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An Improved EigenGAN-Based Method for Data Augmentation for Plant Disease Classification

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ABSTRACT

Plant diseases are caused by a variety of environmental variables, which cause large losses in productivity so the diagnostic systems that are automated play a significant part in agricultural automation. A large number of disease images with appropriate plant village database disease label information must be collected to construct a functional image-based autonomous image diagnostic system. However, manual detection of plant diseases is a time-consuming and error-prone process. Conventional systems showed reasonably good diagnostic performance, however, most of their disease predictions were heavily unfairness owing to "latent similarity" within a dataset (backgrounds, lighting, and/or the separation between the target and the camera) among training and test images, and their genuine diagnosis skills were far lower than stated. To overcome this issue, this paper proposed a Hybrid Fourier Filter De-noising (HFFDF) algorithm and enhanced EigenGAN (Generative Adversarial Network (GAN)), which creates a large number of diverse and large-quality training images and serves as a reliable data supplement for the diagnostic classifier. These produced images may be utilized as resources to improve the efficiency of plant disease diagnostic systems. The results shown that the performance of the new method of HFFDF is effective compared with other denoising filters of Gaussian, Median and wiener filter algorithms. The Experimental result shows that proposed HFFDF and EigenGAN methods clearly outperforms than existing methods.

1. INTRODUCTION

Deep learning is now being integrated with computer vision and artificial intelligence to assist in the detection and recognition of images and videos, as well as in the solution of issues in a variety of fields. One of the most active agricultural research disciplines is the automated identification of plant disease. Detecting plant diseases in an appropriate and effective approach is crucial to ensuring worldwide food protection [1, 2]. Deep learning is now a widely used technology with a wide range of applications such as agriculture and botanical studies, revolutionizing the field of computer vision in recent years. Numerous deep learning methods for computerized identification of plant diseases have been developed to help farmers and reduce plant output losses.

Effective plant disease control is a challenge that is linked to climate change and sustainable agriculture [3]. Climate change, according to research findings, can affect the stages and rates of pathogen growth; it can also impact host resistance, resulting in physiological alterations in host-pathogen interactions [4, 5]. The predicament is exacerbated by the fact that illnesses are now more easily transmitted internationally than ever before. New infections can emerge in previously recognized locations and, inherently, in areas with little local ability to combat them [6, 7].

The process of increasing the volume and diversity of data in deep learning is known as data augmentation. This paper presents to transform existing data instead of gathering new data. Data augmentation enhances the value of base data within an organization by combining information from internal and external sources. Data augmentation is an essential step in deep learning because deep learning requires vast volumes of data and it is not always possible to acquire thousands or millions of data samples, therefore data augmentation come in handy.

A GAN is a methodology for estimating generative models that are composed of two differentiable sub-models that are often implemented as deep neural networks: the discriminator *D* with parameters *dD* and the generator *G* with parameters *dG*. Figure 1 depicts an example of a common GAN configuration. The discriminator and the generator compete with one another. Using a latent noise vector z, the generator is taught to generate images *G(z)* that mimic the training data distribution *pR*. As input, a sample from the distribution *pz*, while the discriminator is fed produced images G(z) as well as real training data x and is trained to distinguish between generated and genuine images.

This paper presents, a novel Hybrid Fourier Filter De-noising (HFFDF) algorithm and enhanced EigenGAN data augmentation method for plant disease images is presented. The objective of the proposed system is to develop a hybrid image de-noising method for plant disease images that effectively eliminates unimportant noises. Following the denoising procedure, an improved EigenGAN data augmentation technique of generated images can be employed to enhance plant disease performance diagnosis systems.

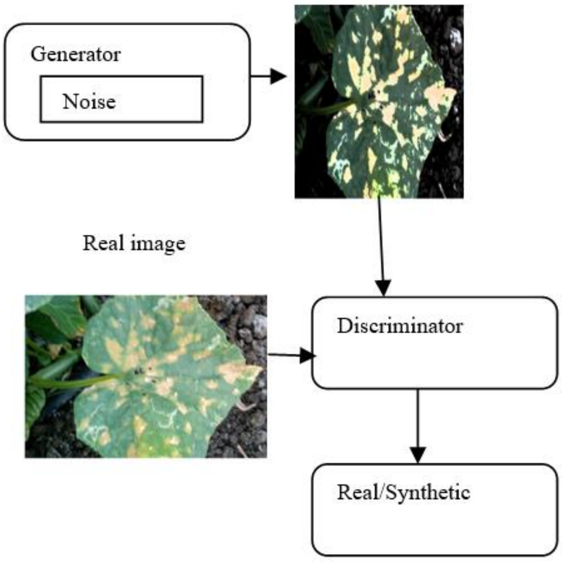

Figure 1. The architecture configuration of a standard GAN

2. RELATED WORK

Saikawa et al. [8] revealed that diagnostic cues are usually confusing and that additional factor, including image conditions; frequently have a important influence on the decision. As an outcome, latent similarities in the dataset frequently cause overfitting, and diagnostic presentation on actual unknown data is typically significantly diminished. Due to the bias caused by dataset similarities, numerous algorithms have showed exceptional diagnostic performance; nevertheless, this issue has not been fully addressed.

According to Cui et al. [9], discussed the incremental usefulness of a new data point decreases with the number of samples. By associating a small adjacent region with each sample rather than a single point, the authors established a novel theoretical framework for calculating data overlap. The volume of samples is a simple formula $(1-\beta n)/(1-\beta)$, where n is the number of samples and $\beta\in[0,1]$ is a hyper-parameter that can be used to calculate the effective number of samples. By employing the appropriate number of samples for each class, they came up with a re-weighting technique that rebalances the loss and produces a loss that is balanced across classes.

Karras et.al. [10] borrowed from the style transfer literature to present an alternate generator design for generative adversarial networks. The novel architecture offers both an automatically learnt, unsupervised separation of high-level properties and random variation in the generated images, and simple, scale-specific synthesis management. The new generator outperforms the state-of-the-art in terms of standard distribution quality criteria, yielding much higher interpolation qualities and better disentangling the hidden sources of variation.

The issue of data augmentation in image categorization was examined and various solutions were contrasted by Perez et al. [11]. The efficacy of data augmentation methods like cropping, rotating, and flipping input images has been demonstrated in prior study. They restrict access to a small portion of the ImageNet dataset and look at each data augmentation method separately. Traditional transformations, as noted above, are one of the more successful data augmentation options. They also used GANs to produce graphics in a variety of styles. Lastly, they developed neural augmentation; it permits a neural network to discover modifications that best enhance the classifier. They discussed the method's strengths and weaknesses on several datasets.

Despite recent advances in generative image modeling, Brock et al. [12] argued that successfully generating high-resolution, varied samples from complicated datasets such as ImageNet remained an elusive aim. To that goal, they trained Generative Adversarial Networks at the biggest scale yet tried and investigated the instabilities that arise at such a vast scale. They discover that by applying orthogonal regularization to the generator, they can perform a simple "truncation trick," providing tight control over the trade-off between sample accuracy and variety by minimizing the variance of the Generator's input.

By enhancing perceptual quality and maintaining semantics, Nazki et al. [13] discussed a GAN-based image-to-image translation technique. They presented AR-GAN, a synthetic image generator that prioritizes feature activations in comparison to the original image in addition to the adversarial loss. They demonstrated artificial images that were more pleasing to the eye than the most popular models of the present, and they assessed the efficiency of their GAN framework using a variety of datasets and metrics. Second, they evaluated how well a baseline convolutional neural network classifier for improved recognition performed in comparison to the conventional data augmentation method, employing the resultant synthetic examples to enrich their training set.

Brahimi et al. [14] proposed a public dataset to test different CNN architectures utilizing three learning algorithms for plant disease classification. These novel structures better state-of-the-art plant disease classification results, with an accuracy of 99.76 percent. In addition, the authors proposed saliency maps as a visualization tool to comprehend and interpret the CNN classification mechanism.

Cap et.al. [15] introduced LeafGAN, an innovative image-to-image translation system using a unique attention mechanism. By transforming healthy photographs into a wide range of diseased images, LeafGAN serves as a data augmentation tool to enhance the accuracy of plant disease detection. Our model's unique attention mechanism allows it to selectively alter relevant regions from images with different backgrounds, enhancing the training images' adaptability.

3. PROPOSED METHODOLOGY

By utilizing the plant disease information, the study strategy accounts for the sequence in which all of the experiments were conducted [16]. The Hybrid Fourier Filter De-noising (HFFDF) technique successfully removes noise from plant images, yielding enhanced and noise-free images suitable for additional processing such as image data augmentation. Figure 2 depicts the overall proposed flow diagram.

3.1 Image pre-processing

Image preprocessing is the process of transforming raw image data into a usable format. The approach to preprocessing is broken into two phases: (i) Image size conversion and (ii) Hybrid Fourier Filter De-noising (HFFDF). This preprocessing phase improves the plant image section by removing unneeded distortions and improving several image properties that are important for subsequent processing. The original plant image database of pixels size (1968× 4160 uint8) is converted into predefined 512 × 512 sizes, excluding pixel uncertainty, using the 'bicubic' interpolation method. Following that, disease database images should be comparable in size and are expected linked with indexed images on a regular gray-scale map.

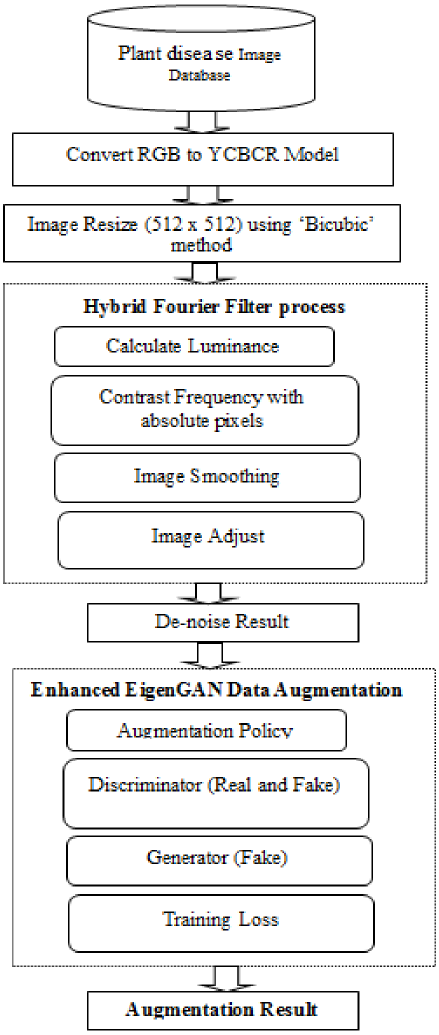

Figure 2. Proposed flow diagram

3.2 Hybrid Fourier Filter De-noising (HFFDF)

The proposed Hybrid Fourier Filter De-noising technique is characterized as having a light and noise variation value of 0.5 and calculates image scaling. Then resized images will be converted to the Fast Fourier Transform technique using FFT. Then calculate luminance and contrast Frequency for image variations, with absolute pixel variation. Next, Image smoothing is a process used to reduce noise, sharp edges, and clutter from the image. Finally, the inverse FFT Image with pixel variation image adjust function is used to display the de-noised image. The acquired de-noised image is displayed using image adjust function. Finally, the result shows the highest PSNR value compared to Existing image denoise filter algorithms.

Algorithm 1: Hybrid Fourier Filter De-noising (HFFDF)
Input: Image ***I***, noise and light variation *n*, *l* = 0.5, contrast Frequency ***cF***, height ***h***, smoothing factor ***smf.***
Output: Result Image ***DR***.
Begin
Step 1: Image dimensions should be calculated.
Step 2: FFT image conversion
Step 3: Initialize FFT Parameters (dimension and image total number pixels (***N***))
Step 4: Optimize absolute FFT Image Pixels
Process
Step 5: Calculate contrast frequency

$$\mathrm{cF} = \mathrm{FFT_{Tp}} \times \mathrm{abs}(\mathrm{FFT_{Tp}} > 0) + \frac{1}{l} \times \mathrm{abs}(\mathrm{FFT_{Tp}} == 0) \tag{1}$$

Step 6: Calculate absolute pixel for noise variation

$$\mathrm{abspixel} = \mathrm{abspixel} \times (\mathrm{abspixel} > n^2) + n^2 \times (\mathrm{abspixel} \le n^2) \tag{2}$$

$$\mathrm{smf} = \frac{\mathrm{cF} \times (\mathrm{absPixel} - \mathrm{n}^2)}{\mathrm{absPixel} \times n^2} \tag{3}$$

$$\mathrm{Result} = \mathrm{smf} \times \mathrm{FFT_{image}} \tag{4}$$

Step 7: Result image

$$\mathrm{DR} = \mathrm{real}(\mathrm{ifft}(\mathrm{Result})) \tag{5}$$

The proposed HFFDF approach contrasts various de-noise filtering algorithms, including the applied median filter, Wiener, and the Gaussian, and median filters. Figure 3 displays the results of the comparison.

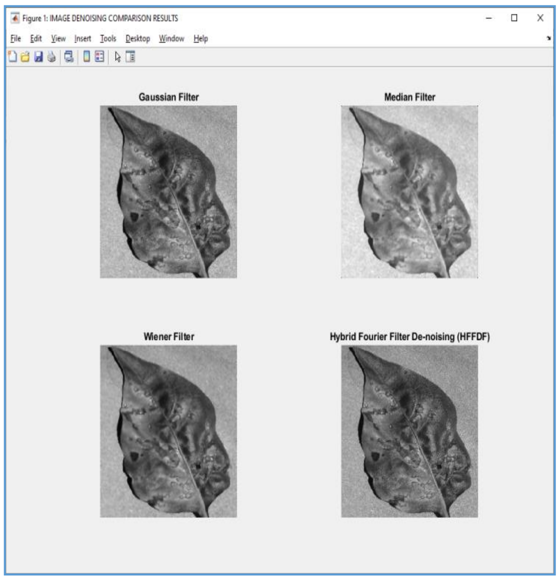

Figure 3. Hybrid Filter De-noising Filter (HFDF) process results

3.3 Enhanced EigenGAN Data Augmentation

Enhanced EigenGAN Data Augmentation is a technique that extends the EigenGAN: Layer-Wise Eigen-Learning for GANs [17] technique. The GAN [18] is a generative model that generates information out of noise. GAN learning competes with a generator and a discriminator. The discriminator, in particular, attempts to identify synthetic samples from actual samples, whilst the generator attempts to create the generated samples as realistic as possible to trick the discriminator. The synthesized data distribution corresponds to the genuine data distribution when the competition approaches Nash equilibrium.

In order to train at layer generator mapping from a set of latent variables $\{y_k \in R^q | y_k \sim N_d(0, I), k = 1,\ldots,t\}$, the EigenGAN Generator with Layer Wise Subspaces is intended to the synthesized image $Im = G(y_1,\ldots,y_t)$, where y_k is added and the solution into the k^{th} generator layer and d specifies the number of aspects of each subspace.

The system embeds a linear subspace model in the k^{th} layer $lsm_k = (O_k, I_k, \mu_k, p_k)$ where,

- $O_k = [o_{k1}, \ldots, o_{kq}]$ is the orthonormal source of the subspace, and every source vector $o_{km} \in R^{Hk\times Wk\times Ck}$ (i.e, Height, Width and Channel) is designed to uncover a "Eigendimension" that keeps unsupervised a variant of interpreted generated samples.
- $I_k = \mathrm{diag}\,(I_{k1},\ldots,I_{kq})$ is a diagonal matrix with I_{km} choosing the "importance" of the source vector o_{km} . To be more specific, a big fixed value of I_{km} indicates that o_{km} controls the considerable variation of the k^{th} layer, however, a low absolute value denotes a little amount of variance, which is also a form of dimension selection.
- Subspace's origin is denoted by μ_k.
- p_k denotes the projection subspace

Then, the research method uses the k^{th} latent variable $y_k = [y_{k1},\ldots,y_{kq}]^T$ as the linear coordinates for sampling one of the subspace's points lsm_k:

$$\emptyset_k = O_k I_k y_i + \mu_k = \sum_{m=1}^{q} y_{km} I_{km} o_{km} + \mu_k + p_k \quad (6)$$

As indicated below, sample point ϕ_k is going to be incorporated as a network feature of the k^{th} layer.

If $h_k \in R^{Hk\times Wk\times Ck}$ denotes the k_{th} layer's feature maps and $Im = h_{t+1}$ denotes the closing fused image, then the further association among the neighboring layers is,

$$h_{k+1} = \mathrm{Conv2x}\,(h_k + f\,(\phi_k));\ k = 1,\ldots,t \quad (7)$$

where "Conv2x" refers to shifted convolutions that double the resolution of the attribute maps and f might be either a unique transform task.

The proposed enhanced EigenGAN technique will be trained on a CPU device with Eigen block using Discriminator and Generator model input parameters of image size, noise dimension, base channels, and max channels. In the Discriminator section, the base and max channels with kernel size are processed using convLayer, and the blocks are returned as output. The blocks are appended with a sequential layer in linear manner. In the Generator model, the image size will increase the power of 2 based on max channels with the number of blocks. Eigenblock was processed with the linear subspace model (lsm) layer in this section. When the last result is converted into projection subspace (p_k), the feature convolution is approximated.

The suggested approach begins by discussing the linear instance of EigenGAN. The linear model, adapted from Equation (6), is written as follows:

$$\mathrm{Im} = \mathrm{OIy}+\mu+\sigma+ p_k \quad (8)$$

Figures 4 to 8 display the results of the EigenGAN method.

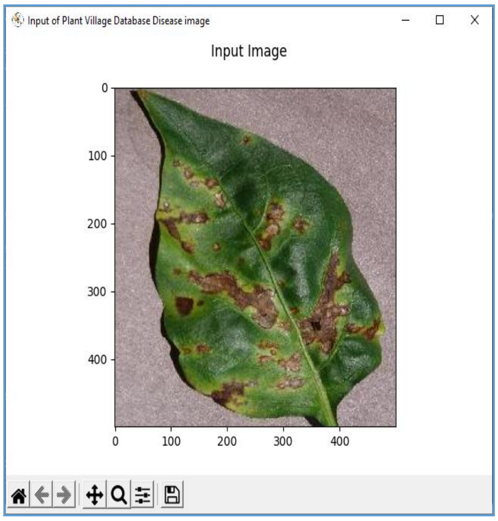

Figure 4. Input of Pepper_bell_Bacterial_spot image

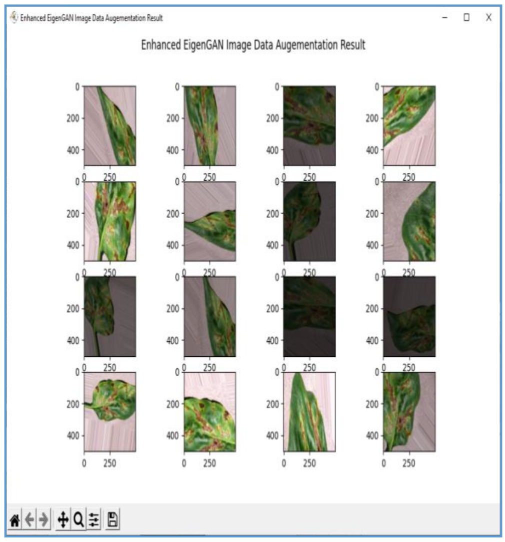

Figure 5. Enhanced EigenGAN result -1

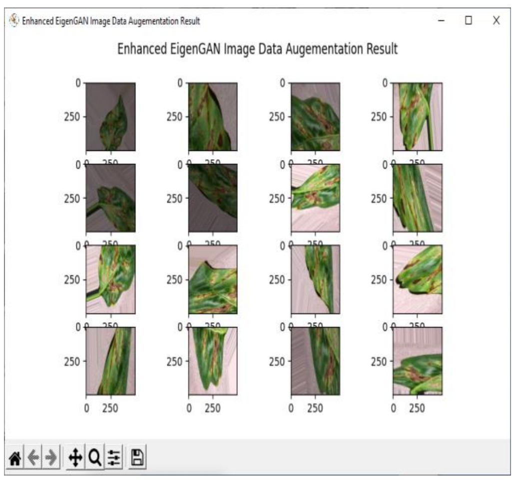

Figure 6. Enhanced EigenGAN result -2

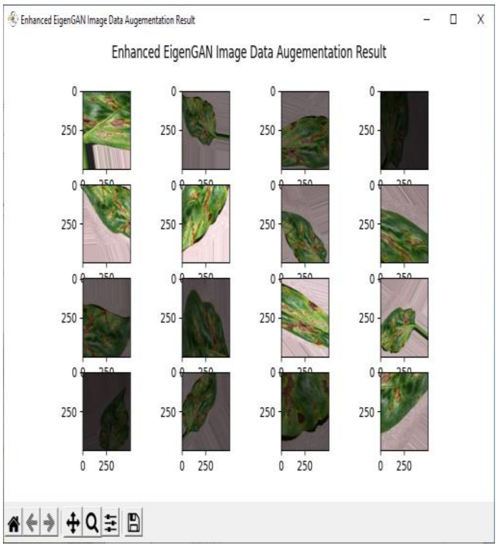

Figure 7. Enhanced EigenGAN result -3

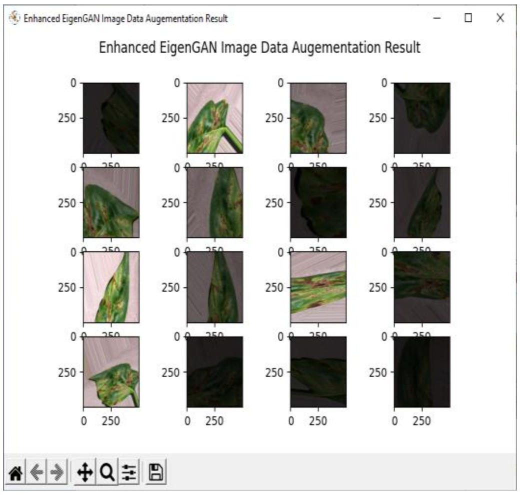

Figure 8. Enhanced EigenGAN result -4

4.EXPERIMENTAL RESULTS

The results of the experiments indicated the effectiveness of the Hybrid Fourier Filter De-noising (HFFDF) denoising filter and the Enhanced EigenGAN data augmentation. The experimentation findings are performed on an Intel I5 CPU with a clock speed of 3.20 GHz, 8GB of RAM, Windows 10 operating system of MATLAB R2014b and python 3.8 simulations. The dataset of Plant Village disease dataset consists of 54303 healthy and unhealthy leaf images divided into 38 categories by species and disease are treated with denoising and image data augmentation is evaluated in this experimental study.

Table 1 and Figure 9 depicts the evaluation of plant diseases and the Plant Village image database de-nosing measures of Root Mean Square Error (RMSE), which is defined as:

$$\text{RMSE} = \text{sqrt (mean ((input - denoise)}^2\text{));} \tag{9}$$

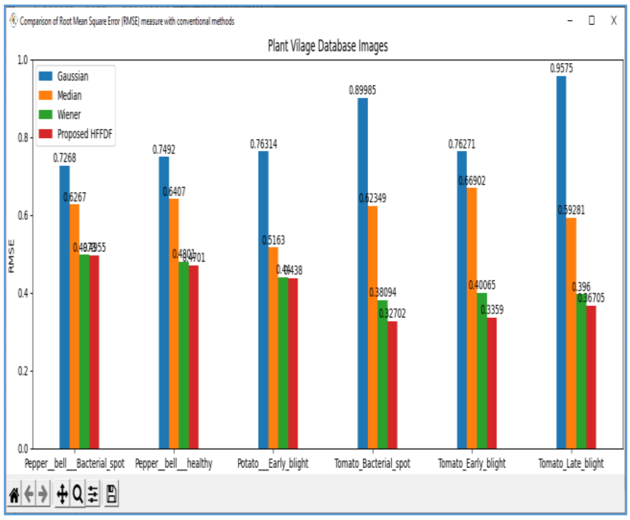

Figure 9. RMSE chart

Table 1: Root Mean Square Error (RMSE) comparison

Images	Gaussian	Median	Wiener	Proposed HFFDF
Pepper__bell___Bacterial_spot	0.7268	0.6267	0.4973	0.4955
Pepper__bell___healthy	0.7492	0.6407	0.4801	0.4701
Potato___Early_blight	0.76314	0.5163	0.4400	0.438
Tomato_Bacterial_spot	0.89985	0.62349	0.38094	0.32702
Tomato_Early_blight	0.76271	0.66902	0.40065	0.3359
Tomato_Late_blight	0.9575	0.59281	0.396	0.36705

Table 2. Peak Signal Noise Ratio (PSNR) comparison

Images	Gaussian	Median	Wiener	Proposed HFFDF
Pepper__bell___Bacterial_spot	31.5028	42.1947	42.6407	58.7179
Pepper__bell___healthy	31.9975	44.3138	44.7612	55.0073
Potato___Early_blight	31.8557	44.476	44.5972	55.7046
Tomato_Bacterial_spot	32.4008	40.7282	41.7191	56.1631
Tomato_Early_blight	31.9801	40.5354	41.6231	56.1813
Tomato_Late_blight	32.5814	41.5142	42.3184	56.0233

Table 2 and Figure 10 shows the Plant image de-noising PSNR measurements on plant diseases and the Plant Village image database is defined as follows:

$$PSNR = 10log_{10}\left(\frac{MAX_f}{RMSE}\right) \tag{10}$$

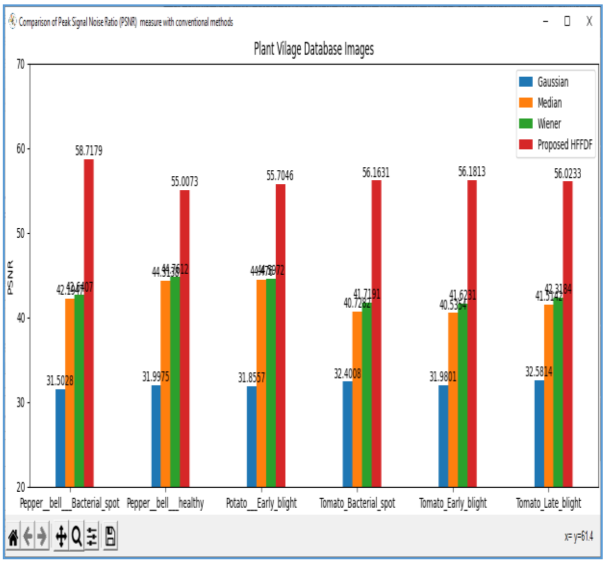

Figure 10. PSNR chart

5. CONCLUSION

The development of information and communication technology in the areas of image preprocessing and data augmentation in Plant Village diseases datasets was examined in this research. The proposed approach has three stages, which are as follows: 1) image dimension reduction: the original plant image database images are shrunk to predetermined sizes; 2) Hybrid Image De-noising: the noise is removed using Hybrid Fourier Filter De-noising (HFFDF). The proposed HFFDF algorithm serves an important purpose in image data augmentation systems. The enhanced EigenGAN with projection subspace model developed here generates a large number of various and large-quality training images and acts as a proficient data supplement for the diagnostic classifier.

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