

High Accuracy Cotton Plant Classification using Transfer Learning with Inception V3

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ABSTRACT: Cotton is one of the most important fibers and a major play in the world's industrial and agricultural economies. Maintaining agricultural productivity depends critically on the health of cotton and disease identification. In this paper, an Inception V3 classification is proposed to quickly identify diseases in cotton plant. Firstly, adaptive wiener filter is applied to cotton diseased detection dataset to reduce the mean squared error between the intended signal and the filter's output are detected to get high quality image. Next, the processed image is given to the watershed segmentation here a topographic surface, divided according to watershed boundaries. After that cotton plant is featured using Discrete Fourier Transform (DFT) for further analysis. Finally, Inception V3 framework is processed to enhance the classification of cotton plant. Using python software the proposed framework is examined and the developed classifier results with accuracy of 92% in detecting disease when compared to other techniques.

Keywords: Inception V3, Discrete Fourier Transform (DFT), Watershed segmentation, Adaptive wiener filtering, Cotton plant.

1. Introduction

Agriculture is the foundation of several South Asian nations, including Bangladesh, China, and India [1]. Cotton is one of the most cost-effective crops, often referred to as "king of fibers" or "white gold". Regional crop diseases are becoming more common as in climate change and global warming, which have significantly reduced agricultural output [2]. Conversely, cotton is a raw material utilized in spinning mills and industrial sectors to make yarn, which is then used in apparel industries. Although cotton is one of the most valuable commodities in many nations, a number of pests and illnesses, as well as climate variations like floods, droughts, high temperatures, etc.,

continuously threaten cotton's ability to thrive [3]. About 80% to 90% of cotton plant diseases are detected on the leaves, which have caused a 25% decrease in cotton production in India [4].

In addition to millions of farmers in India a sizable income, the cotton industry plays a vital role in the country's export and industrial sectors. An historical significance, challenges, and pivotal role of cotton cultivation in India's economy and rural communities for Indigenous Peoples [5] However, India have a long and illustrious history of cotton growing that dates back thousands of years. Ancient records mention cotton garments and trade, signifying that the cotton plant, formally known as *Gossypium*, have grown in the

Indigenous People subcontinent for thousands of years [6]. Moreover, India have a center for cotton cultivation to its indigenous cotton types, which have left a lasting impression on the nation's cultural and economic heritage [7].

Using the pre-processing technique as Gaussian Amended Bilateral filter (GABF) the image is filtered to reduce the noise. Using this approach it is possible to reduce the steady and round-off noise then produce high accuracy [8]. Whereas, a Gaussian Mixture Model (GMM), is used to remove the noise from foreground and background in cotton plant. It effectively enhances the image with good quality. It is computationally costly, with the possibility of over fitting or less-than-ideal value [9]. However, to detect cotton plant diseases using images of both healthy and sick cotton leaves using the entire training and validation procedure for image augmentation. Biases in the original dataset are carried over into the supplemented data [10]. Using a Fuzzy Rough C-Means (FRCM) clustering algorithm for segmentation the image is segmented with higher performances. Computational complexity, sensitivity to initializations, and challenges managing high-dimensional in cotton image [11].

Whereas, a segmentation technique called level set and Chan-Vese techniques were used to segment the cotton disease. Computational expense, complexity in managing many regions and sensitivity to beginning conditions when segmenting cotton disease [12]. More over using Scale Invariant Feature Transform (SIFT) the cotton plant key points are featured. It is slower compared to some other feature detection methods [13]. Conversely, using Random Forest, Support Vector Machine (SVM), Multi-Class SVM, and an Ensemble model the cotton leaves are classified as healthy and diseased. It provides a useful and aesthetically disease detection methods that help to avoid disease and improve crop quality and yield. Long training period when using huge datasets are handled [14]. Moreover, detection and classification of cotton plant using SVM and K-

Nearest Neighbours (KNN) with higher performance. Suffer from the expletive of dimensionality, sensitive to unimportant features, have trouble with big datasets, noisy data [15]. To overcome this limitation a Inception V3 is used to classify the cotton plant.

2. Related Work

Singh et al [16] (2023) have proposed a Convolutional Neural Network (CNN) identify the diseases of cotton plant. According to the machine learning mechanism, the accuracy levels will always be higher when the input size is large. For large datasets, this lead to significant computation times and memory requirements. Substantial calculation times and memory needs for huge datasets.

Rai et al [17] (2023) have proposed a Deep Convolutional Neural Network (DCNN) to detect and classify the cotton plant disease. To detect and forecast the disease state of cotton plants images of leaves and plants gathered in a hyper setting. However, it takes more time to process the single image.

Amin et al [18] (2022) have proposed a VGG-16 model to detect and classify the cotton plant disease. VGG-16 effectively identifies, analyze disease as fresh or diseased and predict a disease type accurately with high performance. Slow convergence and local minima susceptibility are two drawbacks of VGG-16.

Shrotriya et al [19] (2024) have proposed a CNN-Recurrent Neural Network (RNN) ensemble model for cotton disease detection effectively and robustly. CNN and RNN are reliable enough to accurately and efficiently identify and classify cotton plant conditions. It have high processing difficulties, lacking a portion of labeled data.

Tanwar et al [20] (2022) have proposed a Long Short Term Memory (LSTM) algorithm and CNN for cotton disease detection. LSTM is used to find the disease and CNN is used to find the disease detection. Because it is more difficult to describe

the model's predictions, comprehending the process becomes difficult.

The contribution of this study is summarized as follows:

- The input image is used to reduce the mean squared error between the intended signal and the filter's output are detected using adaptive wiener filter to get high quality image.
- Using watershed segmentation the watershed boundaries are divided and Discrete Fourier Transform (DFT) is featured the signals for further analysis.

- Advances an Inception V3 to enhance the accuracy and efficiency of cotton plant.

3. Proposed work

The block diagram in figure 1 shows the proposed Inception V3 classification for cotton plant. Firstly, using adaptive wiener filter the input image reduces the mean squared error between the intended signal and the filter's output. Secondly, the processed image is given as input to watershed segmentation here a topographic surface, recognizing as catchment basins, and dividing them according to watershed boundaries.

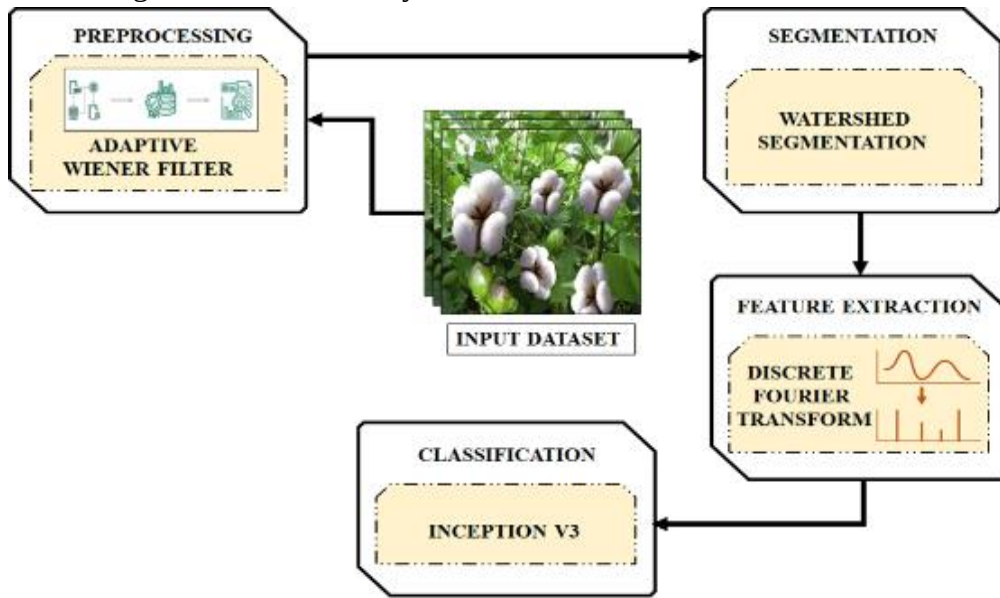


Figure 1: Block diagram of proposed work

Thirdly, by using feature extraction technique the Discrete Fourier Transform (DFT) featured the frequency signal for further classification. Finally, featured image is given to the classification process where Inception V3 is used for classifying the cotton plant disease. The Inception V3 is used to classify the image for getting better accuracy when compared to the other techniques.

3.1 Pre-Processing by Adaptive Wiener Filter

In the cotton plant detection the pre-processing is done by Adaptive wiener filter. Adaptive wiener filtering modifies the filter's output based on the image's local variance. Reducing the mean square

error between the original and restored images is its ultimate objective. These techniques have a better filtering impact than the others and are highly helpful for maintaining the image's edges and high-frequency areas. On the one hand, many window options to handle a variety of situations and automatically select the optimal one. In contrast, the center sample in the moving window should be employed appropriately in rough parts but ignored in smooth regions to suppress subjectively bothersome singularities. When filtering images have been tainted by signal-intendent noise, the issue be represented as

$$y(i, j) = x(i, j) + n(i, j) \quad (1)$$

Where $n(i, j)$ is additive noise, $x(i, j)$ is the noise-free image, and $y(i, j)$ is the noisy measurement. The goal is to "denoise" or eliminate noise from $y(i, j)$. Depending on the region, the filter template is adaptively chosen. To increase efficiency and preserve the borders and texture elements, the tiny window filter is utilized and large window filter is used in the smooth area. The pixels are processed using the following formula to produce the desired outcome.

$$r(i, j) = \mu + (1 - q + \Delta) * (s(i, j) - \mu) \quad (2)$$

$$q = \frac{\sigma_{avg}}{\sigma_{var} + 1} \quad (3)$$

$$\Delta = \frac{\sigma_{var}}{\sigma_{avg} + \sigma_{max} + 1} \quad (4)$$

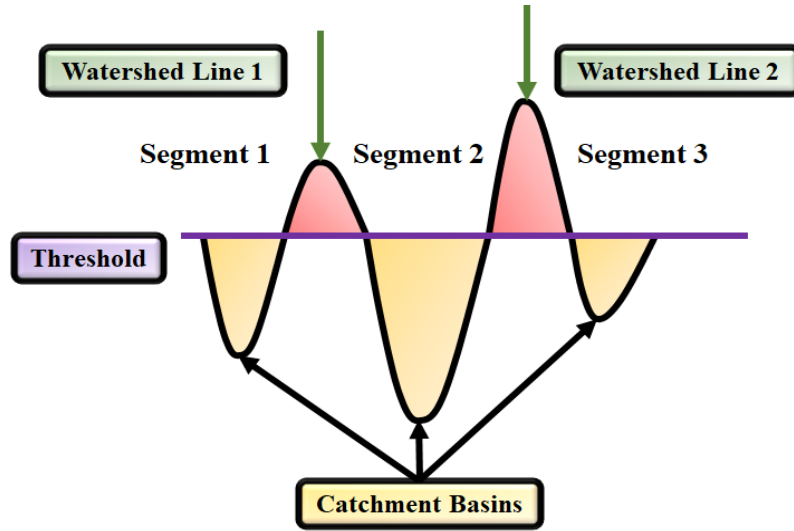


Figure 2: Catchment basin

Each local minimum and its influence area are referred to as a catchment basin in figure 2, and the watershed is the boundary between two adjacent catchment basins. The algorithm's primary function is to locate the catchment basin, and it is explained as follows.

$$T[n] = \{(s, t) | f(s, t) < n\} \quad (5)$$

Where $T[n]$ a collection of is coordinates $[s, t]$, and $f(x, y)$ is an image. The points in the collection are situated beneath the $f(x, y) - n$.

$$C_n(M_i) = C(M_i) \cap T(n) \quad (6)$$

Where $C_n(M_i)$ is the coordinate of the local minimum point of $f(x, y)$ set $C(M_i)$, and the two

The original pixel is denoted by $r(i, j)$, the output pixel by $s(i, j)$, the variance of the current pixel by σ_{var} , the variance of all pixels in the selected window by σ_{avg} , and the maximum variance of all pixels in the image by σ_{max} .

4. Segmentation by Watershed Segmentation

4.1 Principle of Watershed Algorithm

The pre processed image serves as the ideological basis for the watershed algorithm. It depicts a naturally occurring landscape that is covered in water, with each pixel's gray value indicating the point's altitude.

value image provided by formula 6 $\{M_1, M_2, \dots, M_n\}$. This point, represented by the coordinate a , is situated in the catchment basin connected to the local minimum in the M_i .

$$C[n] = \bigcup_{i=1}^n C_n(M_i) \quad (7)$$

Where $C[n]$ is the catchment basin collection for the flooded area at stage n .

$$C[max + 1] = \bigcup_{i=1}^n C_n(M_i) \quad (8)$$

Where min and max stand for the minimum and maximum values of $f(x, y)$, and $C[max + 1]$ is the collection of all the catchment basins. As the water level increases from $n = min + 1$ to $n = max + 1$, the image of the terrain will diffuse

through the water. Every connected component in $C[n-1]$ is a connected component of $T[n]$, according to the analyses above. To find the dividing line, let $C[\min+1] = T[\min+1]$.

then, execute the recursive call to get $C[n]$ based on the $C[n-1]$. Figure 3 shows the watershed segmentation flow chart.

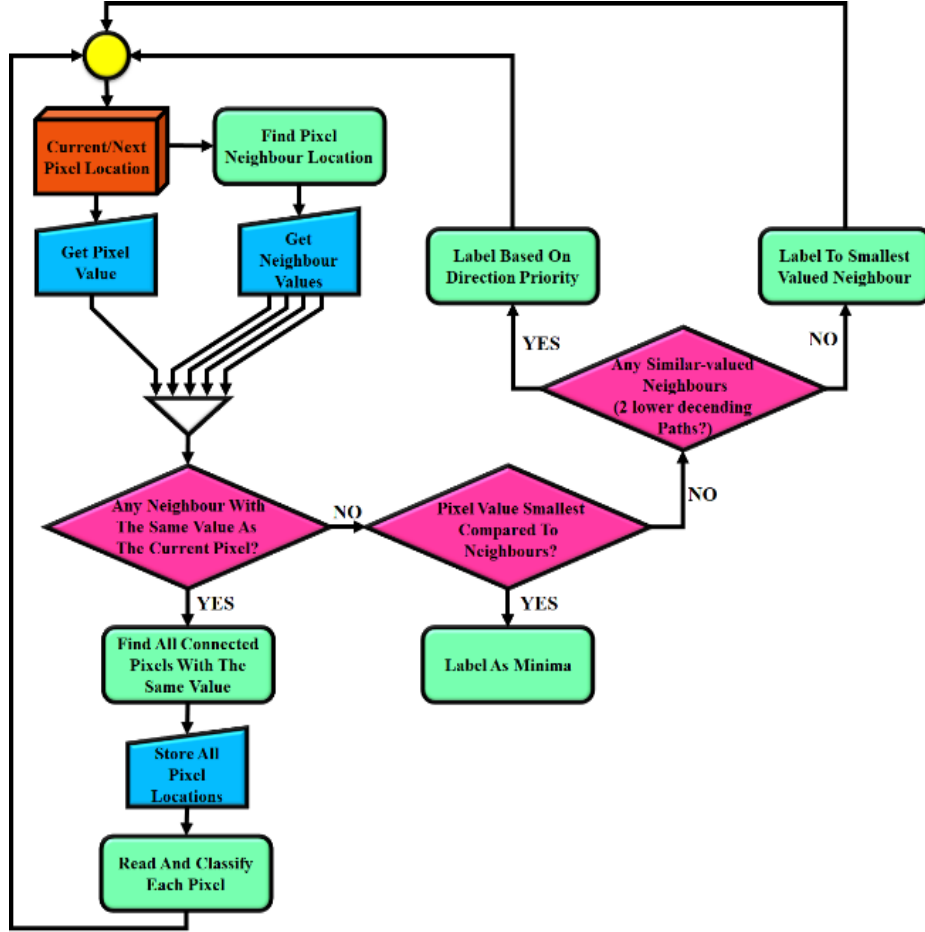


Figure 3: Watershed segmentation flowchart

When the targets are connected to one another, the watershed algorithm produce superior results; however, it is extremely sensitive to changes in the image, and noise and other variables frequently result in over segmentation. Following by feature extraction using Discrete Fourier Transform.

4.2 Feature Extraction by Discrete Fourier Transform

The cotton image in a sliding window method, then use the Discrete Fourier Transform (DFT) to transform it from the spatial domain to the frequency domain. An N -point input signal is converted into two-point output signals via the DFT. The $N/2 - 1$ signal that is being decomposed is contained in the input signal, and

the amplitudes of the sine and cosine wave components are contained in the two output signals. It is said that the input signal is in the time domain. This is due to the fact that the most prevalent kind of signal that enters the DFT is made up of samples that are taken at regular intervals. For every sample, the frequency domain signal is represented by a vector $F[u, v]$ and is composed of two parts. These are known as the Imaginary part of $F[u, v]$, which is written as $ImF[u, v]$, and the Real part of $F[u, v]$, which is written as $ReF[u, v]$.

$$F(u, v) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \cos\left(\frac{2\pi x}{M}\right) - f(x, y)j \sin\left(\frac{2\pi y}{N}\right) \quad (9)$$

For $u = 0, 1, \dots, M-1$, $v = 0, 1, \dots, N-1$ (10)

$$F(u, v) = \text{Re}(u, v) - \text{Im}(u, v) \quad (11)$$

Where,

$$\text{Re } F(u, v) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \cos\left(\frac{2\pi ux}{M}\right) \quad (12)$$

$$\text{Im } F(u, v) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \sin\left(\frac{2\pi vy}{N}\right) \quad (13)$$

"Imaginary part" refers to the sine wave amplitudes in the sample, whereas "real part" refers to the cosine wave amplitudes. Equation 13 for frequency domain transformation provides the fundamental DFT formula for a function $f(x, y)$ of dimension $M \times N$.

4.3 Classification by Inception V3

The cotton plant image is classified using Inception V3 Network Transfer Learning is the series of convolutional neural networks in the history of convolutional neural networks. It is prior to the development of the Inception neural network, the majority of neural networks just increased the convolutional layer to increase the network's depth and improve performance. These approaches have been modified by Inception Neural Networks. To lower the dimension of the image, the Inception module suggested by the Inception Neural Network in figure 4 employs

maximum pooling and filters of varying sizes. These have the benefit of using fewer parameters and much less work to produce richer characteristics.

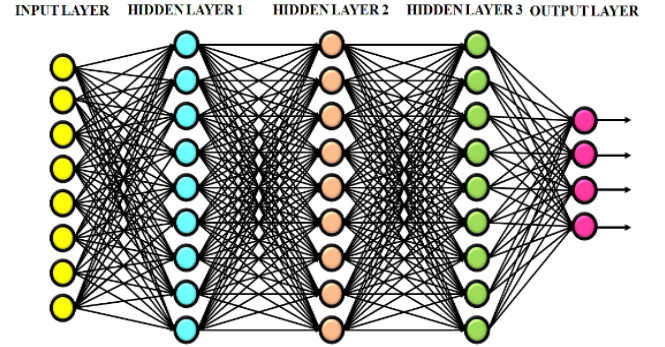


Figure 4: Inception Neural Network Layers

With simultaneous multi-scale convolutions and subsequent neuronal results from each branch, the Inception-v3 model is an improved version of the original Inception. It is made up of the basic convolutional block, the improved Inception module, and the classifier. The incorporation of auxiliary classifiers not only stabilizes learning outcomes and improves gradient convergence, but it also lessens the possibility of over fitting and gradient disappearance. Inception-V3 undervalues the number of feature channels and speeds up training by heavily relying on a 1×1 convolutional kernel. Additionally, the massive convolution is divided into smaller convolutions, reducing the number of parameters and processing expense.

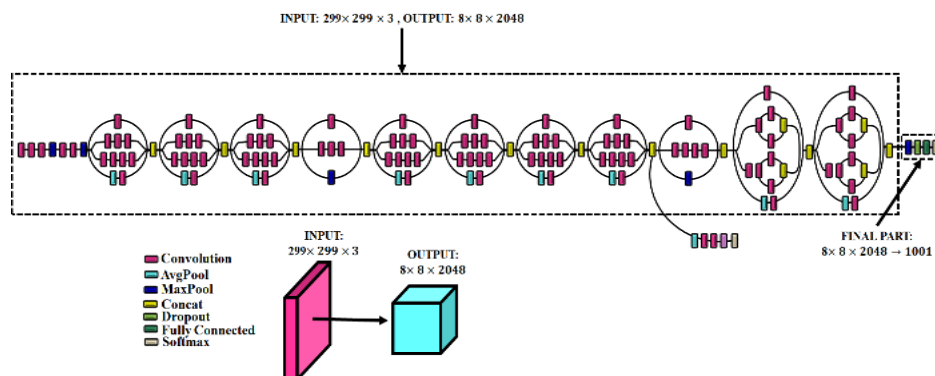


Figure 5: Inception V3

To get more precision without putting a heavy burden on the computational budget, Inception began by approximating a sparse structure (e.g.,

increasing the network's depth and width) and then clustering the related non-uniform sparse data structure nodes into a dense structure. Figure 5

displays the architecture of the deep convolutional neural network inception V3. The following are the fundamental structural tenets of the Inception V3 construction: There are many signals in close proximity to one another. Because nearby signals are frequently associated, it is possible to reduce the dimensions prior to applying the convolution without sacrificing any image. The depth and width of the neural network must be increased simultaneously when raising the free weight of resources for their effective use. Using layers that drastically reduce parameter values is ineffective, particularly at the convolutional neural network's initial layer. "Wide" layers pick things up quickly, which is crucial at high levels.

5. Result and Discussion

The aim of this work is to classify the cotton plant image. Dataset is taken from kaggle.com for disease analysis. Deep learning models are then applied to train cotton disease detection dataset and the software used is Python. Here diseased cotton is 1103 images in train set and 53 images in test set. Whereas for fresh cotton there is about 848 images for train and 53 images in test set.

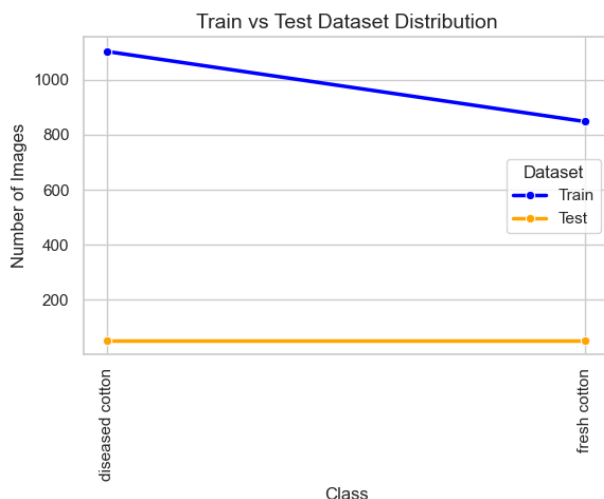


Figure 6: Train vs test dataset distribution

Figure 6 shows the train vs test dataset distribution. Here totally of 1951 images for train samples and 106 images for test samples for diseased cotton and fresh cotton.



Figure 7: Diseased cotton samples



Figure 8: Fresh cotton samples

Figure 7 and 8 shows the diseased cotton samples and fresh cotton samples. Here totally of 6 samples for each diseased cotton and fresh cotton.

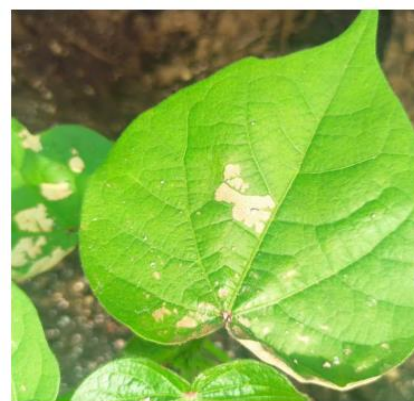


Figure 9: Input cotton image

Figure 9 shows the input images for cotton image. Here the input image is taken from the cotton disease detection dataset.



Figure 10: Resized image

Figure 10 shows the input image and resized images of cotton disease image. Here the input two classes of cotton image are resized for processing. Using image resizing technique the two classes of input cotton image is captured as a flawless image.

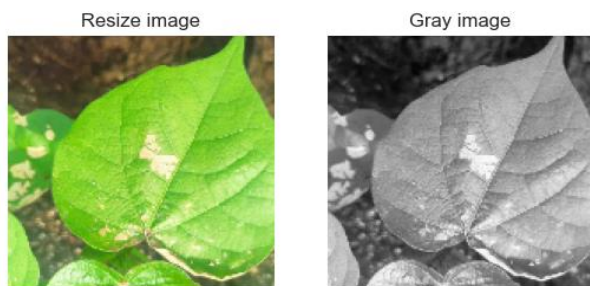


Figure 11: Gray scale image

Figure 11 shows the resized images into grayscale image. Resized images into grayscale conversion for two classes of cotton plant disease are converted by using the grayscale conversion technique. Here R, G, and B image is converted into gray.

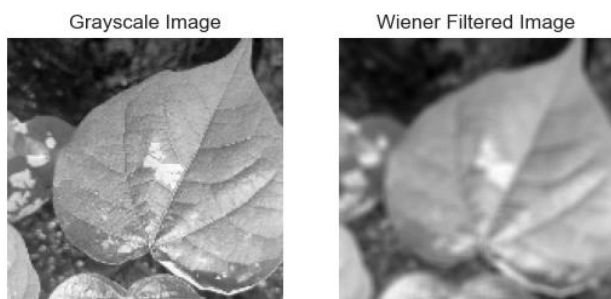


Figure 12: Adaptive wiener filter image

Figure 12 shows the gray scale conversion to wiener filter. After conversion of gray scale image, wiener filter is utilized to pre-process the two classes of cotton plant image to intent the signal and filter the output to reduce noise.

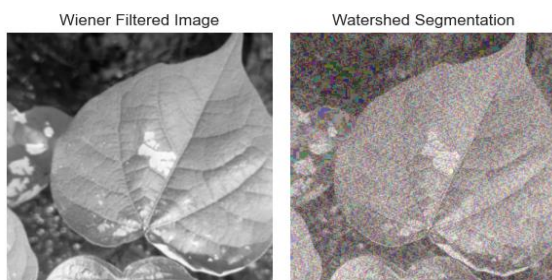


Figure 13: Watershed segmentation

Figure 13 shows the wiener filtered image into watershed segmentation images. Here the two classes of cotton plant disease image are segmented using watershed segmentation. The filtered image is given as input to segmentation stage the image by catchment basin based on their similarities.

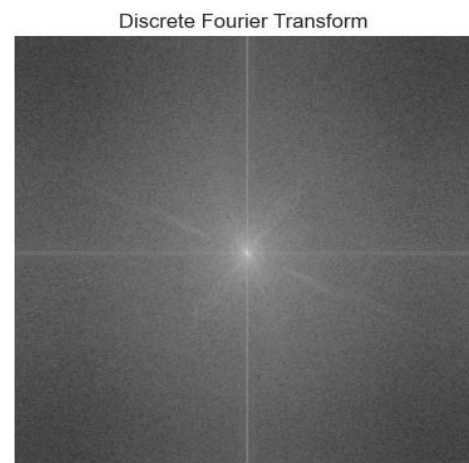


Figure 14: Discrete Fourier Transform

Figure 14 shows the Discrete Fourier Transform for cotton image. Here each of the two classes is distributed as frequency domain and spatial domain.

5.1 Performance Metrics

By examining accuracy, precision, sensitivity, specificity, Area under the Curve (AUC), classification with "positive" and "negative" labels, the performance of each classification model in this study explained in table 1.

Table 1: Performance Metrics

Performance metrics	Formula
Accuracy	$\frac{(TN + TP)}{TS}$
Precision	$\frac{(TP)}{TP + FP}$
Recall	$\frac{(TP)}{(TP + FN)}$
F1 – score	$\frac{(2 * Precision * Recall)}{(Precision + Recall)}$

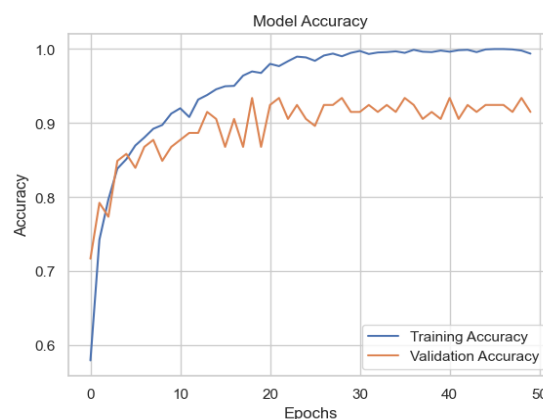


Figure 15: Model accuracy

Figure 15 shows the model accuracy for cotton plant image. The accuracy value is trained using the Inception V3 to classify the model to get the higher accuracy of 92%.

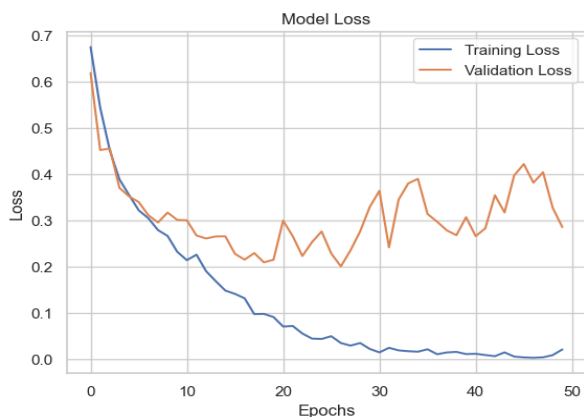


Figure 16: Model loss

Figure 16 shows the model loss. Here in model loss the training loss is going on decreasing and the validation loss is increasing it is calculated up to 50 epochs.

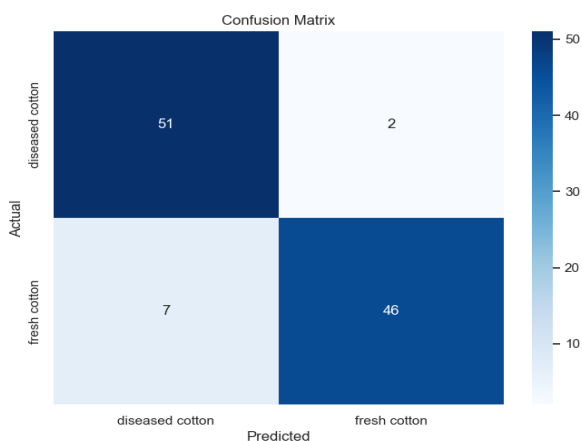


Figure 17: Confusion matrix for Inception V3

Figure 17 illustrates the confusion matrix for Inception V3. This matrix shows the values for actual and predicted labels. Confusion matrices are commonly used to evaluate the performance of classification models, particularly those tasked with predicting categorical labels for input instances. Here the two classes of cotton plant image for fresh cotton and diseased cotton are matrices.

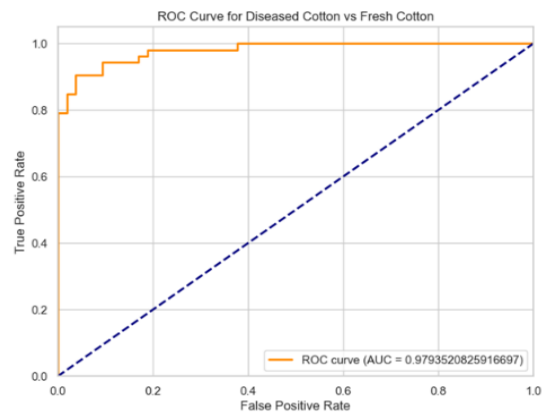


Figure 18: RoC curve for diseased cotton Vs fresh cotton

According to the AUC results shown in figure 18, the cotton disease detection dataset significantly lowers the AUC value of Inception V3, the sub-optimal model on datasets. Here the ROC value for diseased cotton vs fresh cotton is 0.97.

5.2 Comparison for the Proposed Method

The comparison of proposed method with existing method is presented in table 2. The KNN have the classification accuracy of 70% [15], SVM have the accuracy of 80.30% [21] and SVM have the accuracy of 88% [15]. The proposed Inception V3 have the higher accuracy of 92% compared to the existing method in table 2. The proposed inceptions V3 have better performance.

Table 2: Comparison for the proposed method

Study	Method	Accuracy
Dhage <i>et al.</i> [15]	KNN	70%
Caldeira <i>et al.</i> [21]	SVM	80.30%
Dhage <i>et al.</i> [15]	SVM	88%
Proposed approach	Inception V3	92%

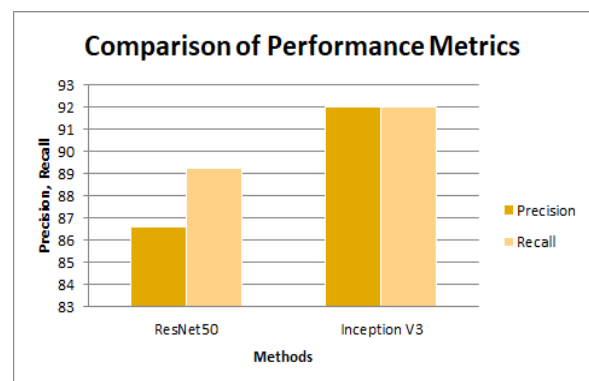


Figure 19: Comparison of performance metrics

The Precision and recall value for classifiers ResNet50 and the proposed is presented in Figure 19. The ResNet50 have the value of 86.6% and recall of 89.2% [21] and proposed Inception V3 methods have the precision value of 92% and recall of 92% respectively.

6. Conclusion

In this study, Inception V3 is proposed for the classification of cotton plant image. The integration of advanced preprocessing techniques, such as resizing, grayscale conversion, adaptive wiener filtering, ensures that the input images are optimized for segmentation. The use of approximate watershed segmentation algorithm for segmentation further enhances the precision of identifying catchment basin in the images. Additionally, the DFT feature analyzed the signal. The performance evaluation, conducted on the cotton disease detection dataset, demonstrates the superior capabilities of the Inception V3 related to existing methods. The improved accuracy of 92% is achieved as a greater accuracy in contrast to the existing techniques.

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