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Efficient Channel Attention Network for Accurate Carrot Disease Detection and Classification

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ABSTRACT: The detection of Carrot Disease (CD) remains significantly impact by agricultural productivity and market quality. Therefore, early and accurate detection of diseases in carrot is essential for maintaining crop health and maximizing yield. This work proposes an automated Carrot Disease Detection (CDD) system that utilizes image processing and deep learning techniques. The Good and bad classification of Fresh CARROT dataset is fed to pre-processing stage where an Adaptive Wiener Filter (AWF) is used. AWF technique is to enhance image quality and reduce noise. This is followed by segmentation using a Kernel-Based K-Means algorithm to isolate diseased regions in carrot. The segmented carrot images are then fed to region-based feature extraction, capturing critical details relevant for disease identification. Finally, classification is performed using an Efficient Channel Attention Network (ECANet), to classify the carrot disease enabling high-accuracy predictions. Using Python software, the proposed framework achieved higher accuracy, F1-score, precision and recall of 94%, is accomplished when compared to other techniques.

Keywords: Carrot Disease, Adaptive Wiener Filter, Kernel-Based K-Means algorithm, Region-based feature extraction, Efficient Channel Attention Network.

1. Introduction

Carrot (Daucus carota) is a widely cultivated root vegetable recognized for its rich nutritional profile and high bioactivity [1]. It is often referred to as a vitamin-rich food, particularly due to its substantial content of vitamins B, C, and E, along with potent antioxidant properties that help combat cellular damage and reduce the risk of various diseases [2]. Although having a limited range of pigment types, carrots exhibit a diverse array of colors. This variability is primarily attributed to two major classes of natural pigments carotenoids and anthocyanin's [3-4]. Carotenoid-rich carrots display taproot colors ranging from white, yellow, and orange to red, whereas anthocyanin-dominant varieties are typically purple in color [5]. Whereas, a seed-propagated and predominantly outcrossing species, carrots naturally undergo hybridization within and across populations, promoting gene flow and enhancing genetic diversity across the germplasm collection [6]. This diversity forms the foundation for on-going efforts in carrot breeding, quality enhancement, and adaptation to varying agro-climatic conditions [7]. For improved identification and detection of CD various pre-processing, segmentation, feature extraction, and classification techniques are employed.

To pre-process the raw images from the original dataset some of the following techniques are used. Carrot image is processed using the pre-processing technique such as, data augmentation for expand the size and variability of training data. Carrot diseases appear differently due to changes in illumination, soil background, or image noise. Augmentation helps simulate these effects for better robustness. Nevertheless, augmentation result in redundant or noisy data that adds little new information but increases training time [8]. Additionally, to remove the noise from input carrot image acquisition is utilized. High-resolution imaging allows for exact identification of infected areas, portion in targeted pesticide application or localized treatment. However, image quality is greatly affected by changes in lighting, shadows, background, leading to inconsistent data and reduced detection accuracy [9]. To overcome the above limitation proposed AWF based pre-processing technique is utilized to remove unwanted noise and enhance the image quality from coconut leaf image for further Processing.

The following existing segmentation method is utilized to segment the CD. Segmentation based on Region of Interest (ROI) is to segment the CD from the background based on the pixel brightness intensity. ROI-based segmentation enables clearer detection of texture, color, and shape features, which are critical for identifying specific carrot diseases such as black rot, soft rot, and nematode damage. Nevertheless, carrot disease appears in multiple or scattered regions, creating it difficult to define a single ROI, especially in early or mild infection stages [10-11]. For the above limitation the boundaries, region, areas and lesion are segmented using the Kernel-based K-means algorithm. In this research Kernel-based K-means approach is proposed that effectively segments the carrot image.

Furthermore, feature extraction methods helps to pick important parts from carrot image to detect the disease easily. In existing method, Gray Level Co-occurrence Matrix (GLCM) to detect the texture features from the carrot image. GLCM identifies carrot image areas and regions; it effectively finds the value of contrast, correlation, homogeneity, energy, and entropy. Also, it efficient and simple method for capturing local texture features in carrot image. However, GLCM method is highly sensitive to image resolution, noise, lighting variation, complex background [12-13]. Therefore, the proposed feature extraction technique utilizes Region based feature extraction for addressing the above limitations and efficiently discriminative patterns from carrot images.

The good and bad carrot image is classified by some of the following technique. In existing method, to classify carrot image Artificial Neural Network (ANN) is utilized. ANN handles multiple input features simultaneously, improving classification speed and robustness. However, requires a large, diverse, and well-labelled dataset to achieve high accuracy, which is a challenge in agricultural domains [14]. Moreover, ResNet101 + SVM classify the carrot image. ResNet101 extracts deep, robust, and high-level spatial features from carrot images, which helps the SVM to classify diseases more accurately. Nevertheless, ResNet101 is computationally intensive, especially on high-resolution carrot images, and adds overhead before SVM training [15]. To overcome the limitations of existing classification, a proposed ECANet is implemented to classify the carrot disease allowing high-accuracy predictions.

2. Related work

Jahanbakhshi *et al* [16] (2021) have proposed a Convolutional Neural Network (CNN) to classify the carrot disease with high accuracy. CNN identify the carrot disease symptoms such as spots, blight, or discoloration. CNN is capable of identifying small or overlapping diseased areas, performs well in complex backgrounds and images with subtle visual changes. Nevertheless, it occur more complex, high computational cost and memory usage due to the multi-stage detection.

Deng *et al* [17] (2021) have presented a Lightweight deep learning model to detect the carrot. Lightweight deep learning model are designed for real-time performance, allowing for quick disease detection directly in the field without heavy processing delays. Lightweight model capture the carrot image color, texture, and shape, such as fungal infections, blights, or discoloration. Performs well on small datasets due to training and captures global and long-range dependencies. However, requires more computational power and memory, especially during training.

Xie *et al* [18] (2021) have developed a CarrotNet based on AlexNet tailored for detecting carrot defects. AlexNet is capable of learning rich hierarchical visual features such as color, texture, and lesion patterns useful in distinguishing between healthy and diseased carrots. Pre-trained AlexNet is fine-tuned on carrot disease datasets to achieve fast and accurate results with minimal data Nevertheless, AlexNet is relatively shallow and fail to capture complex disease patterns in high-variability images.

Ropelewska and Ewa [19] (2022) have proposed a Multilayer Perception (MLP) to identify the carrot disease. MLPs are straightforward to design and train, creating them a good for classification in carrot disease detection. In MLPs the number of layers and neurons is easily adjusted to fit the complexity of the problem. Nonetheless, MLPs unpreserved spatial relationships between pixels, creating them ineffective for raw image-based disease detection.

Zhou *et al* [20] (2022) have proposed a Convolutional – Long Short Term Memory (C-LSTM) prediction model to predict carrot disease. CNNs extract spatial features such as color, shape, lesion texture, whereas LSTM absorb dependencies over time or sequences, useful for tracking disease development stages. C–LSTM acquires progression patterns, improving detection and early diagnosis. However, LSTM layers are prone to over fitting, especially when there's limited sequential image data.

This study, propose an ECANet framework for the early detection and classification of carrot disease. The contribution of the work as follows**:**

- AWF based pre-processing method applied to remove the unwanted noise and enhances image quality.
- A Kernel based K-means segmentation approach used to isolate the disease region in the carrot.
- Region based feature extraction captures critical region for carrot disease identification for further classification.
- An ECANet is proposed to improve the classification and detection of carrot image, achieving high accuracy through attention convolution**.**

3. Proposed Work

Figure 1 shows the proposed framework for carrot disease and the input image is taken from Good and bad classification of Fresh CARROT dataset. In the pre-processing stage, an AWF is applied to reduce noise whereas preserving important features. This is followed by segmentation using a Kernel-Based K-Means clustering technique, which isolates the diseased regions by grouping similar pixels. Next, Region-based feature extraction is performed to capture important visual characteristics from segmented areas. These extracted features are then fed into an ECANet for carrot disease classification. ECANet enhances critical feature channels and suppresses irrelevant ones, leading to better disease identification. The final stage outputs the predicted disease as good or bad with high accuracy, showing the system’s potential for real-time agricultural applications.

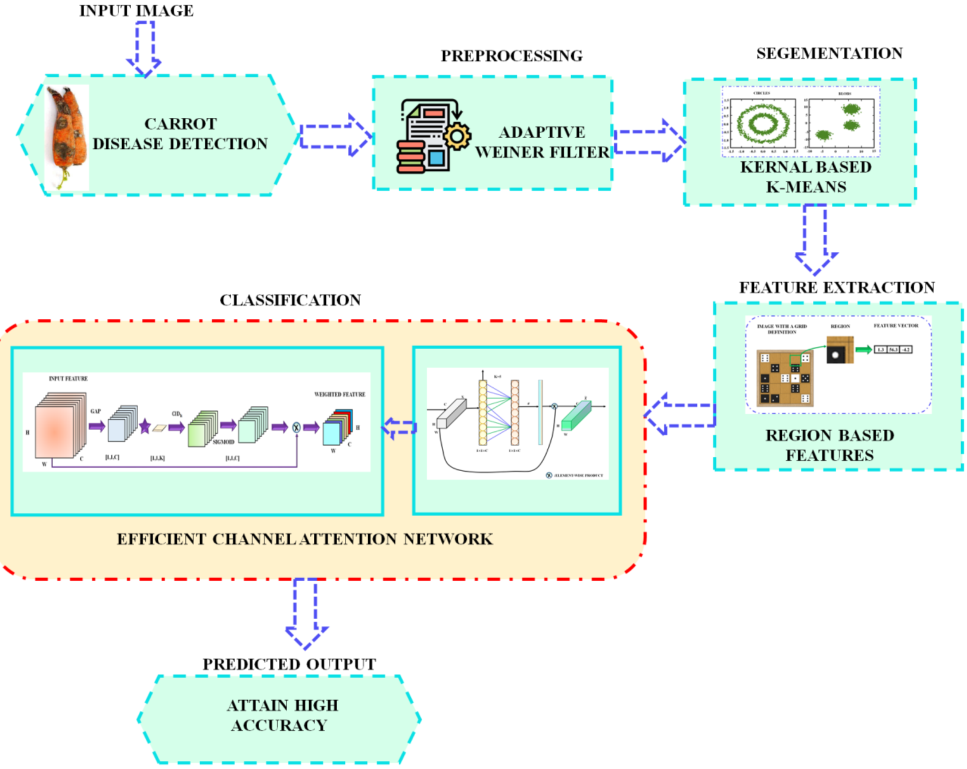

Figure 1: *Block diagram of proposed work*

3.1. Pre-processing by Adaptive Wiener Filter

In CDD, AWF is an effective denoising method that enhances carrot image clarity by reducing Gaussian noise whereas preserving important edge and texture details. It operates locally, adapting to the statistics of each neighbourhood within the carrot image. For a given noisy$I(i,j)$, the filtered output $\hat{I}(i,j)$ is computed using the formula:

$$\hat{I}(i,j) = \mu + \left(\frac{\sigma^2 - v^2}{\sigma^2}\right).I(i,j) - \mu) \quad (1)$$

Where μ and $\sigma^2$the local mean and variance are computed over a neighborhood window centered at pixel (i,j) and v^2 represents the noise variance estimated from the entire image or a noise profile. The adaptive nature of the filter ensures that in flat regions, where noise dominates, stronger smoothing is applied, whereas in areas with high variance (e.g., disease spots or edges), minimal filtering is used to retain crucial features. This balance significantly improves the visibility of disease-related symptoms on carrot surfaces such as lesions, discoloration, or rot thus simplifying more accurate segmentation. The processed image is fed to segmentation based on Kernel-based K-means algorithm.

3.2. Kernel-based K-means segmentation for CDD

In CDD, segmentation function is to isolate carrot diseased regions from healthy tissue. Traditional K-means clustering fall short when carrot disease patterns are non-linearly separable in the pixel feature space. To overcome this, Kernel-based K-means segmentation is employed to segment the carrot image, which extends the standard K-means algorithm by mapping input data into a higher-dimensional space using a kernel function, enabling better separation of complex carrot disease features. Figure 2 shows the basic structure of kernel K-means algorithm for the carrot disease.

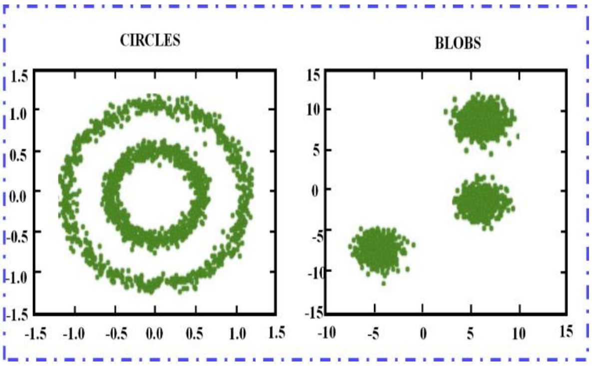

Figure 2: *Basic structure of Kernel K-means*

Instead of using Euclidean distance, kernel K-means minimizes the objective function based on the inner products in the transformed space:

$$J = \sum_{i-1}^{n} \left\| \phi(x_i) - \mu_{k(i)} \right\|^2 \quad (2)$$

Where, $\phi(x_i)$ is the mapping of the pixel (x_i) into a high-dimensional feature space, and $\mu_{k(i)}$ is the centroid of cluster k in that space. The kernel trick allows computation without explicitly performing the mapping, using a kernel function $K = \langle \phi(x_i), \phi(x_j) \rangle$ such as the Gaussian (RBF) kernel:

$$K(x_i, x_j) = \exp(-\frac{\|x_i - x_j\|^2}{2\sigma^2}) \quad (3)$$

This kernel-based approach effectively captures nonlinear textures, color irregularities, and lesion boundaries in carrot images that are indicative of disease. As a result, it segments diseased regions more accurately than linear K-means, improving the reliability of subsequent classification models. This creates Kernel K-means particularly suitable for images with variable lighting, background complexity, or overlapping disease features. Subsequent, the segmented output is fed to feature extraction technique for carrot disease.

3.3. Feature extraction by Region based feature for CDD

Region-based features are widely used to characterize and differentiate diseased areas from healthy tissue by analysing regions of interest (ROI) within a carrot image. These features provide local statistical and structural information, which is critical for identifying carrot disease symptoms such as lesions, rot, or pigmentation changes. Figure 3 shows the basic Region based feature.

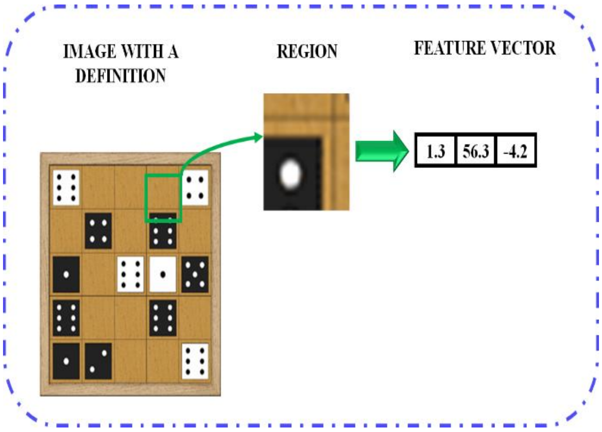

Figure 3: *Basic Region based feature*

After segmentation, each connected region R is analyzed using features like area, perimeter, mean intensity, standard deviation, eccentricity, and shape descriptors. A common computation of the mean intensity of a region, given by:

$$\mu_R = \frac{1}{|R|} \sum_{(i,j)\in R} I(i,j) \quad (4)$$

Where, μ_R is the mean intensity of region $R, I\ (i,j)$ represents the pixel intensity at position (i,j), and $|R|$ is the number of pixels in that region. Similarly, the standard deviation σ_R is calculated to understand local contrast:

$$\sigma_R = \sqrt{\frac{1}{|R|} \sum_{(i,j)\in R} (I(i,j) - \mu_R)^2} \quad (5)$$

These region-based features are effective in distinguishing healthy and diseased tissue in carrots, especially when symptoms affect texture or intensity patterns. By extracting such descriptors from segmented areas, ECANet is to detect and categorize various diseases, leading to efficient and interpretable disease diagnosis. The extracted carrot image is given to the proposed ECANet for further classification.

3.4. Classification by Efficient Channel Attention Network

In CDD, accurate identification of carrot disease such as good and bad carrot is essential. The ECA Network enhances this process by introducing a lightweight attention mechanism that selectively emphasizes the most informative feature channels without increasing computational complexity. Figure 4 shows the channel attention module. A Channel Attention Module learns to assign weights to each channel, emphasizing the ones that are more informative for classification.

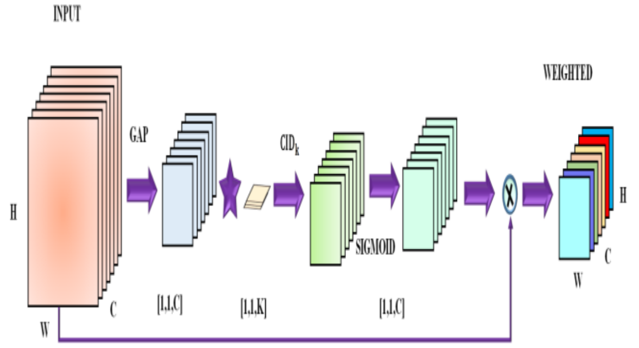

Figure 4 : *Channel attention module*

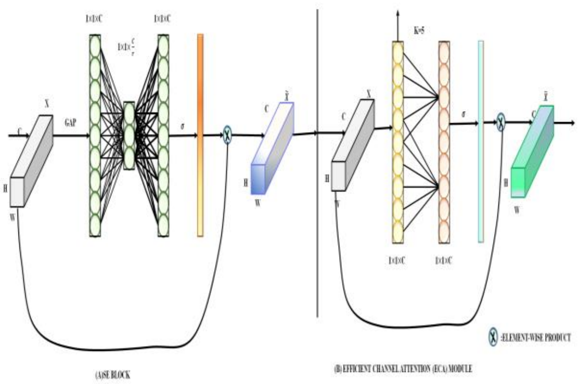

Figure 5: *ECA module*

Figure 5 shows the ECA module for the CDD identification. After feature maps $F \in R^{C\times H\times W)}$ are generated by a convolutional layer, Global Average Pooling (GAP) is applied to each channel to squeeze the spatial dimensions, producing a channel descriptor:

$$Z_c = \frac{1}{W\times H}\sum_{i=1}^{H}\sum_{j=1}^{W} F_c(i,j) \qquad (6)$$

Where Z_c represents the average activation of channel c. The entire set of channel descriptors forms a vectorz $\in R^c$. Instead of using a fully connected layer, ECA introduces a 1D convolutional operation with a kernel size k to capture local cross-channel dependencies:

$$s = Conc1D(z;k) \qquad (7)$$

This operation produces a new vector $s \in R^c$ containing the channel-wise attention weights. These weights are then applied back to the original feature map using element-wise multiplication:

$$F_c' = s_c \,.\, F_c \qquad (8)$$

Feature map F' that highlights important disease-related features whereas suppressing irrelevant or noisy channels. In CDD, this channel attention mechanism significantly improves the ability of the network to focus on lesion regions, infected textures, or abnormal color patterns, leading to higher classification accuracy with minimal computational overhead. This creates ECA-Net a highly effective component in both high-performance and real-time disease detection for smart agriculture.

4. Result and discussion

In result and discussion section the CDD are predicted using the proposed ECANet for identifying disease in carrot. Also, the Good and bad classification of Fresh CARROT dataset is taken from the kaggle.com implemented using Python software. Two classes are identified for the carrot image as good and bad.

Figure 6: *Test and train data distribution*

Figure 6 shows the test and train data distribution for CDD. X-axis indicates the class labels as good and bad and Y-axis indicates the number of images. Good image for the test distribution is 106, good image for the train distribution is 421.

Bad image for the test distribution is 110, bad image for the train distribution is 440.

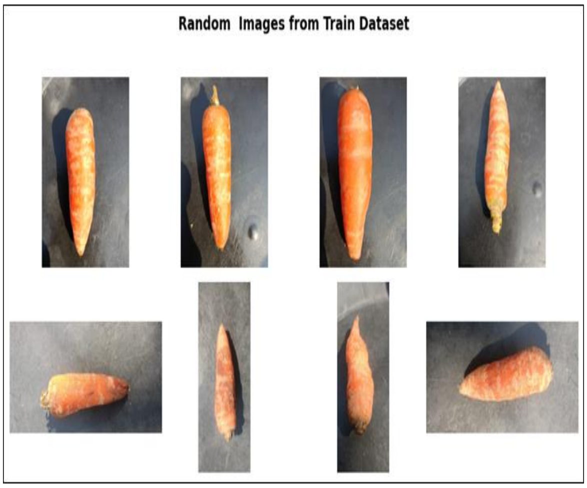

Figure 7: *Random images from train dataset*

Figure 7 shows random images in train dataset for CDD. The random images are taken from the Good and bad classification of Fresh CARROT dataset for further process. Here, two types of carrot images are taken from the dataset. The carrot images have two classes good and bad images are randomly chosen from Good and bad classification of Fresh CARROT dataset to train for further analysis.

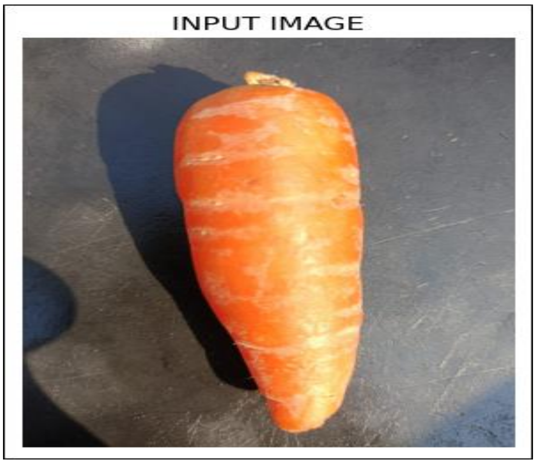

Figure 8: *Input carrot image*

Figure 8 shows the input carrot image taken from the Good and bad classification of Fresh CARROT dataset randomly chosen test and train images. The input image contains large pixel size, raw image and blurry. The carrot image is a raw image from Good and bad classification of Fresh CARROT dataset from kaggle.com uses the following methods such as pre-processing, segmentation, feature extraction and classification for further processes.

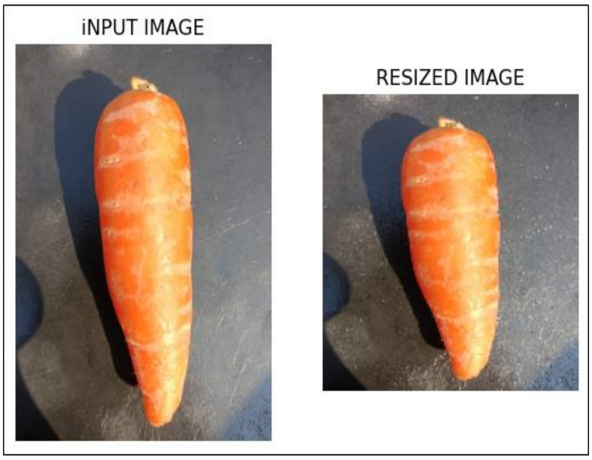

Figure 9: *Input image in to resize image*

Figure 9 shows the input image to resize image. Here the input carrot image is resized using image resizing technique. The input raw carrot image is converted in to resize image for further process. The noises present in the original image are removed and develop the better quality image. By resizing the input image to a fixed dimension, it becomes compatible and processed uniformly.

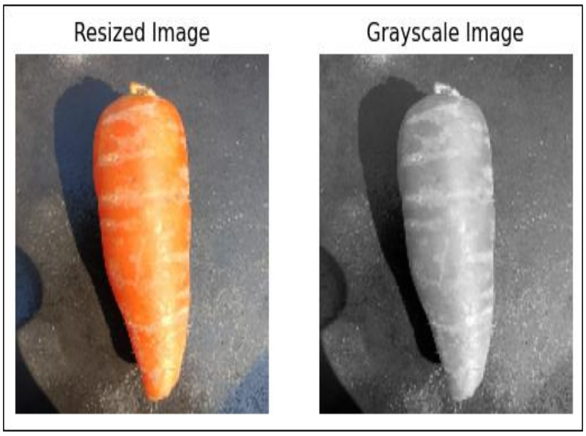

Figure 10: *Resize image in to grayscale image*

Figure 10 shows the resized image into gray scale image for CDD detection. Here resized image is transformed into grayscale image for enhancing the carrot image. Once resized, the image is converted to grayscale, which reduces the image from three color channels (Red, Green, and Blue – (RGB)) to a single intensity channel. This grayscale conversion simplifies the data by retaining only luminance information, effectively highlighting texture, edges, and structure without color distractions.

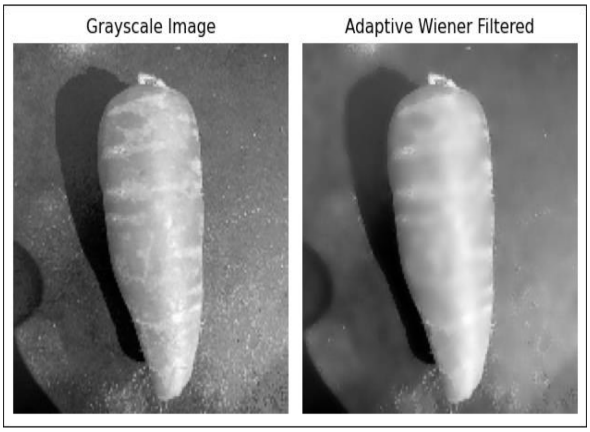

Figure 11: *Grayscale image in to AWF*

Figure 11 shows the grayscale image into AWF for CDD detection. The AWF removes the unwanted noise from the grayscale carrot image and enhance the carrot image as a high quality image. The captured AWF image is given as an input to the segmentation technique. Here the Kernel based K-means algorithm is used as segmentation based technique.

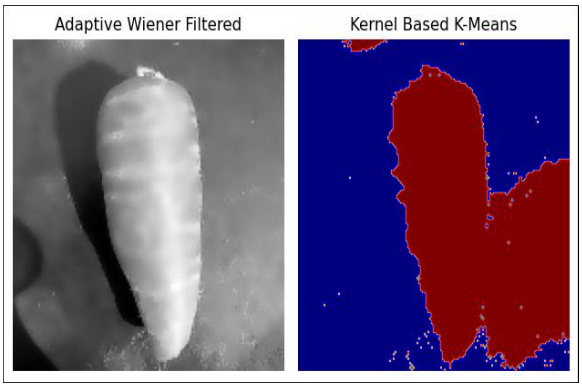

Figure 12: *AWF in to kernel based K-means*

Figure 12 shows the AWF in to kernel K-means algorithm for CDD. A kernel function to handle nonlinear clustering boundaries, creating it suitable for segmenting complex shapes and patterns found in diseased carrots. The segmentation differentiates the object of interest (carrot) from the background, with distinct color regions indicating different clusters such as red for the carrot, blue for the background. Then the segmented output is given as an input to feature extraction.

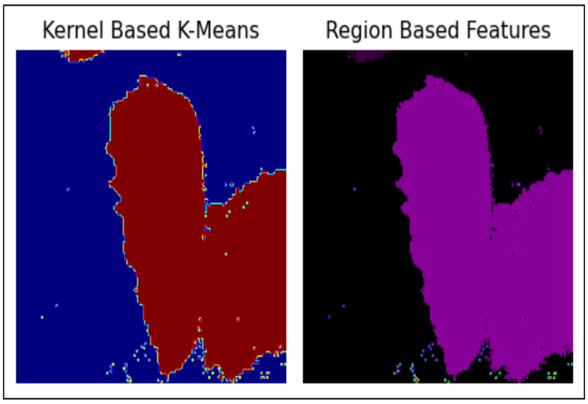

Figure 13: *Kernel based K-means to region based feature*

Figure 13 show the kernel based K-means to region based feature. Region-Based Feature Extraction, where the segmented area is refined and converted into a format suitable for feature computation. This step focuses on extracting meaningful descriptors such as shape, texture, and color from the detected ROI, as indicated by the purple region. This combination of precise segmentation and targeted feature extraction significantly enhances the system's ability to identify and distinguish diseased carrot regions from good ones.

Table 1: *Region based feature*

Regions	**Area**	**Centroid**	**Mean Intensity**	**Eccentricity**	**Solidity**	**Boundary Box**
Region 1	97	1.9, 35.6	145.48	0.964	0.843	0, 24, 6, 49
Region 2	2	2, 89.5	157	1	1	2, 89,3,91
Region 3	1	3, 25	135	0	1	3, 25,4, 26
Region 4	8717	84.4, 99.1	165.13	0.799	0.841	12, 49, 149, 149

Table 1 shows the Region based feature for CDD. Regions 1 have a moderate area of 97 pixels, with a centroid at approximately (1.94, 35.61). Its mean intensity is 145.48, indicating the average grayscale brightness, and it has relatively high eccentricity (0.964), showing that it is elongated. The solidity (0.843) and bounding box values help in identifying its compactness and spatial extent. Region 2 and Region 3 are very small (2 and 1 pixel respectively), which is a noise or minute features. Both exhibit maximum solidity (1.0), implying they are perfectly compact, and Region 3 have zero eccentricity, indicating a circular shape. Region 4 is the largest segment with an area of 8717 pixels and a centroid at (84.49, 99.17). It shows a high mean intensity (165.13) and moderate eccentricity (0.799), suggesting an elongated but substantial region. Its solidity (0.841) and bounding box dimensions (12, 49, 149, 149) it covers a major bad or good portion of the carrot.

4.1. Performance metrics for CDD detection

Performance metrics, such as accuracy, sensitivity, and specificity, indicate that the carrot image is correctly detected and appropriately analysed as the probabilities calculated by ECANet. The performance metrics in this study explained in table 2.

Table 2: *Performance Metrics*

Performance metrics	Values
Acc	94%
Precision	94%
Recall	94%
F1-score	94%

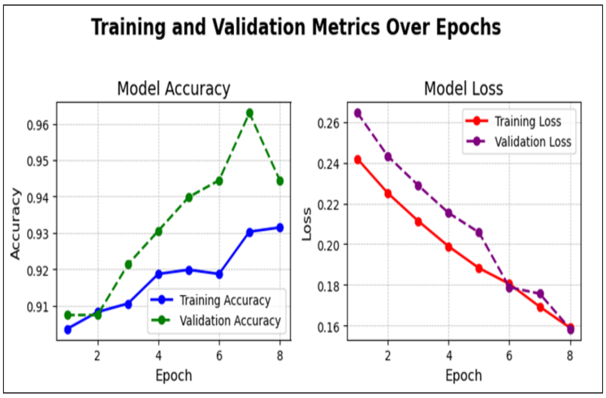

Figure 14: *Training and validation metrics over epochs*

Figure 14 shows the training and validation metrics over epochs. The X-axis denotes the epochs and Y-axis denotes accuracy for carrot image. The model accuracy graph illustrates increasing accuracy of 94%, with the model achieving high performance and minimal over fitting. For model loss the X-axis indicates the epochs and Y-axis indicates the loss. Training and validation loss is reliably declining in training and validation loss, representing improved learning and reduced error.

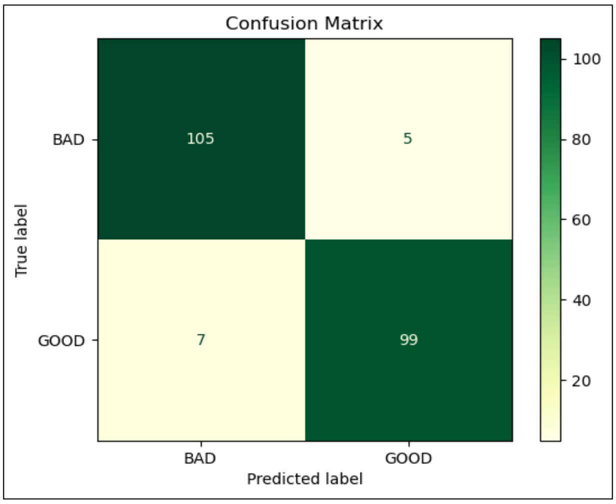

Figure 15: *Confusion matrix for CDD*

Figure 15 shows the confusion matrix for carrot image. Proposed method evaluates the model’s performance for two classes good and bad. The X-axis indicates the predicted label and Y-axis indicates the true label. Bad have the value of 105 and good have the value of 99 respectively.

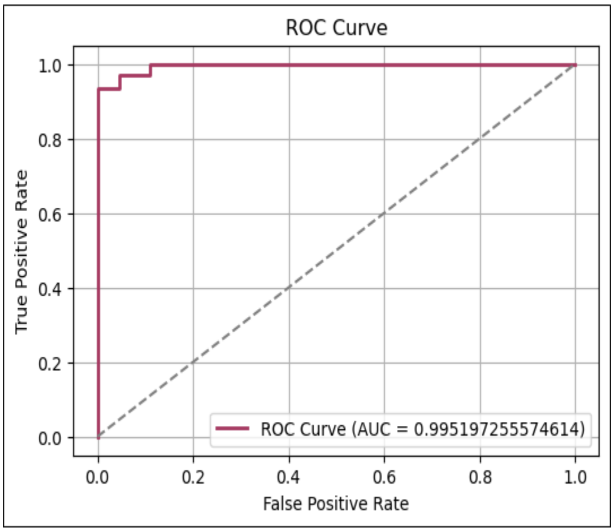

Figure 16: *ROC curve*

Figure 16 shows the ROC curve for proposed ECANet continues to have the highest AUC value of 0.99 demonstrating the unique overview and flexibility of carrot image approach. The X-axis indicates the false positive rate and Y-axis indicates the true positive rates.

4.2. Comparison for the suggested method

The comparison of the suggested method with existing method is presented in table 3. The CNN have the classification accuracy of 90% [16], Lightweight Deep learning model have the classification accuracy of 92.8% [17] and the proposed ECANet have the higher accuracy of 94% compared to the existing method in table 3. The proposed ECANet have better performance for CDD.

Table 3: *Comparison for the proposed method*

Method	Accuracy
CNN	90%
Lightweight Deep learning model	92.8%
ECANet	**94%**

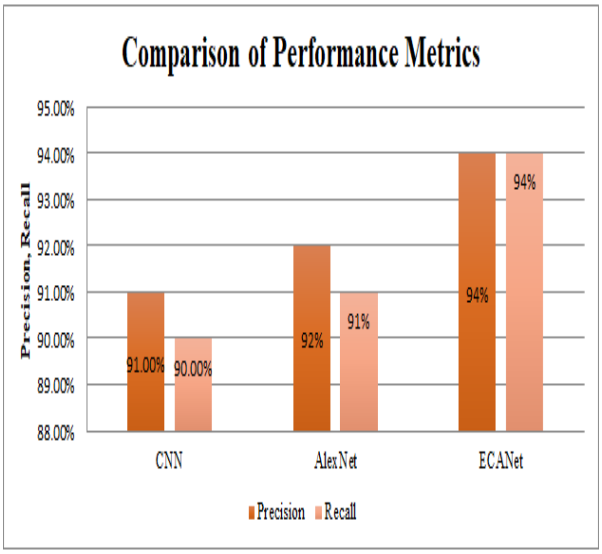

Figure 17: *Comparison of performance metrics*

Figure 18 shows the comparison of performance metrics for precision and recall value of proposed work and the existing work. The CNN have precision value of 91% and recall value of 90% [16], AlexNet have the precision value of 92% and recall of 91% [18] and proposed ECANet have the precision value of 94% and recall of 94% for identifying CDD. The proposed precision and recall value is high compared to the existing method.

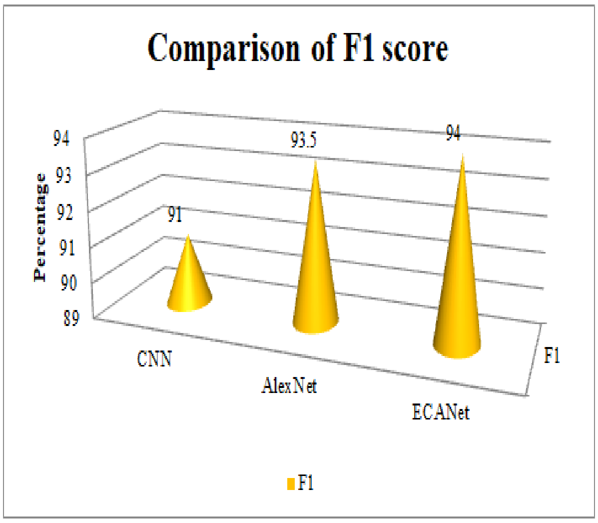

Figure 18: *Comparison of F1 score*

Figure 18 shows the comparison of F1 score value of proposed work and the existing work. The CNN have F1-score value of 91% [16], AlexNet have F1-score value of 93.5% and proposed ECANet have the F1- score value of 94% for identifying CDD detection. The proposed F1 score value is high compared to the existing method.

5. Conclusion

In this paper, ECANet based model is proposed for the identification and classification of CD detection. The two classes of good and bad images are classified successfully using the proposed ECANet. The preprocessing stage reduced the noise and enhances the carrot image quality. Also, Kernel based K-means based segmentation separate a carrot image region and segments the carrot image. Furthermore, Region based feature efficiently captures the four regions from the carrot images. Finally, the proposed ECANet classifies the carrot image with better accuracy. The performance evaluation, conducted on the Good and bad classification of Fresh CARROT dataset, demonstrates the superior capabilities of the ECANet method. The improved accuracy value of 94%, F1-score value of 94%, precision and recall of 94%, is achieved as a greater accuracy and performance in contrast to the existing methods.

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