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De noise of Plant Images Using Generative Artificial Intelligence and Transfer Learning

Md. Gous Azam[1],Dr. Ashok Kumar[2]

[1]Research Scholar, Department of Computer Science, V.K.S.U., Ara
[2]Professor, Ex. Head Department of Physics, V.K.S.U., Ara

Abstract— *In recent years, owing to the rapid evolution of machine learning, especially deep learning, and its outstanding performance in the domain of image processing an increasing number of scholars are turning to convolutional neural networks (CNNs) to address image de noise challenges. To tackle image de noise issue, this paper introduces the implementation of a deep Generative Adversarial Network for image de-hazing. Unlike traditional de-hazing methods that rely on per-pixel loss, our approach leverages a perceptual loss function. This function captures high-level image features by utilizing pre-trained models from Image Net, effectively mitigating the shortcomings associated with per-pixel loss functions, particularly their sensitivity to minor variations in single pixels, even when the images are perceptually similar.*

Keywords— Image De noise, Plant Village, Apple, Generative Artificial Intelligence, Transfer Learning

1. INTRODUCTION

Agriculture plays an important role in India's economy, with nearly half of the population depending on farming for their livelihood. The main aim of agricultural research is to improve the productivity and quality of food while minimizing costs and maximizing profits. The success of agricultural production relies on the effective integration of factors such as seeds, soil, and agrochemicals. Achieving high-quality and valuable products requires stringent quality control measures [1][2]. To ensure efficient production and surplus yields, continuous enhancement of agricultural practices and regular product value assessments remain essential. Plant diseases, however, pose significant challenges by disrupting key processes like photosynthesis, pollination, germination, transpiration, and fertilization, which hinders the plant's overall health and productivity. Unforeseen environmental conditions often lead to the emergence of diseases caused by pathogens such as bacteria, viruses, and fungi. In India, a wide variety of crops are grown across different regions each with its own unique climate and seasonal variations. Early detection of diseases in plant leaves is particularly crucial in agriculture. Plant leaf diseases are a major factor that contributes to reduced crop yields worldwide. Farmers frequently face significant problems in controlling crop diseases, especially at advanced stages [3][4]. Accurate disease diagnosis is vital in agriculture as it allows better management and timely interventions to prevent substantial

crop losses. Therefore, early-stage disease detection remains essential to protect plants from harmful diseases and ensure healthier crops. Farmers require continuous monitoring of their plants to protect them from harmful diseases. However, this process is often expensive and time-consuming in real-world agriculture. To ensure accurate disease detection, image pre-processing plays an important role in improving the quality of images, which helps achieve better diagnostic outcomes. For effective disease identification through automated systems, high-quality image processing is essential. Input images often suffer from excess noise due to environmental disturbances, and if the data is not properly cleaned, reliable results cannot be obtained [5][6]. When distortion-free images are provided as input, diseases can be more effectively detected, allowing for timely and appropriate interventions. However, many existing research studies place less emphasis on the pre-processing stage, leading to suboptimal results. Ineffective pre-processing leads to various problems including degraded image quality, suppressed performance due to excessive noise, loss of crucial information, increased processing time and inaccurate analysis. To ensure effective automated analysis of plant diseases, it is essential that the input images are of high quality. High-quality images allow for a more detailed examination of the data, allowing the extraction of critical information. This, in turn, helps identify diseases early and implement appropriate solutions in a timely manner [7][8].Image de noising is a crucial aspect of image processing and computer vision dealing with noise during image-taking, transmission, or processing. Noise is a factor that results in a decrease in image quality which directly disturbs the accuracy of image-based analysis and it further affects the recognition, segmentation, and tracking tasks. Therefore, image de noising has been a major research topic, which has produced a number of techniques to deal with these challenges [9][10]. The traditional methods of de noising have some shortcomings like demanding high computational power, deficiency of the adaptation to various noise types and levels, and challenges in preserving image details and textures. In recent years, deep learning-based approaches have emerged as a promising solution, achieving state-of-the-art performance in view of both quantitative metrics and visual quality. The effectiveness of deep learning methods

occurs in their ability to learn complex image features and high-level representations directly from training data, eliminating the need for handcrafted features or assumptions about noise distribution. Additionally, deep learning models allow for end-to-end training, facilitating the simultaneous optimization of the de noising process and image representation. These methods can be broadly classified into two categories: discriminative models and generative models [11][12].

Convolutional Neural Networks (CNNs), a prominent type of discriminative model, are capable of mapping noisy images directly to their clean counterparts. These models are trained to minimize the reconstruction error between the predicted clean images and their corresponding ground-truth versions. Typically, training involves paired datasets of clean and noisy images, with a separate model trained for each pair. CNN-based de noising methods have shown remarkable results across various datasets, such as the Plant Village dataset, consistently outperforming traditional de noising techniques by a significant margin. On the other hand, generative models adopt a different approach by learning the underlying probability distributions of clean and noisy images and sampling from these distributions based on the observed noisy input [13][14].

Vibrational Auto encoders (VAEs), a popular type of generative model, utilize a latent representation of images and a decoder to map this representation back to clean images. VAE-based techniques can generate multiple plausible de noised outputs by sampling from the learned distribution, making them particularly useful for tasks like uncertainty quantification. In addition to CNNs, other deep learning architectures have been explored for image de noising. Recurrent Neural Networks (RNNs) leverage temporal correlations between consecutive frames in video sequences to improve de noising performance. Generative Adversarial Networks (GANs) enhance de noising by incorporating an adversarial loss, encouraging the output images to be indistinguishable from clean ones. Attention-based models further refine the de noising process by focusing on the most relevant regions and features within an image, thereby improving efficiency and accuracy [15][16].

2. LITERATURE REVIEW

J. Wu, et al. (2024) presented plant PDN (point cloud de noising network) based on point cloud density gradient field learning to effectively solve the problems posed by plant point clouds [17]. PDN consisted of three main modules: the PDF (point density feature) exception module, the UOF (umbrella operator feature) computation module and the point DG (density gradient) estimation module. The effectiveness of PDN was assessed through experiments using point clouds of multiple plant species with different types of noise. Under many levels of Gaussian noise, this method achieved a relative performance improvement of 7.6% to 19.3% compared to state-of-the-art baseline methods, attaining the best de noising performance. For different types of noise, the majority of these de noising results exceeded the baseline methods. Additionally, this method was 0.5 times faster than the baseline methods when processing point clouds with low noise levels, and 8.6 times faster for point clouds with high noise levels.

F. Aziz, et al. (2024) aimed to increase image quality using the DBPN (Deep Back-Projection Network) technique to improve the classification of plant pests with a CNN (Convolutional Neural Network) [18]. The dataset included 3,150 images of pests from nine different species. The classification process was carried out using a CNN model with four convolutional layers along with hyper parameter tuning, which achieved an accuracy of 94%. Evaluation results showed that the model performed well in terms of precision, recall, and F1-score for most pest classes, although the recall values for mites and sawflies were slightly lower. The application of DBPN to improve image quality resulted in a 10% increase in classification accuracy. This study demonstrated that better image quality helped the model more accurately recognize important features.

Z. Yang, et al. (2024) proposed TFEGAN, a new algorithm designed to create maize leaf disease images. TFEGAN leveraged a TWEM (Two-Way Extraction Module) to improve the perceptual domain of the model and effectively reuse maize leaf disease features [19]. This algorithm used two well-trained GANs (Generative Adversarial Networks) to improve low-light and noisy maize leaf disease images. The low-light enhancement component used a double discriminator and self-regularization to balance global and local enhancement while constraining the distance between the input image and the de noising component. Moreover, the de noising part incorporated a strong coordinated attention mechanism and an environmental encoder to learn noise regions and their surrounding structures, resulting in better local images and enabling more accurate evaluation by the discriminant network. The generators of both networks were encapsulated by two discriminators and combined with a bi-directional feature extraction structure to create normal maize leaf disease images. Experimental evaluations showed the performance of TFEGAN in improving the quality of maize leaf disease images under low-light and noisy conditions, highlighting its potential for practical applications.

N. S. Rani, et al. (2024) proposed a deep semantic linearization model, PLM-Res-U-Net, designed to improve palm-leaf manuscripts [20]. PLM-Res-U-Net was a lightweight model composed of encoding and decoding blocks with skip connections. The model efficiently enhanced the quality of palm leaf manuscripts by retaining

the text strokes while removing degradations including uneven illumination, aging marks, brittleness, and background discolorations. Two datasets of palm leaf manuscript collections, featuring multiple degradation patterns and diverse textured backgrounds were used for experimentation. PLM-Res-U-Net was trained from scratch for 50 epochs with a learning rate of Le −8 and three sampling strategies. The effectiveness of state-of-the-art deep learning models including ResU net, Pspnet, U-Net++ and Signet, was also assessed using two different benchmark datasets. The analysis showed that the results obtained with the proposed PLM-Res-U-Net demonstrated both generalizability and computational efficacy, achieving a Dice score of 0.986.

Y.-C. Chen, et al. (2024) introduced a MSMP-CNN (multi-scale and multi-pooling convolutional neural network) model developed to identify mango leaf diseases using real-world images [21]. The proposed model underwent a pre-training phase, followed by transfer learning and fine-tuning, to optimize its performance. The model initially achieved an accuracy of 95% on its own. After enhancement through transfer learning and fine-tuning, the accuracy improved to an impressive 98.5%. To evaluate the classification performance with without transfer learning and fine-tuning, t-distributed stochastic neighbor embedding (t-SNE) plots were utilized. Additionally, CAM (class activation mapping) heat maps were employed to highlight class-specific regions of the images, helping verify whether the model focused on the appropriate parts of the image for disease identification. These findings highlighted the strong potential of the model, especially when combined with transfer learning and fine-tuning, for advancing mango leaf disease detection.

V. G. Bhujade, et al. (2024) introduced a new pre-processing method called the Optimization Assisted Cascaded Filtering Approach (OptCFA). In the proposed OptCFA model, the Gaussian Amended Bilateral Filter (GABF) was designed, where multilevel thresholds were calculated for the GABF outcomes [22]. The filter parameters were optimized using the Amended Pelican Optimization Algorithm (AmPel) for the first stage of noise removal. The outcomes were then cascaded with an Extended Savitzky-Golay Filter (E_SGF) for the second stage of noise removal. The proposed OptCFA model was a unified method that integrated the GABF, AmPel, and E_SGF methods. In the results section, various existing pre-processing filters such as the median, bilateral, and Gaussian filters were analyzed for comparison.

V. -D. Hoang, et al. (2023) presented a new method that combined an image filtering pre-processing technique with ViT (vision transformer) learning to solve the problem of plant insect pests and diseases recognition [23]. The proposed solution consisted of various stages: neural network-based image filtering, followed by passing the results through a ViT module to extract feature maps, which were then fed into a multi-head network for classification. The method applied image filtering as a pre-processing step to highlight features before passing the results to the ViT processing stage, rather than using the ViT directly on raw input images. Additionally, element-wise multiplication in the frequency domain was used to reduce processing time, instead of relying on convolutional processing in the spatial domain. Experimental results showed that the image filtering pre-processing did not significantly increase the number of learning parameters or the training time compared to using ViT directly.

W. Chang, et al. (2022) suggested a CNN (convolutional neural network) based iterative framework, which was unfolded into a deep network equipped with an unsupervised learning strategy called regularized Noise2Noise [24]. The iterative framework mathematically solved the de noising problem using the half-quadratic splitting and gradient descent methods, benefiting from the CNN's capacity and flexibility in exploiting image properties. Moreover, the regularized Noise2Noise provided a constraint that considered the difference between the ground truth corresponding to the input and the label. The iterative framework was tested on dynamic plant PET images and compared with three popular de noising methods. Experimental results showed that the iterative method effectively improved denoising efficiency, achieving an average signal-to-noise ratio of 34.93 and an average contrast-to-noise ratio of 62.51, outperforming all the compared methods.

H. Jin, et al. (2022) created U-Net-like generator by integrating convolutions with residual blocks and reorganization (reorg) methods to overcome the loss of texture detail data during image generation, simultaneously, the concatenation (concoct) method was used in the generator to retain more scale texture information [25]. To ensure the generated grape images were structurally complete and to prevent misalignment of the petiole and leaf structures, a discriminator was developed with a convolution block and capsule structure. Convolution was used to extract general features, while the capsule structure encoded spatial information and the probability of the presence of spots. In subsequent experiments using the same raw data, Grape GAN was compared to WGAN and DCGAN. The results showed that GrapeGAN outperformed the comparative models, achieving a FID (Fréchet Inception Distance) of 5.495 and a NIMA (Neural Image Assessment) score of 4.937 ± 1.515.

S. O. Oppong, et al. (2021) designed image pre-processing methods to improve specific features of an image that were important for further processing such as edge detection or object recognition. Preprocessing played a main role in image processing applications by removing noise and either suppressing or highlighting certain attributes [26]. This study aimed to preprocess medicinal

plant leaf images by improving their quality using a combination of Homomorphic filtering and Contrast Limited Adaptive Histogram Equalization. This study also used the OTSU global thresholding algorithm to segment the image from its background. Performance metrics for both image enhancement and segmentation were used to assess the efficiency of the proposed method. The experiments conducted using MATLAB showed that the proposed method outperformed the Contrast Limited Adaptive Histogram Equalization in terms of Peak Signal-to-Noise Ratio, Mean Squared Error, and Mean Absolute Error for image enhancement, as well as Jaccard Index, DICE Index and Matthews Correlation Coefficient for image segmentation.

3. RESEARCH METHODOLOGY

This research work is based on to improve quality of the plant images. The Generative artificial intelligence based approach called GAN and transfer learning method called VGG166 is applied to improve quality of plant images. The detailed methodology is explained below:-

3.1. DATA AUGMENTATION

When training a machine learning model, the primary task is to fine-tune its parameters to facilitate the mapping of inputs to desired outputs, with a core objective of minimizing the model's loss. Modern neural networks are equipped with millions of parameters, demanding a substantial amount of data for effective training. Instead of seeking entirely new datasets, the practice of data augmentation comes into play. Data augmentation involves introducing minor variations to existing images, including actions such as flips, rotations, translations, and more. In scenarios where datasets are smaller, augmentation techniques can be applied to all available images. In the case of larger datasets, augmentation is executed on-the-fly for randomly selected images. It's worth noting that the utilization of data augmentation serves the additional purpose of preventing neural networks from learning irrelevant patterns, thereby improving the productivity in general.

3.1.1. Flip

The process of flipping an image both horizontally and vertically results in the creation of new images.

3.1.2. Random Crop

During cropping, random samples are taken from the original images, and these sections are resized to match the size of the source image.

3.2. THE NETWORK ARCHITECTURE

3.2.1. Network Base Layers

The Convolutional layers serve as fundamental building blocks in a convolutional neural network (CNN). When working with high-dimensional data, like images, establishing full connections to all neurons is impractical. CNNs concentrate on square patches of the image and process them through filters of the same size. These filters traverse the entire image, generating the final activation maps. In the Convolutional Layer, neurons compute their outputs by connecting to localized areas of the input, calculating the dot product between their weights and the input region, depending on the filter size.

3.2.2. ReLU Activation

Non-linear activation functions are typically preferred when defining neural networks. The ReLU (Rectified Linear Unit) layer offers a non-linear activation function, which is defined as follows:

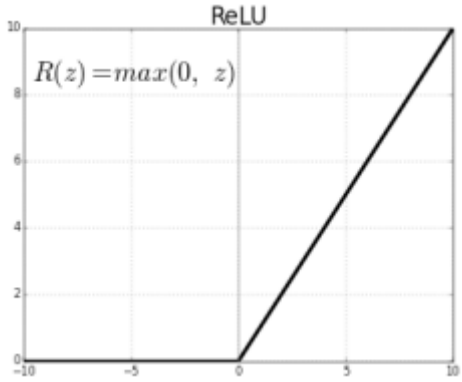


Figure 2. ReLU Activation

$$f(x) = max(0, x)$$

In simpler terms, the activation function involves setting threshold to zero.

- Unlike some other activation functions, ReLU can be implemented by straightforwardly applying a threshold at zero to a matrix of activations.
- It's worth noting that with an exceedingly large learning rate, ReLU can potentially cause certain parts of the neural network to become "dead," meaning they may not activate beyond a specific level.

In the absence of the activation layer, the convolutional layers could essentially function as a single layer.

3.2.3. Pooling Layer

A pooling layer is often inserted between successive convolutional layers in a CNN architecture. It serves to progressively decrease the number of parameters and computations within the network, as well as mitigate over fitting. The pooling layer operates on each depth slice of the input independently and spatially resizes it. A typical configuration involves using 2x2 filters with a stride of 2, which down samples each depth slice by a factor of 2 in both width and height, neglecting 75% of the activations.

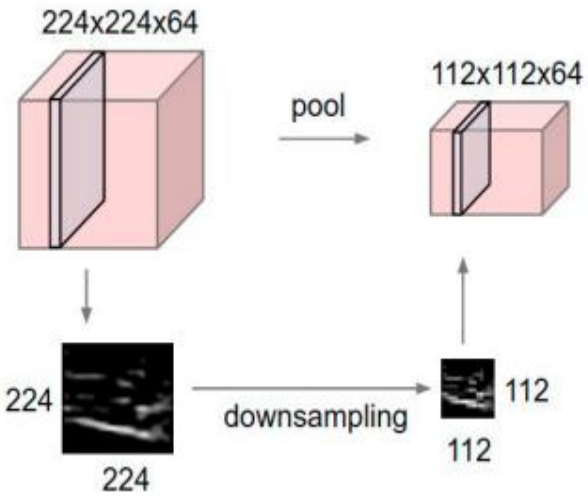


Figure 3. Pooling Layer

In Figure 3.2, the input volume with dimensions [224x224x64] undergoes pooling using a filter of size 2 and a stride of 2, resulting in an output volume with dimensions [112x112x64]. It's important to note that the depth of the volume remains unchanged.

3.2.4. Dropout

In deep neural networks, the number of parameters increases as the number of hidden layers grows. This enables the network to learn various features and relationships between input and output values. However, when there isn't enough data to train these networks, the learned relationships might be influenced by noise in the training set, leading to over fitting. To mitigate over fitting, several techniques have been introduced, such as early stopping during training or averaging the outputs of different networks. However, these methods have limitations. Dropout is a method that addresses these issues. As the name implies, dropout involves randomly removing multiple neural units from the network. Each unit is retained with a probability 'p,' and typically, a probability of 0.5 is effective in practice.

3.2.5. Instance Normalization

Neural networks have the ability to learn features on their own, without the need for handcrafted features, but they do require data normalization. Typically, data normalization is applied to the input data, as it aids in faster convergence. However, during the training process, as model parameters are updated, the distribution of each layer's input may change, which can slow down training. To address this issue, normalization within the network is introduced to prevent such delays. Batch normalization was introduced to address this concern by normalizing each training mini-batch. It has proven effective in training deep learning models. However, when it comes to generating images, factors like contrast and color distribution become crucial. Batch normalization may not adequately address these aspects. Instance normalization independently normalizes the channels of each image batch.

3.3. OTHER PARAMETERS

The speed at which a network converges to the global optimum primarily relies on the activation function employed and the depth of the network. Greater network depth increases the computational effort before convergence. Nonetheless, various parameters can be adjusted as needed, such as learning rate, initial weights, optimization functions, and more.

3.3.1. Weight Initialization

Initializing weights helps mitigate the vanishing or exploding gradient issues, which can significantly prolong the network's convergence time. Initializing weights from a Gaussian distribution with a mean of 0 and a standard deviation of 1 has been shown to be effective, particularly when using ReLU activation functions.

3.3.2. Optimization

Optimization algorithms are crucial for minimizing (or maximizing) an objective function, which is a mathematical function based on the model's internal parameters. These algorithms facilitate the adjustment of weights and biases to steer the output towards the optimal solution. In this context, the Adam optimizer is employed, which is a widely used and highly effective choice for neural networks. Adam is a hybrid algorithm that combines the benefits of AdaGrad and RMSprop, while also incorporating momentum, setting it apart from simple stochastic gradient descent (SGD).

3.4. LOSS FUNCTION

Machine learning and deep learning algorithms are fundamentally built on the concept of learning the optimal weights for each neuron. This process hinges on

the optimization of an "objective function" that quantifies how well the model performs concerning the expected outcomes. The primary goal is to minimize this loss function. It's worth noting that a single loss function is typically expected to generalize well across diverse datasets, although its effectiveness depends on factors such as the nature of the data, the chosen optimization function, and the specific algorithm employed.

In the context of the proposed work, the primary aim is to establish a relationship between two sets of training samples, denoted as X and Y. This involves two functions $G : X \rightarrow Y$ and $F : Y \rightarrow X$. These functions are accompanied by their respective discriminators, D_Y and D_X. The data distributions are defined as $x \sim p_{data}(x)$ and $y \sim p_{data}(y)$.

3.4.1. Adversarial Loss

The objective of the adversarial loss for G can be defined as follows:

$$L_{GAN}(G, D_Y, X, Y) = \mathbb{E}_{y \sim p_{data}(y)}[log D_Y(y)] + \mathbb{E}_{x \sim p_{data}(x)}\left[\log\left(1 - D_Y(G(x))\right)\right]$$

G aims to minimize this loss, while D aims to maximize it. Therefore, the main aim is $min_G max_{D_Y} L_{GAN}$. The same objective applies to estimate the function F.

3.4.2. Cycle Consistency

Adversarial networks, during training, can learn to map both G and F to their respective targets, Y and X. Nevertheless, they may learn to map an image to any random image from the target domain, which means that it's not guaranteed that the individual input x_i will be mapped to y_i. To address this issue, network cycle-consistency is introduced. Therefore, it is necessary to satisfy the sequence $x, x \rightarrow G(x) \rightarrow F(x) \approx x$ and for input $y, y \rightarrow F(y) \rightarrow G(y) \approx y$ for the given input x. To ensure this behavior, a loss function called cycle consistency loss is introduced, defined as:

$$L_{cyc}(G, F) = \mathbb{E}_{x \sim p_{data}(x)}[\|F(G(x) - x)\|_1] + \mathbb{E}_{y \sim p_{data}(y)}[\|G(F(y) - y)\|_1]$$

3.4.3. Perceptual Similarity Loss

When performing an image transformation task, it has been observed that if implemented with per-pixel loss, even minor differences between two perceptually similar images can result in significantly high loss. However, by using perceptual loss instead of per-pixel loss, it's possible to create high-quality images. In this approach, high-level features are extracted using the VGG-19 network, which is pertained on the Image Net dataset. The VGG network, when given an image, can extract feature weights that help make the generated output image perceptually similar to the original target image. Feature extraction is carried out from the second and fifth max-pool layers for both the source image and produced images.

4. RESULT & DISCUSSION

4.1. TECHNIQUES AND TOOLS

The presented approach is simulated using Python3 and its deep learning (DL) libraries. The Google Cloud platform consisted of virtual machine (VM) with 1 vCPU, 16 GB RAM and 1 Nvidia-K80 GPU of 12 GB VRAM, is adopted to implement the presented approach. Pytorch is exploited for generating the program.

4.1.1. The Generator

This work employs a convolutional neural network (CNN) algorithm and images of 256x256x3 are fed into this algorithm. These inputs are undergone from a stride 2 convolution layer. A series of convolution layers is utilized in order to down sample these images which are later gone through a set of residual blocks. A set of transpose convolutions deploys the output for up-sampling the pictures. At last, they are fed into a convolution layer and is execute similarly to the one implemented in neural form of transfer.

4.1.2. The Discriminator

It is a neural network (NN), and plays a role of a classification algorithm. This algorithm majorly emphasized on distinguishing the images after retrieving them from the generator and which are real time images. The generator takes the precise results of classifying data for learning from and focuses on misleading the discriminator. Thus, the network framework adopted in this discriminator has similarity with Patch GAN algorithm or Markovian discriminator. Several Conv-BatchNorm-LeakyRelu layers are deployed to develop this algorithm. Unlike the Patch GAN" discriminatory which utilizes 2 images, an image of 256x256x3 dimension is employed as input in this network and a value, used to illustrate its class, is generated. The training of this network is done using real time images and the images produced from the generator.

4.1.3. Training Details

The batch size is set to 1 for the Adam Solver in order to train the network. For primary fifty epochs, it sets a learning rate to 0.0002 and 0 for a linear decay among rest of the epochs. Around seventy epochs having one thousand images are considered to train the framework. The NYU Depth dataset to gather these pictures. The multiplication of cyclic loss is done with $\lambda = 10$. The value of 0.5 is assigned to β_1 and 0.9 to β_2 of Adam Solver.

4.2. RESULTS

The dataset of apple is collected from kaggle and dataset has four classes which are Cider apple rust, Black rot, Apple Scab and health.

Table 1: Apple Black Rot Images

Original Image	Denoised Image

Table 2: Apple Cider Images

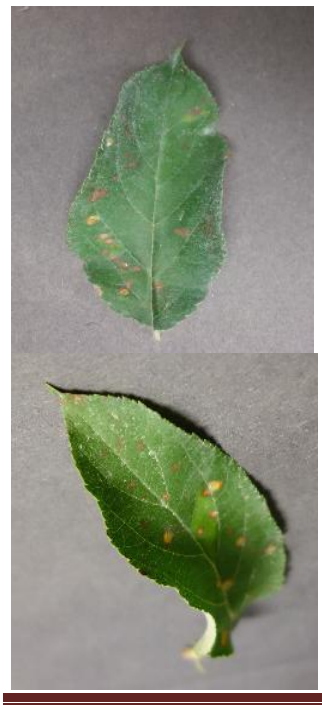
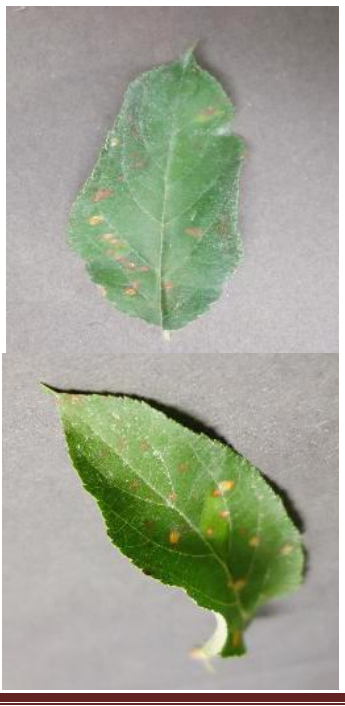
Original Image	Denoised Images
	

Table 3: Apple Scrab Images

Original Image	Denoised Images

Table 4: Apply health Images

Original Image	Denoised Images

4.2.1. Evaluation Metrics

The proposed methodology leads to improve in the quality of image. The image quality is quantified on the basis of diverse parameters. The parameters, namely peak signal-to-noise ratio (PSNR) and Structural Similarity Index (SSIM) are deployed for computing the quality of the generated picture.

Class Name	Gaussian Filter		Median Filter		Proposed Model	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Apple Rot	12.78	0.70	14.56	0.62	17.82	0.56
Apple Cider	13.45	0.68	14.12	0.60	16.89	0.53
Apple Scrab	15.67	0.53	16.80	0.54	19.89	0.50
Apple Healthy	10.78	0.41	11.78	0.49	12.90	0.42

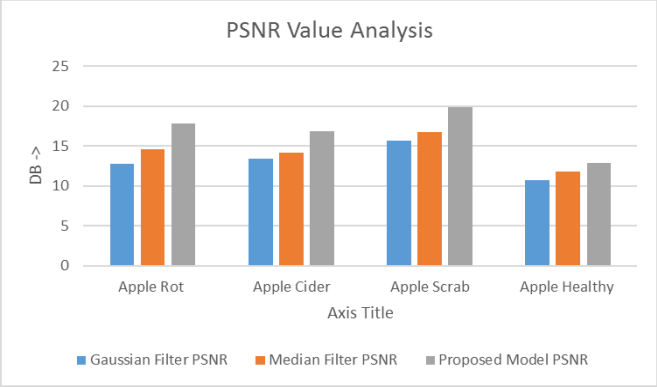


Figure 4: PSNR Analysis

As shown in figure 4, the PSNR value of proposed model is compared with existing filters like Gaussian filter and median filter for image denoising. It is analysed that proposed model has high PSNR value as compared to Gaussian and median filter.

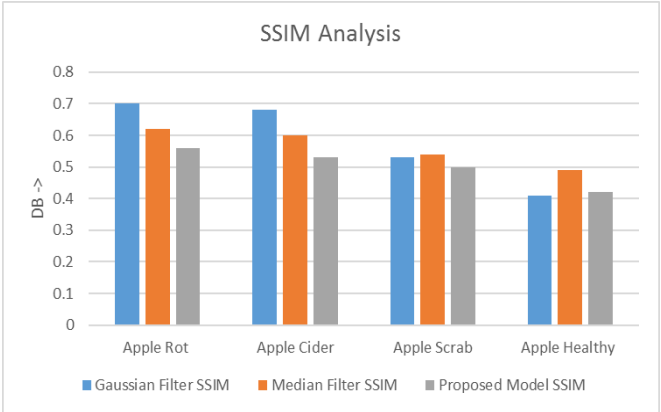


Figure 5: SSIM Analysis

As shown in figure 5, the SSIM value of proposed model is analyzed and it shows that proposed model has least SSIM value as compared to Gaussian filter and median filter. The least SSIM represents that images are denoised efficiently.

5. CONCLUSIONS

The existing work employs the addition of perceptual loss function (LF) due to which the quality of image is greatly affected. A deep-learning (DL) method is suggested in this work for creating haze free pictures, and no human intervention is required in it. Moreover, the cyclic framework utilizes a lossy function for enhancing an output for specific input and ensuring the no generation of other kinds of output is done. According to results attained quantitatively and qualitatively, the suggested method works efficiently to de-haze the images in comparison with the traditional methods. Furthermore, the supremacy of VGG19 algorithm is proved over the existing algorithm concerning perceptual-consistency loss values. The proposed model is implemented in python and proposed model show least SSIM, maximum PSNR as compared to Gaussian filter and Median Filter.

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