International Journal of Advanced Trends in Engineering and Management
(ISSN 2583-7052)

Vol. IV, No. 12, pp. 28-40, December

Pepper Leaf Disease Detection Using Stockwell Transform-Based Feature Extraction and AdaBN-DenseNet Classifier

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ABSTRACT: Agricultural production plays a vital role in a country's economy, and leaf diseases are a common and natural occurrence. Early and accurate identification of these diseases is essential to prevent significant losses in crop yield and ensure sustainable agricultural output. This paper presents an efficient and intelligent framework for Pepper Leaf Disease (PLD) detection by integrating advanced image processing, segmentation, feature extraction, and classification techniques. The Black Pepper Leaf Blight and Yellow Mottle Virus dataset is applied to preprocessing stage using a Spatially Adaptive Difference of Gaussians (SADoG) filter, which enhances disease-affected regions by preserving essential edge information while effectively suppressing background noise. To accurately localize infected areas, a Noise-Resilient Fuzzy C-Means (NR-FCM) clustering algorithm is employed for segmentation. This method leverages fuzzy membership and spatial context to robustly handle noise and variation in leaf textures. Feature extraction is then carried out using the Stockwell Transform (S-Transform), which provides a rich time-frequency representation capable of capturing both global and localized disease patterns in pepper leaf images. Finally, the extracted features are fed into a Dense Convolutional Neural Network enhanced with Adaptive Batch Normalization (AdaBN-DenseNet) classifier. This classifier dynamically adjusts to variations in input data distributions, enabling precise and robust disease classification. Using Python software, the proposed framework achieved higher accuracy, F1-score and recall of 92%, precision of 93% is accomplished when compared to other techniques. Experimental results demonstrate that the proposed system achieves high accuracy and resilience in detecting various PLD, making it suitable for real-time agricultural diagnostics and smart farming applications.

Keyword: Pepper Leaf Disease, Spatially Adaptive Difference of Gaussians Filter, Noise-Resilient Fuzzy C-Means clustering, Stockwell Transform, Dense Convolutional Neural Network enhanced with Adaptive Batch Normalization.

1. Introduction

Black pepper (Piper nigrum L.), often referred to as the king of spices and black gold, is one of the most significant and widely used spices globally. It is cultivated in over 26 countries, with an annual production of approximately 561,500 tones [1]. Among pepper-producing nations, India ranks third, contributing 64,000 tones, cultivated across 278,050 hectares. Within India, the state of Kerala is the second-largest producer, accounting for 32.6% of the country's output with 21,000 tones [2]. Since the early 21st century, the global cultivation area and yield of black pepper have steadily increased. Particularly, China have emerged as one of the leading producers worldwide. As an essential crop, pepper is not only a staple in culinary practices but also holds significance for human health and nutrition [3]. However, the growing global demand for pepper have been challenged by a range of plant diseases, which are major factors limiting both yield and quality [4]. Several of these diseases have caused substantial economic losses in recent years. Whereas, Pepper mild mottle virus (PMMoV) reduce yields by up to 40%, and in areas like Himachal Pradesh, India, where disease incidence reach 100%, losses climb as high as 90%. Pepper blight, prevalent in East Asia, is caused by aggressive pathogens that destroy entire crops, resulting in severe financial damage [5]. Brown spot, a fungal disease, also poses a serious threat in East Asia, capable of wiping out entire pepper harvests and causing extensive economic losses [6]. To address these challenges, various pre-processing, segmentation, feature extraction, and classification techniques are employed for disease identification and detection.

The raw images from the original dataset are pre-processed by some of the following techniques. Pepper leaf image is processed using the pre-processing technique such as, Gaussian Amended Bilateral Filter (GABF) to improve edge-preserving and smoothing. GABF have the ability to preserve edges more effectively whereas reducing noise. Gaussian improvement in suppressing outliers and reducing artifacts, thereby improving the overall visual quality of the filtered image. Nevertheless, computationally intensive, especially for high-resolution images, due to its non-linear nature [7]. Consequently, Gaussian Filter (GF) is utilized to smooth the blur images and reduce noise from the pepper leaf image. The GF applies uniform blurring in all directions, ensuring that the smoothing is consistent across the image. Nevertheless, GF distort lesion boundaries, it is harder to distinguish between healthy and diseased regions on pepper leaves [8]. To overcome the above limitation proposed SADoG filter based pre-processing technique is utilized to enhance disease-affected regions by preserving essential edge information from pepper leaf image for further Processing.

Some of the following existing segmentation techniques are used to segment the PLD from the pepper leaf. Segmentation based on Kernelized Gravity-based Density Clustering (KGDC) technique is a kernel methods to group data points based on their density and similarity in pepper leaf. KGDC is to form clusters of irregular shapes, it suitable for segmenting complex disease-affected regions. However, computationally expensive, especially for large image datasets or high-resolution images, real-time diagnosis are more difficult [9]. Additionally, Semantic segmentation precisely identifying and localizing disease-affected regions on pepper leaves. Semantic segmentation provides pixel-level labeling, enabling precise identification of diseased areas, it is critical for monitoring disease spread and severity. Nevertheless, model performance depends heavily on pepper leaf image quality, lighting, and background conditions [10-11]. For the above limitation the boundaries, region, areas and lesion are segmented using the NR-FCM. In this research NR-FCM approach is proposed that effectively segments the pepper leaf image.

Furthermore, feature extraction methods helps to pick important parts from pepper leaf images to detect the disease easily. In existing methods, Speeded-Up Robust Features (SURF) is to identify and match key points in diseased regions across different pepper leaf images. SURF is invariant to image scale and rotation, which is useful for analyzing pepper leaves captured at different angles and distances in field conditions. Nonetheless, blurred, low-contrast, or noisy images reduce the accuracy of key point detection, leading to poor performance [12]. Consequently, Local Binary Pattern (LBP) used to extract features based on the local texture patterns of pepper leaf image. LBP is excellent for detecting disease symptoms like spots, patches, scabs on pepper leaves. Nonetheless, LBP captures local texture and ignores global shape or color features, which is important in identifying complex PLD symptoms [13]. Moreover, Superlet Transform (SLT) for PLD enhancing feature extraction technique through frequency analysis of pepper leaf image textures and patterns. SLT is effective in extracting complex and multi-scale patterns; it is suitable for detecting a small spots to large blighted areas. However, SLT need image normalization, noise reduction, or segmentation beforehand, especially when applied to real-world pepper leaf images with cluttered backgrounds [14]. Therefore, the proposed feature extraction technique utilizes S-Transform for addressing the above limitations and efficiently capturing both global and localized disease patterns from pepper leaf images.

The healthy and infected pepper leaf image is classified by some of the following technique. In existing method, to classify PLD using Convolutional Neural Network (CNN) based on the disease identification system in a real cultivation environment. CNN achieve very high accuracy in detecting and classifying various PLD, capable of detecting and classifying multiple diseases in a single model, even if symptoms are complex. However, CNN require large, labeled datasets for optimal performance, high-quality PLD images is time-consuming and expensive [15]. To overcome the limitations of existing classification, a proposed AdaBN-DenseNet classifier is implemented for handle variations in data distribution caused by changes in lighting, background, leaf texture to get high accuracy and efficiency of PLD detection.

2. Related work

Devi *et al* [16] (2021) have proposed a Histogram-based Gradient Boosting HistGradient Boosting Classifier to classify the PLD. HistGradient Boosting is a highly efficient implementation of Gradient Boosting Decision Trees (GBDT). HistGradient Boosting continue features into discrete histograms, reducing computation time and memory usage especially for large datasets and it is suitable for large-scale agricultural disease datasets. Nevertheless, cannot process raw image pixels directly, needs careful hyper parameter tuning to avoid over fitting.

Shao *et al* (2024) have presented a Successive Projections Algorithm (SPA) with Back-Propagation (BP) neural network to identify the pepper leaf image. The SPA-BP model aids in selecting relevant, non-redundant features from high-dimensional data, which improves classification performance by removing noise and redundancy. SPA have faster training times and lower computational complexity for the BP neural network. Nevertheless, SPA depends heavily on the initial features extracted from the images. Poor feature choices will reduce the effectiveness of SPA-BP.

Bhagat *et al* [18] (2024) have invented an Xception and VGG-16 architecture to identify and classify the PLD image. Diseases like leaf rot, leaf blight, and yellowing are identified using the pepper leaf image. It is used to segregate and classify the disease types of PLD images with higher accuracy. Every layer in VGG-16 receives input from all previous layers, promoting reuse of learned features and improving representation. However, due to its depth and parameter size, prediction of leaf disease is slower.

Sachdeva *et al* [19] (2021) have proposed a deep CNN model using Bayesian learning for detection and classification of PLD. Bayesian learning is applied on top of the residual network to enhance feature learning by effectively capturing and modelling the dependencies between pixels, leading to more efficient and robust representation of image features. Deep CNNs are excellent at learning complex patterns (color, texture, lesions) from raw leaf images, providing high performance in identifying various PLD. However, Bayesian models often require multiple forward passes to estimate uncertainty, slower than deterministic CNNs during PLD prediction.

Duan *et al* [20] (2024) have presented a Partial Least Squares Discriminant Analysis (PLS-DA) and One-Dimensional Convolutional Neural Network (1D-CNN) to identify the PLD image. PLS-DA efficiently reduces high-dimensional input data like extracted features, isolating the most discriminative components to PLD classification. Nevertheless, PLS-DA captures linear relationships between features and classes. If the disease patterns are non-linear, this method might miss important information unless complemented with deeper modelling.

The contribution of the work as follows:

- Pre-processing based SADoG filter for PLD detection efficiently enhances disease-affected regions by preserving edge and suppressing background noise, improving further segmentation.
- NR-FCM based segmentation provides accurate and noise-tolerant segmentation of infected pepper leaf areas, especially in noisy images.
- S-Transform for extracting time-frequency domain features, capturing both localized and global patterns in diseased leaf textures.
- AdaBN-DenseNet architecture, allowing the model to dynamically adjust to distributional shifts in input data, improved robustness and generalization across different PLD types

3. Proposed work

The proposed work introduces a robust and intelligent system for PLD detection that integrates multiple advanced techniques. Figure 1 shows the block diagram for the proposed AdaBN-DenseNet classifier. The preprocessing based SADoG filter, which enhances the contrast of leaf textures by preserving fine disease-related areas whereas suppressing background noise. Following this, NR-FCM based segmentation is applied to accurately isolate diseased regions by incorporating spatial neighborhood information, creating the segmentation process more robust to noise and intensity variations commonly found in pepper leaf images.

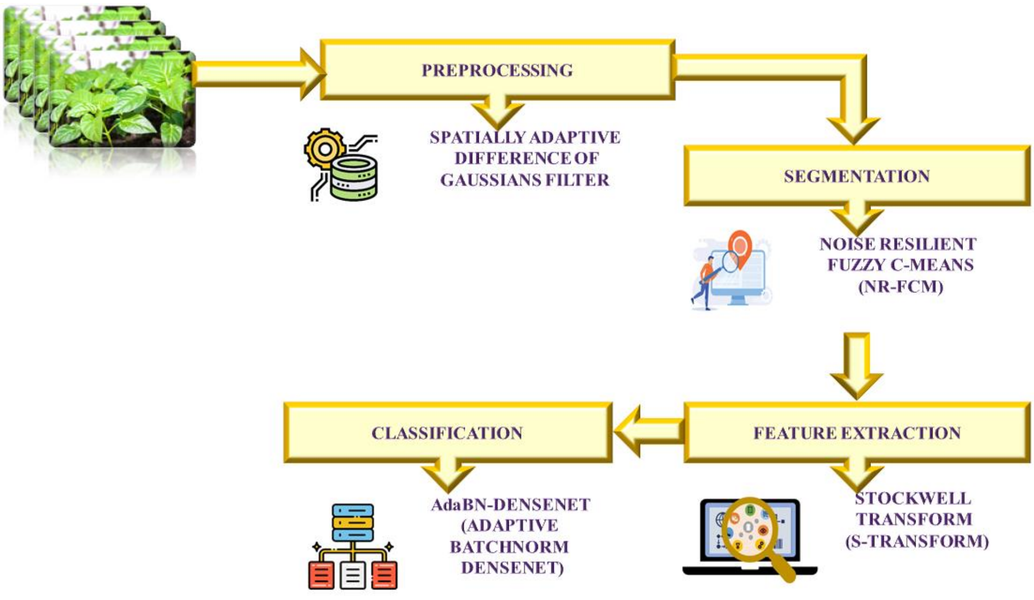

Figure 1: *Block diagram of the proposed work*

After segmentation, feature extraction is performed using the S-Transform, a powerful tool that combines time and frequency domain analysis to capture both localized and global patterns of disease symptoms on the pepper leaf surface. These highly discriminative features are then fed into an AdaBN-DenseNet classifier, which adapts to variations in data distributions and improves generalization performance, especially across different lighting conditions, leaf orientations, or environmental backgrounds.

3.1 Pre-processing by Spatially Adaptive Difference of Gaussians (SADoG) filtering,

In the PLD detection, pre-processing stage is utilized using the SADoG filter, a variant of standard DoG filter that dynamically adjusts to local image content to enhance important details whereas suppressing background noise and irrelevant textures. The traditional Difference of Gaussians (DoG) is defined as:

$$DoG(x,y) = G_{\sigma_1}(x,y) - G_{\sigma_2}(x,y) \quad (1)$$

Where $G_\sigma(x,y)$ is the Gaussian function applied to the image with standard deviation σ, $\sigma_1 < \sigma_2$ are two different scales (typically small and large), (x,y) are spatial coordinates in the image. In Spatially Adaptive DoG, the filter adapts the values of σ_1 *and* σ_2 based on the local properties of the image, such as brightness variance or texture complexity. This adaptability ensures that fine details such as disease spots, discoloration, vein deformation, and fungal patterns are preserved and highlighted, whereas non-essential variations such as shadows or background clutter are minimized.

This enhancement improves the clarity of affected leaf regions, which is vital for downstream segmentation and classification stages. By enhancing high-frequency components (like edges and lesions), SADoG significantly boosts the reliability of disease pattern detection in varying lighting and image quality conditions. The processed image is fed to segmentation based on Noise-Resilient Fuzzy C-Means algorithm.

3. 2 Segmentation by Noise-Resilient Fuzzy C-Means algorithm

In the PLD detection, the NR-FCM algorithm is used for the segmentation stage, where it effectively separates diseased regions from healthy parts of the leaf. Traditional clustering methods like K-Means assign pixels to only one cluster, whereas Fuzzy C-Means (FCM) allows each pixel to belong to multiple clusters with varying degrees of membership an advantage when dealing with the soft boundaries of disease spots. The basic objective function of FCM is:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} (\|x_i - c_j\|)^2 \quad (2)$$

Where, N is the total number of pixels, C is the number of clusters, x_i is the i^{th} pixel feature vector, c_j is the center of the j^{th} cluster, u_{ij} is the membership degree of x_i to cluster j, $m > 1$ is the fuzziness parameter (typically m=2). In NR-FCM, the standard FCM in figure 2 is enhanced by introducing spatial information into the membership function. This means that the clustering process not only considers pixel intensity but also the relationship between neighboring pixels, improving its ability to resist noise and image artifacts.

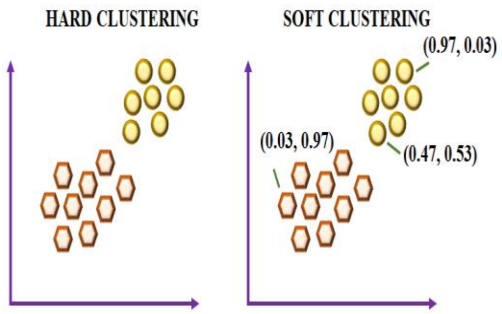

Figure 2: *Basic FCM function*

NR-FCM enhances segmentation by assigning smoother and more context-aware membership values. This is especially useful in pepper leaf images, where disease symptoms appear as irregular spots, blurs, or mild discolorations that are difficult to isolate using hard thresholds. By accounting for local spatial continuity, NR-FCM reduces the effect of noise and small texture variations, enabling precise detection of infected regions even under non-uniform lighting or complex backgrounds. This accurate segmentation forms a strong foundation for effective feature extraction and classification in the overall disease detection system. Following, the segmented output is fed to feature extraction technique for pepper leaf image.

3. 3 Feature extraction by Stockwell Transform

In PLD detection, the S-Transform is utilized as an advanced feature extraction technique that captures both spatial and frequency characteristics of leaf texture patterns. Unlike traditional transforms that provide limited resolution in either time or frequency, the S-Transform offers a multi-resolution time–frequency representation, creating it highly suitable for detecting localized disease symptoms like spots, streaks, fungal textures, and pigment alterations on pepper leaves. For 2D image, the S-Transform is extended from 1D as follows:

$$S\left(x, y, f_x, f_y\right) = \iint I(\xi, \eta).\, g\,(\xi - x, , \eta - y,) f_x, f_y). e^{-j2\pi(f_x\xi + f_y\eta)} d\xi d\eta \quad (3)$$

Where $I(\xi, \eta)$ is the input image (intensity values of the pepper leaf), (x, y) are spatial coordinates in the image, f_x, f_y are spatial frequency components, $g(\cdot)$ is a frequency-dependent Gaussian window, the exponential term $e^{-j2\pi(f_x\xi + f_y\eta)}$ localizes frequency content at each pixel.

The 2D Stockwell Transform processes the segmented pepper leaf image by sliding a frequency-scaled Gaussian window over each region and computing the local spectral content at every spatial position. This allows the system to extract detailed frequency-domain features that are localized in space, which is critical for identifying disease-infected areas with varying sizes, orientations, and intensities. Disease symptoms often manifest as complex texture variations that not easily captured using traditional spatial filters or edge detectors. The S-Transform overcomes this by offering scale-adaptive filtering, which enhances both fine features (like small fungal spots) and coarse features (like widespread discoloration or wilting).

These extracted S-Transform coefficients form a rich, discriminative feature set that describes the underlying pathology in the leaf's surface. The result is a robust input for deep learning classifiers (like AdaBN-DenseNet), improving classification accuracy across a variety of disease types and leaf conditions. In essence, the S-Transform bridges the gap between spatial and spectral analysis in image processing, providing a powerful foundation for reliable PLD detection.

3. 4 Classification by Adaptive Batch Normalization DenseNet

In the classification stage of PLD detection system, the AdaBN-DenseNet model is employed

to classify extracted features into specific disease categories. This classifier enhances the standard DenseNet architecture by incorporating AdaBN, which enables the network to handle variations in data distribution caused by changes in lighting, background, or leaf texture common challenges in real-world agricultural imagery. A typical Batch Normalization layer in a neural network standardizes the input to each layer:

$$BN(x) = \gamma . \frac{x - \mu B}{\sqrt{\sigma_B^2 + \epsilon}} + \beta \quad (4)$$

Where, x is the input feature, μB and σ_B^2 are the batch mean and variance, ϵ is a small constant for numerical stability, γ *and* β are learnable parameters (scale and shift). In AdaBN, instead of using fixed batch statistics across all domains, the model adapts the mean μB and variance σ_B^2 to match the distribution of the target domain, which in this case includes various pepper leaf images affected by different diseases and environmental conditions. Figure 3 structure of AdaBN for the PLD disease.

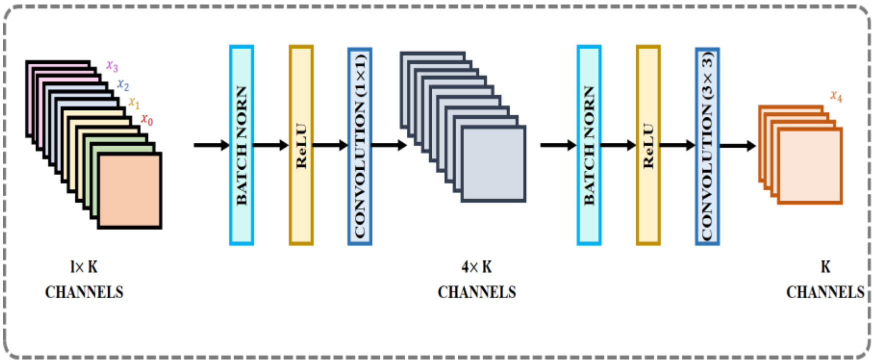

Figure 3: *Structure of Adaptive Batch Normalization*

3.4.1 DenseNet Integration

Figure 4 shows the DenseNet component and introduces dense connectivity, where each layer receives feature maps from all preceding layers:

$$x_l = H_l([x_0, x_1, \dots x_{l-1}]) \quad (5)$$

Here, H_l is a composite function (batch normalization, ReLU, convolution), and the concatenation [x_0,x_1,…x_(l-1)] promotes feature reuse and strengthens gradient flow. In AdaBN-DenseNet, the BatchNorm layers within H_l are replaced with adaptive versions that dynamically adjust to the dataset, improving classification generalization across diverse leaf types and conditions.

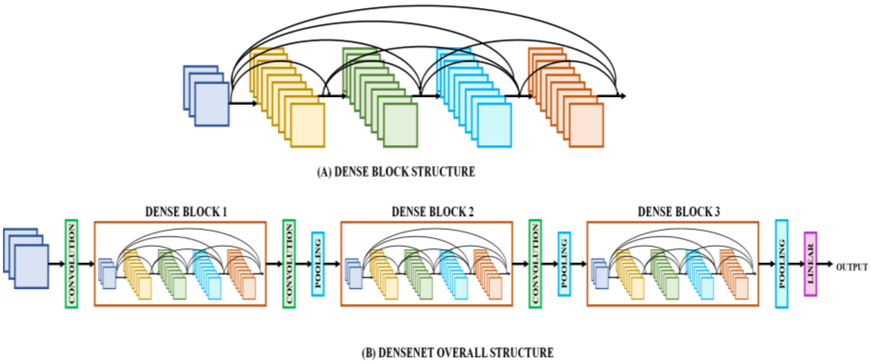

Figure 4: *Dense block structure and dense overall structure*

The AdaBN-DenseNet classifier serves as a powerful deep learning model for the classification of PLD. By combining dense connections with adaptive normalization, this architecture allows deep layers to effectively learn and propagate detailed texture and shape features extracted from diseased leaf regions. Table 1 shows the algorithm for the AdaBN for the PLD detection.

Table 1: *Algorithm for AdaBN*

Algorithm AdaBN
for neuron j in DNN **do**
Concatenate neuron responses on all images of target
Domain t:X_j=[….,$x_j(m), \dots .$]
Compute the mean and variance of the target
Domain:$\mu_j^t = E(X_j^t), \sigma_j^t = \sqrt{Var(X_j^t)}$
end for
for neuron j in DNN, testing image m in target domain
do
Compute BN output $y_j(m) \coloneqq$

$$\gamma_j \frac{\left(x_j(m) - \mu_j^t\right)}{\sigma_j^t} + \beta_j$$

end for

Figure 5 shows the DenseNet's connectivity ensures that important low-level and high-level features are retained throughout the network, whereas Adaptive Batch Normalization enhances the model's ability to handle domain shift such as different lighting, leaf orientations, or background clutter.

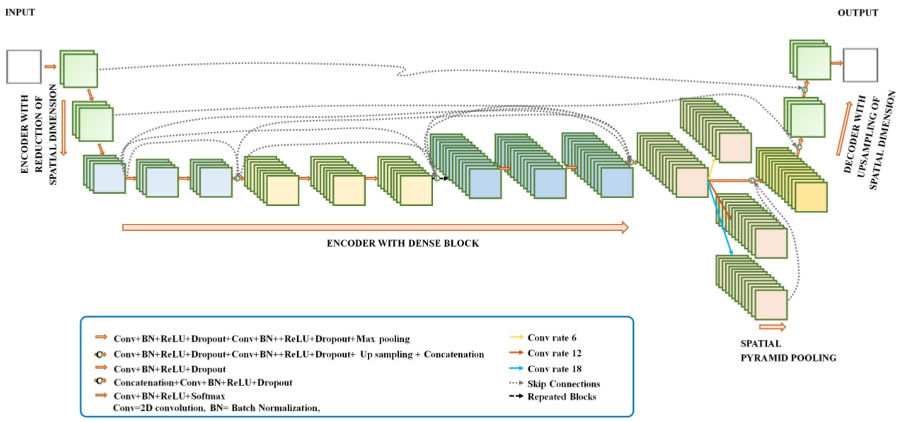

Figure 5: *DenseNet connectivity with AdaBN*

This is especially crucial in agricultural scenarios, where environmental inconsistencies are common. By adjusting the normalization the model to remain stable and accurate, reducing misclassification due to dataset variability. As a result, the AdaBN-DenseNet architecture offers high precision, robustness, and scalability, making it a highly suitable solution for real-time, automated PLD diagnosis in precision agriculture systems.

4. Result and discussion

In result and discussion section the PLD are predicted using the proposed AdaBN-DenseNet Classifier for identifying disease in pepper leaf. Also, Black Pepper Leaf Blight and Yellow Mottle Virus dataset is taken from the kaggle.com implemented using Python software. The test and train images are split as 80% and 20% for healthy and diseased pepper leaf.

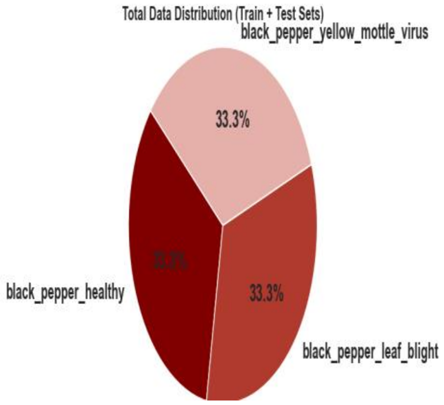

Figure 6: *Total data distribution*

Figure 6 shows the total data distribution as train and test set. The pie chart illustrates the total data distribution of pepper leaf images across three categories healthy, leaf blight, and yellow mottle virus for both training and testing sets. Each class is represented equally, with a distribution of 33.3%, indicating a balanced dataset. This balanced representation ensures that the model receives an equal number of samples from each class during training.

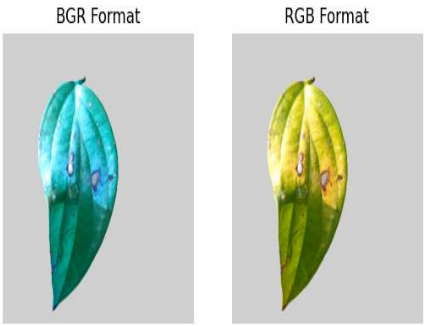

Figure 7: *BGR format to RGB format*

Figure 7 shows the BGR format to RGB format for PLD detection. The image demonstrates the visual difference between BGR (Blue-Green-Red) and RGB (Red-Green-Blue) color formats using a pepper leaf. BGR format appears with an unnatural bluish tint, which occurs because the blue and red color channels are reversed. The same image in RGB format displays the pepper leaf with its natural green and yellow hues, accurately reflecting its real appearance. Converting BGR to RGB ensures consistency, especially when using visualization tools or deep learning models trained on RGB images.

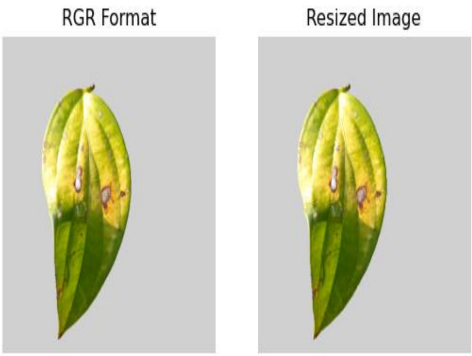

Figure 8: *RGB format to resized image*

Figure 8 shows the RGB format to resized image for PLD detection. RGB Format, indicating that have been an incorrect channel order where the red and green channels were repeated potentially leading to distorted color representation. The image is shown after being resized, maintaining the correct RGB color order whereas adjusting the dimensions of the image. Resizing is essential to standardize all images to a fixed size, ensuring uniformity and compatibility during training and inference. Overall, these preprocessing steps are crucial for improving model performance and ensuring consistent and meaningful input data.

Figure 9: *Resized image in to grayscale image*

Figure 9 shows the resized image in to grayscale image. The resized images maintains its original color in the RGB format but have been scaled to a standard dimension, which is essential for ensuring consistent input size. The grayscale image is derived from the resized color image by converting it into shades of gray, eliminating color information whereas preserving structural and intensity features. Grayscale conversion simplifies image data by reducing it to a single channel. The pre-processing steps prepare the image for efficient and focused analysis in disease detection

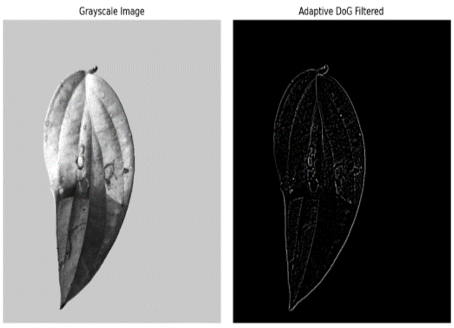

Figure 10: *Grayscale image in to SADoG*

Figure 10 shows the grayscale image in to SADoG for PLD detection. The grayscale image retains the structural details of the leaf without color, helping highlight texture and intensity variations. The SADoG filtered image enhances the edges and fine details by applying a difference between two Gaussian blurs. This filtering technique sharpens regions with high spatial frequency (edges and spots), which is especially useful for detecting disease patterns, lesions, texture anomalies on the leaf surface.

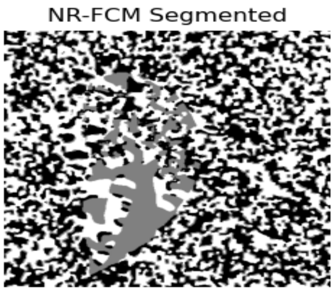

Figure 11: *NR-FCM segmented*

Figure 11 shows the NR-FCM segmented for PLD detection. The pepper leaf region have been segmented and highlighted in gray, whereas the background and noise are represented by black and white speckles. NR-FCM incorporates spatial information and robust distance metrics to better differentiate between leaf image regions and noise. This technique is useful for precise segmentation of infected leaf regions.

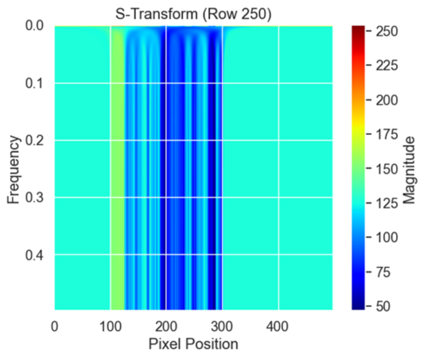

Figure 12: *S-transform*

Figure 12 shows the S-Transform for PLD detection. S-Transform is a time-frequency analysis tool that provides localized frequency information for each pixel. The X-axis denotes pixel position, whereas the Y-axis indicates frequency, and the color scale represents magnitude (intensity) of the frequency components. Higher magnitudes are shown in yellow to red, whereas lower magnitudes appear in blue to cyan. The vertical bands regions with concentrated frequency activity, possibly corresponding to structural or textural features in the original image row.

4.1 Performance metrics for PLD detection

Performance metrics, such as accuracy, sensitivity, and specificity, indicate that the pepper leaf is correctly detected and appropriately analysed as the probabilities calculated by AdaBN-DenseNet Classifier. The performance metrics in this study explained in table 2.

Table 2: *Performance Metrics*

Performance metrics	Values
Accuracy	92%
Precision	93%
Recall	92%
F1-score	92%

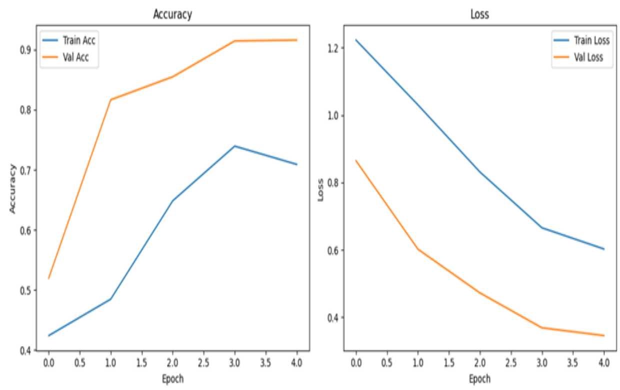

Figure 13: *Accuracy and loss*

Figure 13 shows the training and validation accuracy and loss. The X-axis denotes the epochs and Y-axis denotes accuracy for pepper leaf image. The model accuracy graph illustrates increasing accuracy of 92%, 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.

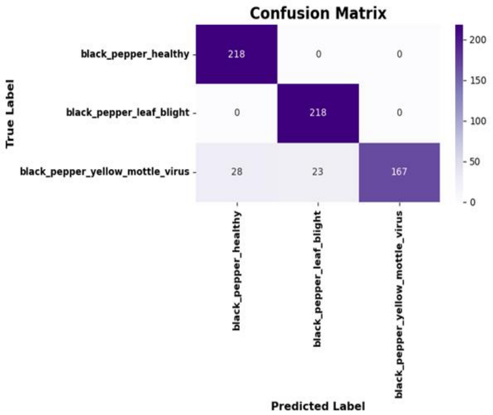

Figure 14: *Confusion matrix*

Figure 16 shows the confusion matrix for pepper leaf image. Proposed method evaluates the model's performance for three classes' black pepper healthy, leaf blight and yellow mottle virus. The X-axis indicates the predicted label and Y-axis indicates the true label. Black pepper healthy have the value of 218, leaf blight have the value of 218 and yellow mottle virus have the value of 167 respectively.

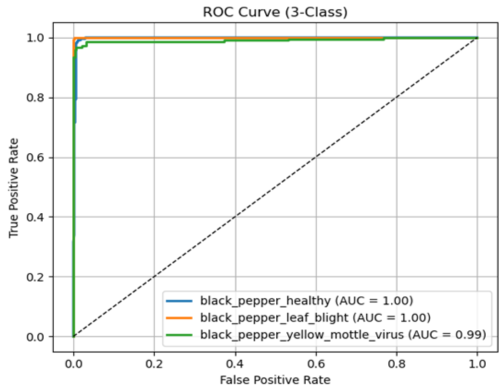

Figure 15: *ROC curve*

Figure 15 shows the ROC curve for proposed AdaBN-DenseNet Classifier continues to have the highest AUC value of 1 demonstrating for healthy and leaf blight , yellow mottle virus have the AUC value 0f 0.99 of pepper leaf image approach. The X-axis indicates the false positive rate and Y-axis indicates the true positive rates. The ROC curve shows the orange color curve it have the value 1 for leaf blight, blue color indicates the healthy and green color indicates the yellow mottle virus.

4.2 Comparison for the suggested method

The comparison of the suggested method with existing method is presented in table 3. The HistGradient Boosting Classifier have the classification accuracy of 89.11% [16], a deep CNN model using Bayesian learning have the accuracy of 90% [19], Xception and VGG-16 have the classification accuracy of 91.7% [18] and the proposed AdaBN-DenseNet have the higher accuracy of 92% compared to the existing method in table 3. The proposed AdaBN-DenseNet have better performance for PLD detection.

Table 3: *Comparison for the proposed method*

Method	Accuracy
HistGradient Boosting Classifier	89.11%
Deep CNN model using Bayesian learning	90%
Xception and VGG-16	91.7%
AdaBN-DenseNet	92%

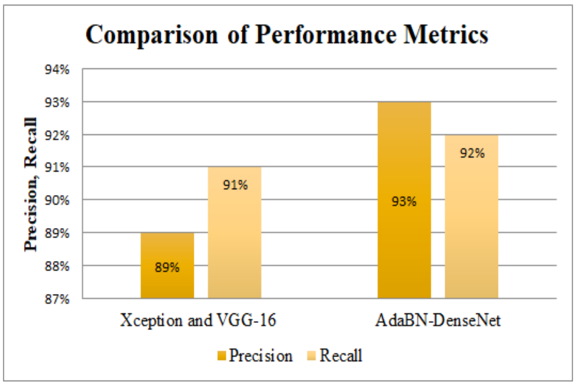

Figure 16: *Comparison of performance metrics for precision and recall*

Figure 16 shows the comparison of performance metrics for precision and recall value of proposed work and the existing work. The Xception and VGG-16 have precision value of 89% and recall value of 91% [18], and proposed AdaBN-DenseNet have the precision value of 93% and recall of 92% for identifying PLD. The proposed precision and recall value is high compared to the existing method.

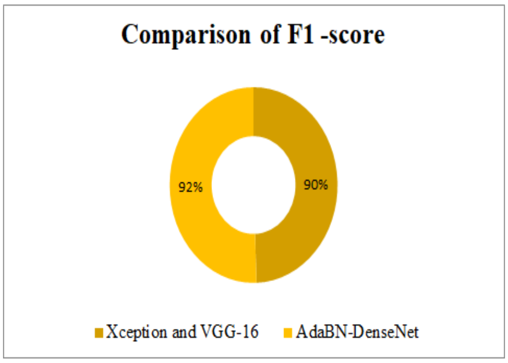

Figure 17: *Comparison of F1 score*

Figure 17 shows the comparison of F1 score value of proposed work and the existing work. The Xception and VGG-16 have F1-score value of 90% [18], and proposed AdaBN-DenseNet classifier have the F1- score value of 92% for identifying PLD detection. The proposed F1 score value is high compared to the existing method.

5. Conclusion

In this study, the proposed AdaBN-DenseNet is utilized to predict the PLD to achieve high prediction accuracy. Pre-processing by SADoG filtering, the model enhances critical leaf textures whereas reducing background noise, setting a clean foundation for analysis. The NR-FCM based segmentation further refines the process by effectively isolating diseased regions, even under noisy or inconsistent conditions. The S-Transform for feature extraction enables the system to capture both localized and global frequency information from affected leaf areas, creating it especially effective in identifying a wide range of disease patterns. Finally, the AdaBN-DenseNet classifier passes adaptability and depth to the learning process by adjusting batch normalization parameters based on input variations, ensuring improved generalization across different leaf samples. The improved accuracy, F1-score and recall of 92 %, precision of 93% is achieved as a greater accuracy and performance in contrast to the existing methods. Overall, this integrated approach demonstrates superior performance in accurately detecting PLD and significant for real-world agricultural applications, enabling early intervention, disease monitoring, and improved crop management.

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