International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)

Vol. 11-No.2 (2025) pp. 1965-1973
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

Prediction of Groundnut Leaf Disease Detection and Classification Using Augmented Capsule Neural Network

T. Kosalairaman[1*], A. Nirmala[2]

[1]Research Scholar, Department of Computer Science, Dr. N.G.P Arts and Science College, Bharathiar University, Coimbatore, Tamilnadu, India
* **Corresponding Author Email:** kosalairamanphd@gmail.com - **ORCID:** 0009-0002-6067-9302

[2]Professor and Head, Department of Computer Science with Cognitive Systems, Dr.N.G.P Arts and Science College, Bharathiar University,Coimbatore,Tamilnadu, India.
Email: email@email.edu.tr - **ORCID:** 0009-0002-6067-930X

Article Info:

DOI: 10.22399/ijcesen.771
Received : 02 November 2024
Accepted : 23 December 2024

Keywords :

Groundnut Leaf Disease,
Aug-CapsNet, Prediction,
Deep Learning,
DFT,
Thresholding Method.

Abstract:

Groundnut is a significant capital crop grown across over 100 nations worldwide, with India being one of the top producers, including an average yield of 756 kg/ha. The groundnut plant is prone to diseases and viruses which induce damage in the plant, stems, including roots, which reducing output. Early detection, identification, as well as treatment may significantly decrease overall ecological and economic losses. This paper proposed an Augmented Capsule Neural Network (Aug- CapsNet) for classifications and risk stratification estimation in plants. The first approach is designed to diagnose plant diseases using images from plant leaf. Image Enhancement is done by combining the Discrete Fourier Transform (DFT) as well as Thresholding techniques. The Second job is to classify plant leaves. The presented architecture is validated using Plant Village datasets, which includes over 50,000 images representing diseased as well as normal plants. While compared to previous plant disease classification techniques, the Aug-CapsNet model shows significant gains in prediction accuracy. The generated model's experimental outcomes obtained an overall evaluation accuracy of 96.07%, with an F1 score of 95.15%.

1. Introduction

The groundnut plant is susceptible to a variety of diseases, including those that are caused by fungus, soil-borne organisms, and viruses. The detection and identification of leaf diseases at an early stage is required to prevent the further spread of infection and also contributes to the production of the highest possible yield. The identification and categorization of groundnut leaf diseases by naked eye inspection by an expert is a time-consuming and costly process, especially in underdeveloped nations. Attacks from diseases are among the most significant elements that contribute to poor yield. The plant illness, which may be caused by fungus, bacteria, or viruses [1]. The illness that affects the leaf fully degrades the leaf's quality. The disease known as cercospora affects ground nuts often. It is some of the types of diseases that might affect ground nut leaf in its early stages. During the pre-processing phase, the median filter is used because it has the maximum PSNR value. This is done with the intention of reducing the amount of noise that is present in the groundnut dataset. The percentage of greenness in groundnut leaves was determined using color characteristics, and it was discovered that this percentage is directly linked to the amount of nitrogen (N) nutrient [2]. Disease is the most important factor that ultimately results in a lower yield. The groundnut plant is susceptible to diseases caused by fungus, viruses, and soil-borne organisms. When dealing with huge datasets, calculating the ideal solution is quite time-consuming, which brings the overall performance of the system down.

Peanuts are susceptible to two of the most serious and destructive fungal foliar diseases: early leaf spot and late leaf spot. Peanut infections have been linked to significant economic losses, which emphasizes the need for more effective diagnostic technologies to be developed. In this work, the early identification of peanut leaf spot was accomplished by the use of point & image spectroscopy as well as thermal imaging. There is a large amount of variation in the spectral reflectance variables depending on the health status [3]. The leaves of the peanut plant that was healthy exhibited a reflection that was decreasing in 1015 nm, but the leaves of the peanut plant that was highly damaged showed a reflection that was growing. The oil that is extracted from the groundnut is often used in the culinary industry as well as in the treatment of obesity, and the fats extracted from the groundnut are frequently utilized in the manufacture of soaps. Diseases of many types, including fungus, viruses, and bacteria, have an impact on the production of groundnuts. As a result, the leaf, root, and stem of the groundnut plant get infected with various diseases, which results in a significant decrease in yield [4].

Traditional plant disease diagnostic techniques are primarily reliant on expert diagnosis, which may easily lead to a backwardness in crop disease management & field management. The indications of plant illnesses may be seen in a variety of areas of a plant; nevertheless, it has been discovered that the leaves are the portion of a plant that is most often studied for identifying an infection. As a result, researchers [5] have sought to automating the process of disease identification and categorization in plants by utilizing photographs of leaf lesions. Several works made efficient use of computer vision technology and contributed significantly to the advancement of this field.

A significant amount of food and oil may be extracted from groundnuts. On the leaf section of the groundnut plant are the principal illnesses that are occurring. The illnesses that affect the leaf will have a significant influence on the overall quality, and the yield of groundnuts will also suffer as a result. Peanuts are a significant kind of commercial crop & oil crop, and the leaves are home to several illnesses that are visible to the naked eye. It is very important to appropriately identify the leaf disease that peanuts are susceptible to [6]. When it comes to the identification of photos of peanut leaf disease, the CNN have a significant impact. Disease is almost always to blame for a decline in the quality & quantity of agricultural goods, most notably peanuts and ground nuts. Deep learning, which is a kind of machine learning, might be used to automatically identify and diagnose the problem.

It is recommended that the pooling layer be removed from the design and spatial information be sent across levels using capsules. This would allow the Capsule Network (CapsNET) to solve the limitation. The harvesting and production of agricultural crops may be negatively impacted by diseases that are ubiquitous and widespread on plant leaves [7]. Crop diseases are a crucial factor in Africa's high rate of food insecurity, as well as malnutrition and poverty, all of which are caused by the continent's predominant agricultural industry. It is common practice to manually identify plant diseases; however, these approaches are restrictive, inefficient, expensive, and time-consuming. As a result, there is a growing need for the development of automated and effective ways of identification.

Evaluation of performance is an essential component of deep learning (DL), and it must be carried out with extreme care in order to improve confidence and dependability. There are many different measures that may be used to assess DL models; however, picking the right one for a particular model is not easy since there is no "one size fits all" approach. Within the realm of practical application, the assessment measure that is most often used to capsule networks is accuracy. Plant diseases have a negative impact, both quantitatively and qualitatively, on the total amount of food that can be produced [8]. Plants may be infected by a wide variety of pathogens. Excitation Networks, prior to being processed by the first generation of Capsule Networks (CapsNet), which is responsible for categorization.

2. Related Works

The groundnut plants consist of a number of phases, such as image capture and image processing, which is based on a method that automatically recognizes and classifies the groundnut leaf diseases. The procedure that has been suggested [9] The H2K algorithm is a combination of the Harris corner detector, the Histogram on Oriented Gradient (HOG) classifier, and the KNN classifier, and it was developed to accurately identify and classify groundnut leaf diseases. The streamlined processing pattern includes four primary stages of progression. At first, a color renovation framework that will be used for the RGB image that will be input is generated. After that, the RGB is converted into HSV since RGB is used for color creation and HSV is used for color description [10]. The next stage is the separation of the planes. The color characteristics were then carried out.

The percent of greenness in groundnut leaves was determined using color characteristics, and researchers discovered that it is directly linked to the amount of nitrogen (N) nutrient [11]. The software program to robotically identify and categorize groundnut leaf illnesses is provided to us in this work [12], which we may get here. The output of the crops will increase as a result of using this strategy. Image capture, image preprocessing, segmentation, feature extraction, and classifier utilizing KNN are some of the processes that it consists of.

When dealing with huge datasets, calculating the ideal solution is quite time-consuming, which brings the overall performance of the system down. IoT-based real-time automated detection and classification approach of groundnut leaf disease utilizing hybrid machine learning techniques is suggested in this research [13] as a solution to these challenges. In this work, the early identification of peanut leaf spot was accomplished by the use of both point and image spectroscopy as well as thermal imaging [14]. There is a large amount of variation in the spectral reflectance variables depending on the health status.

The quantity of groundnut leaf diseased images for the training and testing procedure is chosen from the dataset of plant villages, and it is employed [15]. For training on the dataset, the stochastic gradient decent momentum technique is applied, and its results have proven that it performs more effectively than the suggested DCNN. A plant disease detection and classification approach that is based on the optimized lightweight YOLOv5 model is presented in this study [16] in order to increase the speed of disease classification as well as the accuracy of disease classification.

Therefore, researchers have sought to automated the process of disease identification and categorization in plants by utilizing photographs of leaf lesions. Several works made efficient use of computer vision technology and contributed significantly to the advancement of this field. The aim of this publication [17] is to shed light on a variety of essential research elements by providing a summary of the benefits and drawbacks of all such investigations. In this study, artificial intelligence is used to detect the illness that affects groundnut leaves [18]. This is done with the goal of reducing the number of diseases that develop and the problems that are caused by diseases.

However, when the images are processed, it is simple to lose the spatial links between them, and CNNs are unable to tackle the issue of rotational invariance in an effective manner [19]. The decision of which capsule may be sent on to a higher level capsule is the central focus of dynamic routing. However, research and development on this technology have not yet been carried out in the context of the peanut leaf spot disease [20]. One of the reasons for this is that there is not yet sufficient data available to be used in the process of training and validating the model. For the purpose of determining the accuracy and precision of the findings, a confusion matrix was used. The objective of the CapsNET model [21] was to determine how applicable different feature learning models are used to boost the learning capacity of DL models by measuring the applicability of these models.The results of the experiments [22] show that the proposed 5DB-DenseConvNet performs better and is more reliable than previous transfer learning systems when it comes to detecting plant diseases. This study [23] may be applied to other crops and has the potential to serve as a valuable tool for the identification of plant diseases that cannot be noticed under circumstances of poor weather and poor light.

Traditional manual diagnosis issues from poor accuracy and leads to inefficient use of personnel [24], both of which are caused by the low amount of professional knowledge held by plant producers. In order to remedy the issue of tilted data distribution, the data balancing algorithm was put into action. Within the realm of practical application, the assessment measure that is most often used to capsule networks is accuracy. This causes issues for applications that are very sensitive [25,26]. The metrics are useful for assessing the actual performances of the models in terms of precision (93.03% for the proposed model), and they do so effectively.

On the tomato dataset, the suggested model (26), which had an overall test accuracy of 98.80%, beat a baseline CapsNet by 8.37%, making it comparable to state-of-the-art models that were trained on the same datasets. The authors of this research [27] present a new method for the computing of features that is based on Squeeze & Excitation Networks. The main distinguishing characteristics are then included into the ensemble baggage tree classifier for the purpose of completing the recognition [28].

3. Proposed Methodology

This research paper's primary contribution comprises the following: The images were accurately pre-processed as well as changed to PNG format. Image procedures such as the Discrete Fourier Transform are used to the RGB image dataset. Image Enhancement like Thresholding methods were performed, and also the images throughout the groundnut plant dataset were refined. The Aug-CapsNet is developed, and also the source images were classified either normal or diseased. The effectiveness of the Aug-CapsNet in classifying, the input images from several datasets produced using different techniques for image processing was analyzed and contrasted using performance measures.

3.1 Discrete Fourier Transform

The Fourier Transform is a well-known approach for image processing that separates an image into sine and cosine components. When a picture is provided in the spatial domain, the Fourier transform transforms it into the frequency domain. The central part of Fourier space represents low frequency, whereas the peripheral section represents high frequency. Typically, a pixel in a picture is represented as a frequency range between 0 and 20,000 Hz with 1Hz spacing between them. The RGB picture is converted into a grayscale image using the following equation.

$$X = ((0.2 \times r) + (0.58 \times G) + (0.12 \times b)) \qquad (1)$$

The calculation for encoding continuous frequency pictures,

$$x(f) = \int_0^p \quad x(t)e^{-j\epsilon kt}dt \qquad (2)$$

Where f represents frequency levels ranging from $(-\infty, \ldots \ldots + \infty)$.The image's frequency value is amplified by a sinusoidal expression represented as (ϵ), and the result is determined as

$$x\epsilon = e^{j2\pi nk/\,n} \qquad (3)$$

The DFT equation for expressing an image is provided by

$$X(f) = \sum_{n=0}^{n-1} \quad x(n)x(t)e^{-j\epsilon kn} \qquad (4)$$

Where f denotes the frequency values$(0, 1, \ldots n - 1)$.

$$e^{-\epsilon i} = cos\, cos\, (\vartheta) - sin\, sin\, (\vartheta)i \qquad (5)$$

Using the equation, the image after DFT is expressed in the time domain (t).

$$x(t) = \sum_{n=0}^{n-1} \quad x[n].(cos\, cos\, (\vartheta) \; - sin\, sin\, (\vartheta)i\,) \; (6)$$

3.2 Thresholding Techniques for Image Enhancement

This is probably of the most significant strategies for distinguishing animage from its backdrop and foreground. The RGB picture is converted to a binary value, and the system determines an automated threshold value. If the binary value of the picture is less than the threshold, it is assigned the value zero; if it is higher than the threshold, it is assigned the value 255. The following equation describes how to calculate the threshold value.

$$\int_{maxval}^{o} \quad if\ src\ (x, y) > thresh\ Otherwise \qquad (7)$$

3.3 Pixel Augmentation

The process of modifying the colour characteristics of an image by adjusting the values of its pixels is referred to as pixel augmentation or colour jittering. Pixel Augmentation may train the images from the datasets using brightness, Contrast, Saturation, Hue for getting better accuracy. The pseudo code for pixel augmentation is given below:

Pseudocode for Pixel Augmentation

```
Brightness_pixel_aug = transforms.PixelAugmentation(brightness=2)
image = loader_ Brightness_pixel_aug (image)
ij[0, 0].set_title('brightness')
ij[0, 0].imshow(brightness_image)
```

```
Contrast_pixel_aug = transforms. PixelAugmentation (contrast=2)
image = loader_ Contrast_pixel_aug (image)
ij[0, 1].set_title('contrast')
ij[0, 1].imshow(Contrast_image)
```

```
Saturation_pixel_aug = transforms.PixelAugmentation (saturation=2)
image = loader_ Saturation_pixel_aug (image)
ij[1, 0].set_title('saturation')
ij[1, 0].imshow(Saturation_image)
```

```
Hue_pixel_aug = transforms. PixelAugmentation (hue=0.2)
image = loader_ Hue_pixel_aug (image)
ij[1, 1].set_title('hue')
ij[1, 1].imshow(Hue_image)
```

3.4 Capsule Neural Networks

In order to reduce challenges in the segmentation & detection operations, the capsules in this method represent a group of neurons that hold minute information about the item's spatial location. For example, while detecting an item, the object is subdivided internally into numerous pieces, and a connection (hierarchical relationship) is created among all the sub parts of the object to represent the thing.

The input layer is made up of pre-processing operations. To minimize calculation, the input images are scaled to 2828 pixels. There is a convolution layer having a kernel size of 9. The dot product across the filter and portions of the input image is used by the convolution layer. Capsules arise after convolution and the primary caps layer. Capsules is a series of layered neural layers. Classification: The last layer of the neural network is a completely connected layer following by softmax activation, which provides the probability distribution. Every neuron in one layer is linked to every neuron in another layer via the completely connected layer. The softmax equation is as follows:

$$softmax = SF(Z)_i = \frac{e^{xi}}{\sum_{j=1}^{n} e^{xi}} \qquad (8)$$

Where $(Z)_i$represents the vector's i-th element.

Finally, for classifying, deep learning model prediction loss is assessed using categorical cross-entropy.

$$loss(p, e) = -\sum_x \quad p(x)log\big(e(x)\big) \qquad (9)$$

Where p is true probability distribution.

Figure 1 depicts the architecture of the capsule neural network. The input layer, the hidden layer, as well as the output layer are the three key components of this CapsNet. Three more layers comprise the hidden layer. Using a 9x9 kernel and proper padding, this first convolutional layer generates 256 feature maps. We also preserved a kernel size of 9x9 for convolution inside the principal capsules, with x1 and x2 totally dependent on the size of the input image. The dimensions of each capsule are G1xG2, which are calculated automatically depending on x1 and x2. D1 and D2 (the diameters of the output vectors in the primary and routing capsules), F (the number of channels in the main capsule layer), and C are other parameters we modified for various datasets.

Aug-CapsNet models have been successfully employed in agriculture for plant species and plant identification, fruits counting, plant disease detection, overall yield calculation, and so on. However, certain drawbacks have been identified, such as discounting the spatial relationship between various features in a pixel augmentation transformations such as brightness, Hue, Saturation and Contrast of objects in images, for training. Aug-CapsNet are known to lose spatial information during the pooling step, making them invariant rather than equivariant. Aug-CapsNet can preserve spatial data as well as distinguish between various textures, orientations, and postures. A capsule is a collection of neurons, each with its own activity vectors that collects several

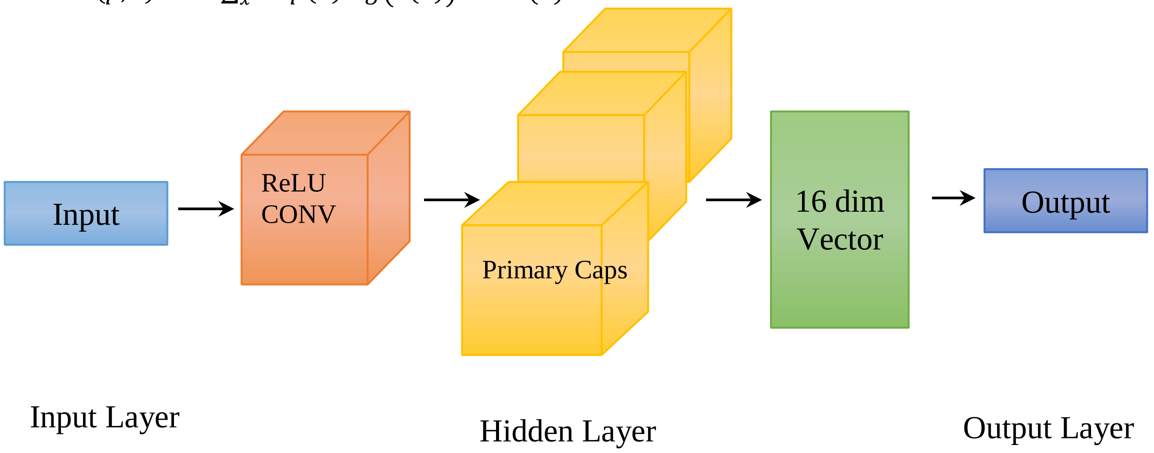


Figure 1. *Architecture of Capsule Neural Network.*

instantiation characteristics for recognising a specific type of entity or component element. Both length as well as orientation of the vectors characterise the likelihood or possibility of an object's existence and its generalised location. Lower layer capsules transmit these vectors to higher layer capsules. Coupling coefficients exist among these capsule regions. In other words, if the present capsules discovers a densely clustered cluster of past recommendations that strongly supports the existence of an object, it assigns a high probability to the item's presence; this is also known as channelling by consensus.

To begin, the classification vector is calculated as follows:

$$\widehat{u_j} = W_{ij} u_i \qquad (10)$$

Where classification vector uˆj is denoted inthe capsule jthlevel. Wij is the load matrix &ui is the prediction. It is capable of capturing spatial connections as well as interactions between sub-objects and objects. The coupling coefficients are determined using the softmax function.

$$c_{ij} = exp(b_{ij}) \, / \, \sum_k \quad exp(b_{ik}) \qquad (11)$$

Where bij is the initialization log proportion among the two capsules and k is the no. of capsules. A weighted sum of the routing algorithm's learning uˆj|i vectors, is calculated as follows:

$$s_j = \sum_i \quad c_{ij}\widehat{u_j} \qquad (12)$$

Finally, To constrain the final value to the range from 0 and 1, a function that combines, results in the probability being calculated as,

$$v_j = \frac{\|s_j\|^2}{1 + \|s_j\|^2} \frac{\|s_j\|}{\|s_j\|} \qquad (13)$$

$$l_k = T_k max(o, m^+ - \|v_k\|)^2 + \vartheta(1 - T_k) max(o, \|v_k\| - m^-)^2 \qquad (14)$$

Where Tk is a constant with a value of 0.5, if vk is more than 0.9, the loss score is 0; or else, it is non-zero.

Algorithm 1: Aug-CapsNet

```
functionTraining_Pixlel_augmented_images (dataset)
pre-processing_data□pixel_augmentation
fori□1; i<pixel_augmentation_images_iter do
    train_ pixel_augmentation_images_iter
end for
fori□1; i<pixel_augmentation_images_iter do
processing_pixel_augmentation_data□
pre-processing_data+pixel_augmentation_data
for j □1; j <pixel_augmentation_iter do
    train_ pixel_augmentation_images_iter(processing_pixel_augmentation_data.new)
end for
end for
returnpixel_augmentation
end function
```

According to the algorithm, n iterations in above algorithm are the most suitable. We used n iterations during our experiments as well. Capsule Network Architecture: Finally, capsule network Aug-CapsNet is as follows as given in paper.

4. Results

Adam is used as an optimizer for training our model Aug-CapsNet, Loss is calculated using categorical cross entropy, and precision is employed as an evaluation metric. The proposed model is validated using Plant Village datasets, which includes over 50,000 images representing diseased as well as normal plants. Table 1 provides the parameters and their values that have been altered for Aug-CapsNet training and testing, while Table 2 contains the details of each layer developed for testing, training, and validation of the Aug-CapsNetmodel.

Total images: 6, 500
Validation images: 6, 477
Classes: 48

Table 1. *Aug-CapsNethyperparameters are configured for training.*

Factors	Significance
$Size\ of\ Batch$	64
$Epochs$	150
$Size\ of\ image$	$222\ x\ 222\ x\ 4$
$Rate\ of\ Learning$	0.001
$Adam\ update\ Momentum$	0.4
$Loss$	$Entropy$

Table 2. *Details of individual Aug-CapsNet layer.*

$\boldsymbol{Layer}$	$\boldsymbol{Output\ shape}$	$\boldsymbol{Param\ \#}$
$Layer\ of\ Input$	$(24, 236, 236, 6)$	0
$Conv2D$	$(24, 236, 236, 12)$	224
$Max\ Pooling\ 2$	$(24, 116, 116, 8)$	0
$Reshape$	$(24, 116, 116, 8)$	$5{,}540$
$Conv\ Capsule\ Layer$	$(24, 16, 16, 256)$	$284{,}256$
$Flatten$	$(24, 45728)$	0
$Dense$	$(32, 36)$	$1, 902, 286$

Total_Parameters: 2, 202, 562
Trained_parameters: 2, 202, 562
Non_Trained_parameters: 0

In addition, the learning curves that were acquired when calculating the accuracy of training and validation are shown in Figure 2. However, trained models at 100, 150 and 200 epochs were also created for comparison. The Aug-CapsNet system is built to last 200 epochs. Additionally, early halting was used at the epoch 100 time point in order to prevent over fitting.

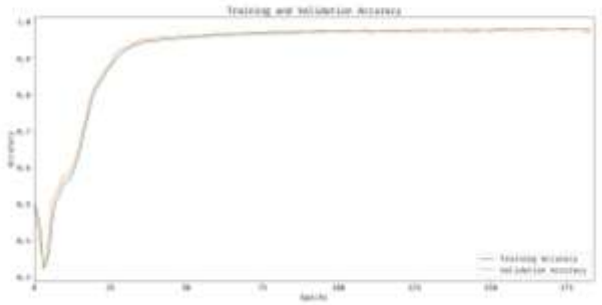


Figure 2. *Training and Validation Accuracy.*

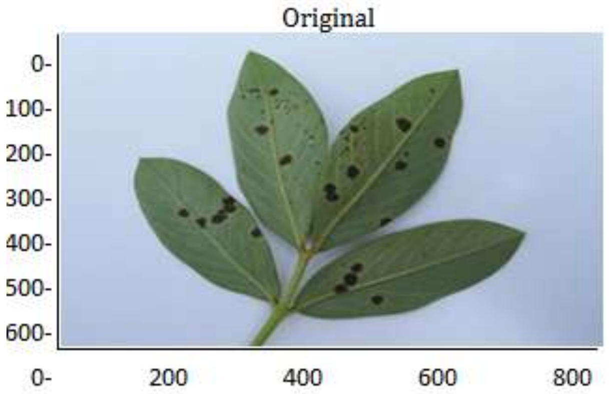


Figure 3. *Original Image.*

Python 3.8 is used as the programming language for the implementation of the Aug-CapsNet. The integrated development environment (IDE) that was used was Anaconda Navigator, and Spyder 5.0.0 was used for the coding. The methods provided in the numpy library is used to turn the RGB image into a DFT. The input image is then shown. The np.fft.ifft2() technique is used to convert the image that has been transformed using the DFT. The original image of input is shown in figure 3 and the preprocessing method using DFT and Thresholding Method is shown in figure 4.

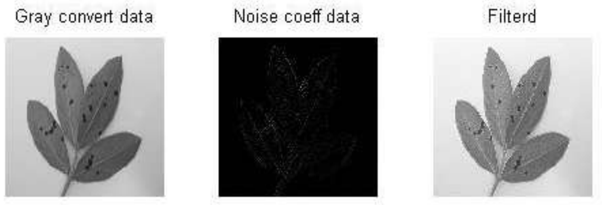


Figure 4. *Pre processing using DFT and Thresholding Method.*

The dct and idct functions, both of which can be found in the scipy.fftpack package. The discrete wavelet transform is carried out by utilizing the pywt library's pywt.wavedec2() and pywt.waverec2() methods. These are located in the methods directory. The input image is given a transformation using level 2 wavelet conversion before entering periodization mode. In this work, the image enhancing methods that were employed include thresholding with morphology operations, homo morphic filters, & contrast stretching. The Thresholding approach is achieved by using the built-in function that is available inside the cv2 library. This is done so that the image may be improved. The input image is then read, and the cv2.median Blur() function is used to blur it. This is done in order to get the desired effect.

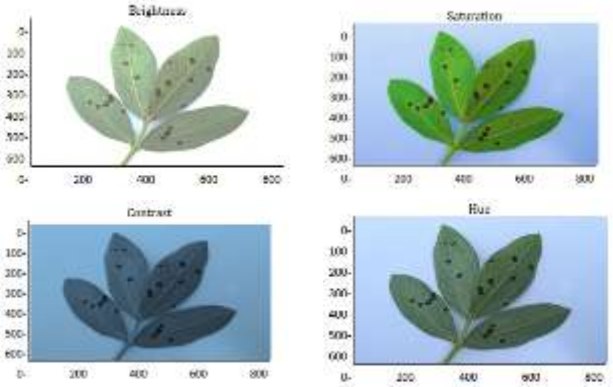
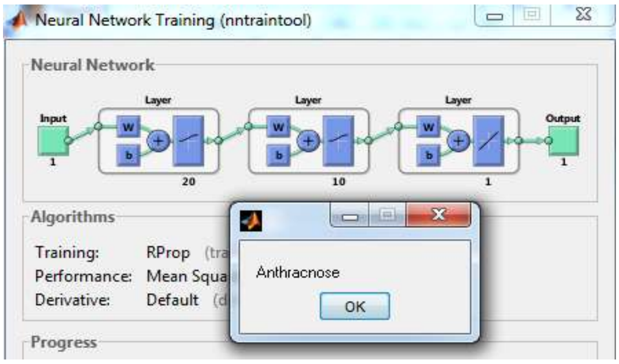


Figure 5. *Pixel Augmentation.*



Algorithms

Training: RProp (tra

Performance: Mean Squa

Derivative: Default (d

Progress

Anthracnose

Figure 6. *Groundnut Leaf Disease Classification*

Table 3. *Comparison Proposed with CNN model.*

$Typical$	$Accuracy\ for\ Training$	$Accuracy\ for\ Validation$	$Accuracy\ for\ Test$	$Accuracy$	$Recall$	$F1 - score$	%
CNN	82.85%	82.93%	82.83%	91.02	89.3	92.3	89.87%
$Aug - CapsNet$	97.05%	93.32%	92.06%	96.07%	92.06%	95.15%	92.48%

The anti-aliasing of the filtered image is accomplished with the help of the Gaussian Blur() technique included in the cv2 package. PIL library is used to provide an implementation of the contrast stretching technique. The output of the input image that was acquired after applying the different image processing algorithms is shown in the figure 5. Figure 6 is groundnut leaf disease classification.

Comparing the suggested Aug-CapsNet model with other models that are considered to be state-of-the-art in the field of plant disease categorization and detection is done in order to illustrate the usefulness of the model even further. Table 3 presents a variety of assessment metrics that were computed using multiple models for the Plant Village dataset. These metrics clearly demonstrate that Aug-Capsnet performs better than earlier models.

5 Conclusion

Timely detection, classification, and treatment have the potential to dramatically reduce total ecological and economic losses. In this research, proposed an Aug- CapsNet for classification and risk stratification prediction in groundnut plants. The first method is intended to identify plant diseases by utilising images from groundnut plant leaves. The Discrete Fourier Transform (DFT) and Thresholding methods were applied to enhance images. The second task is to classify the groundnut plant leaves. The provided architecture is verified using Plant Village datasets, which include over 50,000 photos of damaged and healthy plants. The Aug-CapsNet model outperforms earlier plant disease classification algorithms in terms of prediction accuracy. The experimental results of the constructed model achieved an overall evaluation accuracy of 96.07%, with an F1 score of 95.15%.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] Feng, Q., Xu, P., Ma, D., Lan, G., Wang, F., Wang, D., & Yun, Y. (2022). Online recognition of peanut leaf diseases based on the data balance algorithm and deep transfer learning. *Precision Agriculture*. 24(2);560–586. https://doi.org/10.1007/s11119-022-09959-3.

[2] Mensah, P. K., Weyori, B. A., &Ayidzoe, M. A. (2021). Capsule network with k-means routing for plant disease recognition. *Journal of Intelligent & Fuzzy Systems*. 40(1);1025-1036. https://doi.org/10.3233/jifs-201226.

[3] Mensah, P. K., & Ayidzoe, M. A. (2022). Overview of CapsNet Performance evaluation methods for image classification using a dual input capsule network as a case study. *International Journal of Computing and Digital Systems*. 11(1);29-43. https://doi.org/10.12785/ijcds/120104.

[4] Verma, S., Chug, A., Singh, R. P., Singh, A. P., & Singh, D. (2022). SE-CapsNet: Automated evaluation of plant disease severity based on feature extraction through Squeeze and Excitation (SE) networks and Capsule networks. Kuwait Journal of *Science*. 49(1). https://doi.org/10.48129/kjs.v49i1.10586.

[5] Saeed, F., Khan, M. A., Sharif, M., Mittal, M., Goyal, L. M., & Roy, S. (2021). Deep neural network features fusion and selection based on PLS regression with an application for crops diseases classification. *Applied Soft Computing*. 103, 107164. https://doi.org/10.1016/j.asoc.2021.107164.

[6] Patayon, U. B., & Crisostomo, R. V. (2022). Peanut leaf spot disease identification using pre-trained deep convolutional neural networks. *International Journal of Electrical and Computer Engineering*. 12(3), 3005. https://doi.org/10.11591/ijece.v12i3.pp3005-3012.

[7] Dong, M., Mu, S., Su, T., & Sun, W. (2019). Image recognition of peanut leaf diseases based on capsule networks. In *Artificial Intelligence: Second CCF International Conference, ICAI 2019, Xuzhou, China, August 22-23, 2019, Proceedings 2. Springer*

Singapore. 43-52. https://doi.org/10.1007/978-981-32-9298-7_4

[8] ArunPandian, J., & Kanchanadevi, K. (2022). An improved deep convolutional neural network for detecting plant leaf diseases. *Concurrency and Computation: Practice and Experience*. 34(28), e7357. https://doi.org/10.1002/cpe.7357.

[9] Devi, K. S., Srinivasan, P., &Bandhopadhyay, S. (2020). H2K–A robust and optimum approach for detection and classification of groundnut leaf diseases. *Computers and Electronics in Agriculture*. 178, 105749. https://doi.org/10.1016/j.compag.2020.105749.

[10] Ramakrishnan, M. (2015, April). Groundnut leaf disease detection and classification by using back propagation algorithm. In *2015 international conference on communications and signal processing (ICCSP). IEEE*. 0964-0968. https://doi.org/10.1109/iccsp.2015.7322641.

[11] Janani, M., &Jebakumar, R. (2023). Detection and classification of groundnut leaf nutrient level extraction in RGB images. *Advances in Engineering Software*. 175, 103320. https://doi.org/10.1016/j.advengsoft.2022.103320.

[12] Vaishnnave, M. P., Devi, K. S., Srinivasan, P., &Jothi, G. A. P. (2019, March). Detection and classification of groundnut leaf diseases using KNN classifier. In *2019 IEEE International Conference on System, Computation, Automation and Networking (ICSCAN)*. IEEE. 1-5. https://doi.org/10.1109/icscan.2019.8878733.

[13] Seetharaman, K. (2022). Real-time automatic detection and classification of groundnut leaf disease using hybrid machine learning techniques. *Multimedia Tools and Applications*. 1-29. https://doi.org/10.1007/s11042-022-12893-1.

[14] Omran, E. S. E. (2017). Early sensing of peanut leaf spot using spectroscopy and thermal imaging. *Archives of Agronomy and Soil Science*. 63(7);883-896. https://doi.org/10.1080/03650340.2016.1247952.

[15] Vaishnnave, M. P., Suganya Devi, K., &Ganeshkumar, P. (2020). Automatic method for classification of groundnut diseases using deep convolutional neural network. *Soft Computing*. 24(21);16347-16360. https://doi.org/10.1007/s00500-020-04946-0.

[16] Wang, H., Shang, S., Wang, D., He, X., Feng, K., & Zhu, H. (2022). Plant disease detection and classification method based on the optimized lightweight YOLOv5 model. *Agriculture*. 12(7), 931. https://doi.org/10.3390/agriculture12070931.

[17] Kaur, S., Pandey, S., &Goel, S. (2019). Plants disease identification and classification through leaf images: A survey. *Archives of Computational Methods in Engineering*. 26(2);507-530. https://doi.org/10.1007/s11831-018-9255-6.

[18] Maheswaran, S., Indhumathi, N., Dhanalakshmi, S., Nandita, S., Mohammed Shafiq, I., &Rithka, P. (2022). Identification and Classification of Groundnut Leaf Disease Using Convolutional Neural Network. In *International Conference on Computational Intelligence in Data Science. Springer, Cham*. 654;251-270. https://doi.org/10.1007/978-3-031-16364-7_19.

[19] Dong, M., Mu, S., Su, T., & Sun, W. (2019, August). Image recognition of peanut leaf diseases based on capsule networks. In *International CCF Conference on Artificial Intelligence. Springer, Singapore*. 43-52. https://doi.org/10.1007/978-981-32-9298-7_4.

[20] Patayon, U. B., & Crisostomo, R. V. (2022). Peanut leaf spot disease identification using pre-trained deep convolutional neural network. *International Journal of Electrical and Computer Engineering*. 12(3), 3005. https://doi.org/10.11591/ijece.v12i3.pp3005-3012.

[21] ALTAN, G. (2020). Performance evaluation of capsule networks for classification of plant leaf diseases. *International Journal of Applied Mathematics Electronics and Computers*. 8(3);57-63. https://doi.org/10.18100/ijamec.797392.

[22] ArunPandian, J., &Kanchanadevi, K. (2022). An improved deep convolutional neural network for detecting plant leaf diseases. *Concurrency and Computation: Practice and Experience*. 34(28), e7357. https://doi.org/10.1002/cpe.7357.

[23] Kwabena, P. M., Weyori, B. A., & Mighty, A. A. (2020). Gabor capsule network for plant disease detection. *International Journal of Advanced Computer Science and Applications*. 11(10). https://doi.org/10.14569/ijacsa.2020.0111048.

[24] Feng, Q., Xu, P., Ma, D., Lan, G., Wang, F., Wang, D., & Yun, Y. (2022). Online recognition of peanut leaf diseases based on the data balance algorithm and deep transfer learning. *Precision Agriculture*. 1-27. https://doi.org/10.1007/s11119-022-09959-3.

[25] Mensah, P. K., &Ayidzoe, M. A. (2022). Overview of CapsNet Performance evaluation methods for image classification using a dual input capsule network as a case study. *International Journal of Computing and Digital Systems*. 11(1);29-43. https://doi.org/10.12785/ijcds/120104.

[26] Mensah, P. K., Weyori, B. A., &Ayidzoe, M. A. (2021). Capsule network with K-Means routing for plant disease recognition. *Journal of Intelligent & Fuzzy Systems*. 40(1);1025-1036. https://doi.org/10.3233/jifs-201226.

[27] Verma, S., Chug, A., Singh, R. P., Singh, A. P., & Singh, D. (2022). SE-CapsNet: Automated evaluation of plant disease severity based on feature extraction through Squeeze and Excitation (SE) networks and Capsule networks. *Kuwait Journal of Science*. 49(1). https://doi.org/10.48129/kjs.v49i1.10586.

[28] Kanna, R. R. (2018). An Efficient Web Log File Classification Techniques to Identify the Fault Data Identification Using Multi-Class Support Vector Machine Algorithm. *Journal of Computational and Theoretical Nanoscience*. 15(9);2831–2835. https://doi.org/10.1166/jctn.2018.7547.