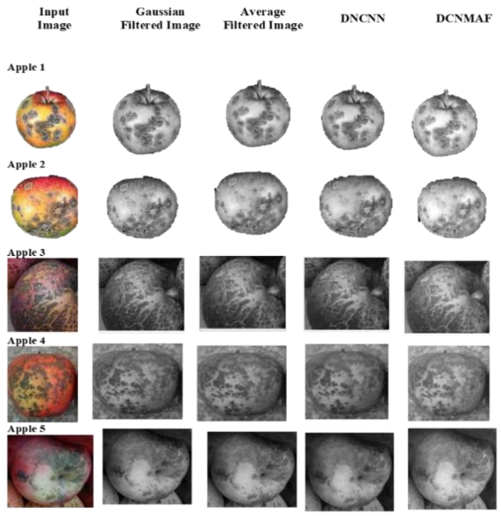
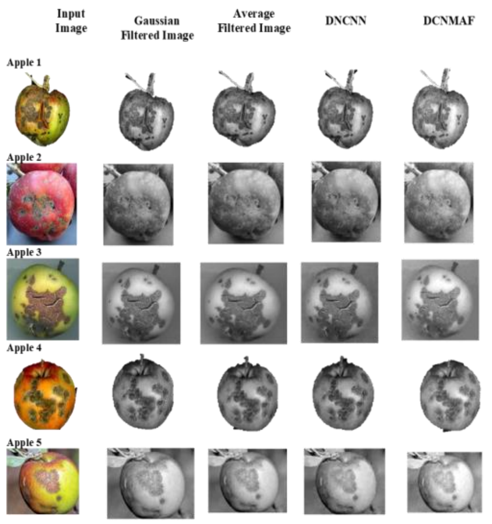


(b)



(c)

Fig. 4 – Apple Disease Images De-Noising Using Various Filters. (a) Rot (b) Blotch (c) Scab

V. DISCUSSION

The goal of performance evaluation is to assess the quality of an original image and the filtered image. It is evaluated based on PSNR (Peak Signal to Noise) and SSIM (Structure Similarity Index) values.

A. PSNR-Peak Signal-to-Noise Ratio

Peak Signal-to-Noise Ratio (PSNR) is a metric frequently used to evaluate the quality of denoised images. In the context of apple fruit image denoising, PSNR measures the similarity between the original noisy apple fruit image and the denoised image. A higher value of Peak Signal-to-Noise Ratio (PSNR) signifies superior image quality. PSNR is expressed as:

$$PSNR = 10log_{10}(peakval^{2)}\ /MSE$$

B. SSIM - Structural Similarity Index Method

Structural Similarity Index method is another important metric for evaluating the quality of denoised apple fruit images. It measures the similarity between the denoised image and the original image in terms of structural information, luminance, and contrast. A higher SSIM value indicates a better preservation of image quality, textures, and structures after denoising. The SSIM is represented as,

$$\text{SSIM}=\frac{(2*\underline{x}*\underline{y}+c1)(2*\sigma_{xy}+c2}{(\sigma_x{}^2+\sigma_y{}^2+c2)*((\underline{x}^2+\underline{y}^2+c1)}$$

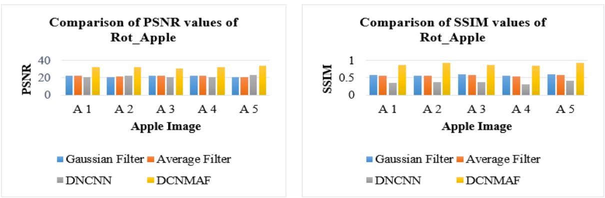
Table 2 shows the result comparison of PSNR values and SSIM of Gaussian, Average, DNCNN and the proposed model. The PSNR and SSIM value of the proposed model gave better results.

TABLE 2 - COMPARISON OF PSNR VALUES AND SSIM VALUE

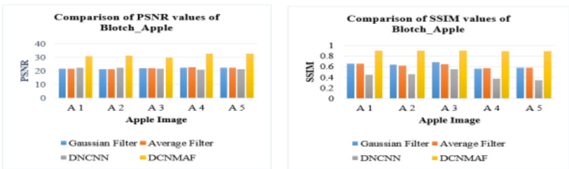
Type of Apple Disease	Input Image	Gaussian Filtered		Average Filtered		DNCNN		**DCNMAF**	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Rot	Apple 1	22.28	0.58	22.4	0.56	21.14	0.36	**32.28**	**0.88**
	Apple 2	20.96	0.56	21.25	0.57	22.56	0.38	**32.74**	**0.93**
	Apple 3	22.09	0.61	22.08	0.58	21.03	0.38	**30.45**	**0.88**
	Apple 4	22.44	0.56	22.38	0.54	21.11	0.32	**32**	**0.86**
	Apple 5	20.91	0.61	21.10	0.59	23.18	0.42	**34.08**	**0.94**
Blotch	Apple 1	21.51	0.66	21.60	0.66	22.38	0.45	**31.07**	**0.9**
	Apple 2	21.18	0.64	21.21	0.62	22.55	0.46	**31.35**	**0.9**
	Apple 3	21.87	0.69	21.94	0.65	21.61	0.55	**29.89**	**0.9**
	Apple 4	22.46	0.56	22.64	0.57	21.08	0.37	**32.88**	**0.89**
	Apple 5	22.24	0.58	22.38	0.58	21.18	0.34	**32.93**	**0.89**
Scab	Apple 1	20.77	0.62	20.81	0.61	23.19	0.46	**31.14**	**0.9**
	Apple 2	22.37	0.64	22.42	0.6	20.86.	0.42	**29.95**	**0.88**
	Apple 3	22.49	0.57	22.48	0.56	20.95	0.37	**31.28**	**0.87**

	Apple 4	21.73	0.65	21.69	0.64	22.61	0.45	**31.19**	**0.89**
	Apple 5	22.3	0.62	22.51	0.61	21.22	0.43	**31.22**	**0.89**

From Table 2 it can be inferred that the proposed DCNMAF method can perform better and give higher PSNR and SSIM values in the range of [29, 34] and [0.86, 0.94] respectively. Averagely achieved 31.63 dB of PSNR and 0.89 of SSIM value. The PSNR and SSIM value of the proposed model gave better results. Comparative Analysis of PSNR and SSIM Values of Apple Disease Images Rot, Blotch and Scab are shown in Fig. 5,



(a)



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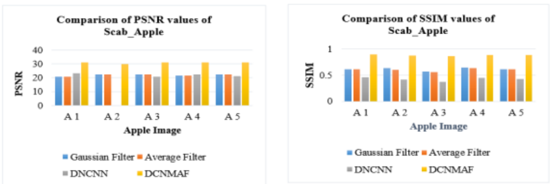

(c)

Fig. 5 Comparative Analysis of PSNR and SSIM Values of Apple Disease Images
(a) Rot (b) Blotch (c) Scab

VI. CONCLUSIONS

Pre-processing reduces noise in an image without compromising its information in order to enhance its quality to make it appropriate for future processing. The quantitative analysis is performed using visual quality of the image and using parameters like PSNR and SSIM. The proposed model DCNMAF preserves information of edges and doesn't blur the image. The experimental result shows high PSNR and improved the quality of diseased apple images than the other filters such as Gaussian, Average filters and DNCNN. As a result, this work will be carried out in future research for better segmentation, feature extraction, and classification for detection of disease in Apple fruit..

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