PADDY LEAF DISEASE CLASSIFICATION USING ADVANCED DEEP LEARNING MODELS WITH NOISE REMOVAL APPROACHES

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ABSTRACT
Effective noise removal is essential for enhancing the quality of paddy leaf images used in disease prediction and analysis. This study compares the performance of three widely used filters: the Median Filter, the Bilateral Filter, and the Non-Local Means (NLM) Filter. The evaluation focuses on three key metrics: Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM). Experimental results demonstrate that the NLM Filter consistently outperforms the Median and Bilateral Filters across all metrics. The Median Filter, although effective at removing salt-and-pepper noise, introduces slight blurring and fails to preserve intricate image details. The Bilateral Filter balances noise reduction and edge preservation but is less effective for complex noise patterns. The NLM Filter, leveraging its ability to identify and average similar patches throughout the image, achieves the lowest MSE, highest PSNR, and highest SSIM values, preserving both texture and structural details. This study highlights the superiority of the NLM Filter for noise removal in paddy leaf images, making it the preferred choice for preprocessing tasks in agricultural image analysis. After noise removal, classification was conducted using ResNet, InceptionNet, and EfficientNet. The combination of noise removal and classification methods—NLM + ResNet, NLM + InceptionNet, and NLM + EfficientNet—was analyzed. Among these, NLM + ResNet produced better results in terms of accuracy rate, precision, recall, and F1 score. The findings can guide researchers and practitioners in selecting optimal filters and DL models for improving image quality in automated disease detection systems.

1. INTRODUCTION

Rice serves as a fundamental food source in East and Southeast Asia, which collectively house over half of the global population and occupy 11% of the world's cultivated land. Research on rice monitoring offers valuable insights into food security and water resource management (Xin Zhang et al., 2018). The handling of noisy images often leads to inaccurate results. While many existing methods utilize a variety of filters to eliminate noise and improve image quality, the majority fail to deliver superior results due to limited effectiveness and higher processing times (Vaishali G. Bhujade et al., 2024).

Accurate disease prediction in paddy crops is crucial for ensuring high yields and maintaining food security.Recognizing leaf disorders is crucial for the economic prosperity of any nation (Chittabarni Sarkar et al., 2023).Rice is a vital food crop grown across numerous countries. However, diseases affecting rice leaves can severely harm crop production, resulting in lower yields and financial losses. Conventional methods for disease detection tend to be time-intensive, require significant manual effort, and demand specialized expertise (ChinnaGopiSimhadri et al., 2024). With the advent of digital imaging and machine learning, automated analysis of paddy leaf images has become a vital tool for early disease detection. However, noise in images—arising from environmental factors, camera sensors, or transmission errors—can significantly affect the accuracy of subsequent analysis. Effective noise removal techniques are therefore a critical preprocessing step to enhance image quality while preserving vital structural details necessary for accurate disease identification.

This study investigates the effectiveness of different noise removal techniques for improving the clarity and structural integrity of paddy leaf images. The evaluation focuses on key performance metrics such as image fidelity, error minimization, and structural preservation. By analyzing the comparative performance of these techniques, the study aims to identify the most effective approach for preprocessing agricultural images and classify the paddy leaf diseases using modern DL techniques. The findings provide valuable insights for researchers and practitioners seeking to optimize image quality and reliability in automated crop disease detection systems.

2. RELATED WORKS

In recent years, agriculture has gained greater significance than ever before. While plants were traditionally used to sustain humans, animals, and other living organisms, they are now also being utilized to generate electricity and other forms of energy, improving living conditions for society. Consequently, proper care of plants is essential to maximize their benefits. One of the critical areas requiring attention is the issue of diseases affecting plant leaves. These diseases can cause substantial damage, impacting economic, social, and environmental aspects. Aakrati Nigam et al. 2020 explored various leaf infections using detection and classification techniques in image processing. Initially, images of paddy leaves were captured digitally, and the RGB model was converted to the HSV model to resize the images through k-means clustering and image segmentation. Specific features were then extracted using the PCA algorithm. Additionally, a feature extraction method combined with the BFO-DNN technique was implemented to classify paddy leaf diseases. This classification approach significantly enhances detection accuracy and reduces entropy loss, effectively identifying diseases across multiple categories such as bacterial blight, sheath rot, brown spots, and normal leaves.

Experimental evaluations were conducted to assess performance metrics, including accuracy, true positive rate (TPR), true negative rate (TNR), false discovery rate (FDR), cross-entropy, and false positive rate (FPR). Comparative analyses demonstrated improved results with the proposed system. The accuracy of the hybrid BFOA-DNN system was recorded at 98%, outperforming DNN (93.5%) and BFOA-DNN (97%). For cross-entropy loss, the hybrid BFOA-DNN achieved a value of 0.0011, compared to 0.0100 and 0.0170 for BFOA and DNN, respectively. These findings highlight the efficiency and reliability of the proposed system in detecting and classifying paddy leaf diseases.

Rice is one of the world’s most important cereal crops, serving as a staple food and primary energy source for more than half of the global population. However, the yield and quality of rice grains are influenced by a variety of abiotic and biotic factors, including precipitation, soil fertility, temperature, pests, bacteria, and viruses. Farmers often invest significant time and resources into disease management, relying on the traditional method of visual inspection with the naked eye. This outdated approach often results in ineffective farming practices. The integration of advanced technology in agriculture has made it possible to automatically identify infectious agents affecting rice plant leaves. Among the deep learning algorithms, the convolutional neural network (CNN) has proven to be highly effective in addressing computer vision challenges, such as image classification, object detection, and image analysis. In their study, Krishnamoorthy N. et al. 2021 employed the InceptionResNetV2, a type of CNN model, in combination with a transfer learning approach to detect diseases in rice leaf images. By optimizing the parameters for classification, the proposed model achieved an impressive accuracy of 95.67%.

The early detection of rice diseases is crucial for minimizing damage to agricultural production and maintaining both the quality and quantity of yields. Traditional methods of manually observing rice diseases are not only labor-intensive but also expensive and time-consuming, particularly when identifying disease patterns, colors, or non-native diseases. As a solution, image processing combined with Machine Learning (ML) techniques has been utilized to detect rice diseases more efficiently and within a shorter time frame. Md. Mehedi Hasan et al. 2023 conducted a critical review of various ML techniques applied in rice disease detection using image processing. Their study analyzed the outcomes of prior research to compare the performance of different disease classification methods. The evaluation was based on key factors such as feature extraction, clustering, segmentation, noise reduction, and the accuracy of disease detection methods. The paper further highlights the use of various algorithms applied to different datasets, detailing their training methodologies, image preprocessing techniques (including clustering and filtering), and testing processes, which yielded reliable results. This comprehensive review provides valuable insights into the current advancements in ML-based approaches for the early detection of rice diseases. It also serves as a guide for future research and development in the field. Furthermore, the paper identifies several challenges that need to be addressed to enhance the effectiveness of rice disease identification systems.

The prevalence of diseases in rice leaves poses a significant challenge for farmers worldwide, threatening global food security as the population continues to grow. Timely detection and prevention of these diseases are critical to reducing their impact. PardeepSeelwal et al. (2023) conducted a thorough review of existing literature on rice disease detection, spanning the years 2008 to 2023. The study selection process followed Kitchenham's guidelines, resulting in the inclusion of 69 relevant studies. Notably, a considerable portion of the research focuses on key diseases such as rice brown spot, rice blast, and rice bacterial blight. The primary performance metric identified in the review was accuracy. Researchers emphasized the potential of hybrid methodologies that integrate deep learning and machine learning techniques to enhance the accuracy and effectiveness of rice leaf disease recognition. This systematic review highlights a robust collection of scholarly work dedicated to detecting and analyzing diseases affecting rice leaves, particularly rice brown spots, rice blasts, and rice bacterial blight. The focus on accuracy underscores the critical role of precision in the detection and diagnosis of such diseases. This review showcases the effectiveness of hybrid approaches in improving recognition capabilities for rice leaf diseases. By combining deep learning with machine learning techniques, these methodologies offer promising solutions for addressing the challenges posed by agricultural diseases. This comprehensive evaluation sheds light on significant research efforts in rice disease detection over the past decade and underscores the importance of adopting advanced hybrid techniques to overcome these persistent agricultural threats.

The agricultural industry increasingly relies on automated methods for detecting and analyzing rice diseases to minimize resource wastage, reduce crop losses, enhance processing efficiency, and ensure healthy yields. Advances in deep learning techniques have had a profound impact on agricultural disease diagnosis. Rice plant leaf diseases, in particular, can severely affect crop production, making accurate and timely diagnosis essential to mitigate these effects. However, many existing methods fall short in effectively detecting diseases from leaf images, often failing to accurately assess conditions due to limitations in segmentation and computational efficiency. Complex disease stages require significant processing time, and current segmentation techniques often lack the precision, affordability, and reliability needed for practical application. To address these challenges, K. Mahadevan et al. 2024 proposed a novel approach using a Deep Spectral Generative Adversarial Neural Network (DSGAN2) combined with Improved Artificial Plant Optimization for the detection of rice plant leaf diseases. The process begins by feeding both healthy and diseased leaf images from a collected dataset into the system. The Improved Threshold Neural Network (ITNN) is then applied to enhance image quality. Subsequently, the Segment Multiscale Neural Slicing (SMNS) algorithm is used for segmentation, identifying color saturation in the enhanced images. Following segmentation, the Spectral Scaled Absolute Feature Selection (S2AFS) method is utilized to extract optimal features from the segmented leaf images. To refine the analysis further, the Social Spider Optimization algorithm selects features with the closest weight values (S2O-FCW). Finally, the proposed Soft-Max Logistic Activation Function integrated with DSGAN2 detects rice plant diseases based on the selected features. The proposed DSGAN2 system demonstrates superior performance by significantly reducing the false detection rate compared to existing systems. Specifically, it outperforms the ACPSOSVM-Dual Channels Convolutional Neural Network (APS-DCCNN) with a false rate of 55.2%, AlexNet with 50.4%, and traditional CNN with 49.5%. These results highlight the effectiveness and accuracy of the DSGAN2 system in addressing the challenges of rice plant disease detection.

3. MATERIALS AND METHODS

Rice holds a firmly established position as one of the most essential food crops globally. For most Chinese people, rice serves as a staple food, with an average yearly consumption of approximately 180 million tons (Meng et al., 2019). This research emphasizes assessing the effectiveness of three different filters in reducing noise from images of paddy leaves.The aim of the proposed model for paddy leaf disease classification is to develop a robust and efficient system that can accurately identify and classify diseases in paddy leaves by applying advanced noise removal and DL techniques.

3.1 Proposed Methodology

Figure 1 presents the workflow of the proposed noise removal system applied to the Paddy Crop and Weeds Digital Image Dataset. The process starts with the input of the dataset, which contains raw images of paddy crops and weeds. These images are typically noisy due to various environmental and technical factors, making it necessary to apply preprocessing techniques to clean them up for further analysis.

Next, in the preprocessing step, three different filtering techniques are applied to the images to remove noise. The Median filter is a simple yet effective method that replaces each pixel with the median value of its neighboring pixels, which is particularly useful for removing salt-and-pepper noise. The Bilateral filter is more advanced, aiming to preserve edges while smoothing the rest of the image, making it suitable for images with varying noise levels. The NLM filter, considered the most sophisticated, works by averaging pixels with similar characteristics, even if they are far apart, which leads to superior noise reduction while preserving the fine details of the image.

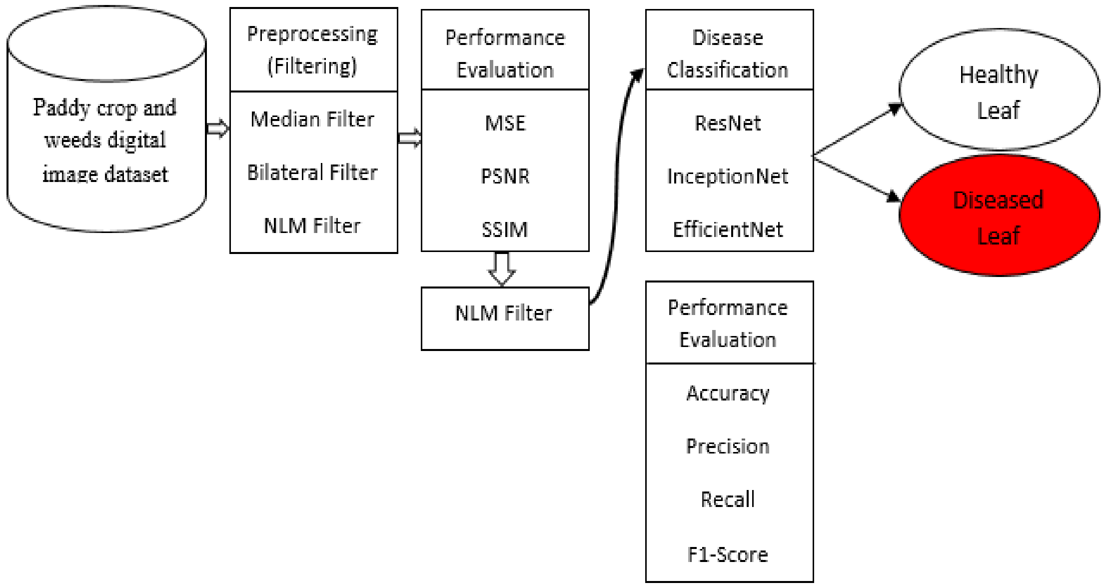

Fig 1 Workflow of the Proposed Leaf Disease Classification System

Once the images are filtered, proceed to the performance evaluation stage. Here, the effectiveness of each filter is assessed using three key metrics: MSE, PSNR, and SSIM. MSE measures the error between the filtered and original images, with lower values indicating better performance. PSNR evaluates the quality of the image, with higher values suggesting better quality. SSIM examines the structural similarity between the original and processed images, with values closer to 1 indicating higher similarity.

After noise removal, the processed images were fed into DL models for classification. Three advanced architectures—**ResNet**, **InceptionNet**, and **EfficientNet**—were used to classify the diseases:

This methodology showcases a streamlined and effective workflow for paddy leaf disease classification, demonstrating how integrating advanced denoising techniques with advanced DL models can lead to accurate and reliable results.

3.2 Image Preprocessing

Image de-noising and de-blurring are crucial tasks within the fields of image processing and signal analysis. In practical applications, contamination during image acquisition and transmission is often unavoidable (AsmatUllah et al., 2017). Noise or impurities can affect images during the conversion of color images to binary formats, primarily due to interference from equipment or environmental factors (Yangfan He et al., 2023).

Filtering is essential in the analysis of paddy leaf diseases, as it helps enhance the quality of the images used for detection and diagnosis. Paddy leaf images are often contaminated with various types of noise caused by environmental conditions, poor lighting, or camera limitations. If this noise is not removed, it can obscure important details and lead to inaccurate disease identification. By applying effective filtering methods, the noise can be reduced while preserving the critical features of the leaf, resulting in clearer, more informative images. This clarity is essential for accurate analysis, ensuring that the disease detection process is based on high-quality visual data. Moreover, filtering significantly improves the performance of automated systems used in disease detection. By cleaning up the images, filtering makes it easier for algorithms to extract relevant features and identify diseased areas more accurately. This is particularly valuable in precision agriculture, where early and precise disease detection allows for better crop management decisions, such as reducing pesticide use and optimizing resource allocation. In this way, filtering plays a key role in enhancing the efficiency and reliability of disease detection systems, ultimately contributing to healthier crops and higher yields.

3.2.1 Median Filter (MF)

The **Median Filter** is a nonlinear digital filtering technique commonly used to remove noise from images, especially salt-and-pepper noise. It replaces each pixel value in the image with the median value of the intensity levels in a defined neighborhood (kernel or window) around that pixel.

For a given pixel $P(x,y)$ and a kernel Karound it, the filtered pixel value $P^{'}(x,y)$ is:

$$P^{'}(x,y) = Median\{P(i,j) | (i,j) \in K\} - - - (1)$$

Where:

- $P(i,j)$are the intensity values of the pixels within the kernel K.
- The median is the middle value of the sorted list of $P(i,j)$.

The median filter was previously the most widely used nonlinear filter for eliminating impulse noise due to its strong denoising capability and computational efficiency (E. Ramaraj et al., 2010).

3.2.2 Bilateral Filter (BF)

The bilateral filter is a nonlinear filtering method that performs spatial averaging while preserving edges. It has proven to be an effective technique for image denoising as well as for other applications (Ming Zhang et al., 2010). For a pixel $P(x,y)$, the filtered value $P^{'}(x,y)$ is determined as:

$$P^{'}(x,y) = \frac{\sum_{i,j} P(i,j).w(i,j)}{\sum_{i,j} w(i,j)} - - - (2)$$

Where:

- $P(i,j)$: Intensity value of the pixel at (i,j).
- $w(i,j)$: Combined weight of spatial and intensity similarity, given by:

$$w(i,j) = \exp\left(-\frac{(i-x)^2 + (j-y)^2}{2\sigma_s^2}\right).\exp(-\frac{\left(P(i,j) - P(x,y)\right)^2}{2\sigma_r^2} - - - (3)$$

Here:

- σ_s^2: Controls the influence of spatial proximity (spatial Gaussian).
- σ_r^2: Controls the influence of intensity similarity (range Gaussian).

The **BF** is a non-linear, edge-preserving smoothing technique used for noise removal in images. Unlike traditional filters that consider only spatial closeness, the Bilateral Filter takes into account both spatial proximity and intensity similarity, making it particularly effective in preserving edges while reducing noise.

3.2.3 Non Local Means Filter (NLM)

The **NLM Filter** is an advanced noise reduction technique that works by denoising a pixel based on the similarity of surrounding patches rather than just local neighbors. This makes it highly effective in preserving fine textures and structural details, crucial for analyzing paddy leaf images. For a pixel $P(x,y)$, the denoised value $P^{'}(x,y)$is calculated as:

$$P^{'}(x,y) = \frac{\sum_{i,j} w(i,j) \,.P(i,j)}{\sum_{i,j} w(i,j)} - - - (4)$$

Where:

- $P(i,j)$: Intensity value of the pixel at (i,j) in the search window.
- $w(i,j)$: Weight of similarity between the patch around (i,j) and the patch around (x,y).

The weight $w(i,j)$ is computed as:

$$w(i,j) = \exp\left(-\frac{\left\|N_{x,y} - N_{i,j}\right\|^2}{h^2}\right) - - - (5)$$

Where:

- $N_{x,y}$: Patch around (x,y).
- $N_{i,j}$: Patch around (i,j).
- $\|\cdot\|^2$: Squared Euclidean distance between patches.
- h: Filtering parameter controlling the degree of smoothing.

The NLM filter offers several advantages in noise removal, particularly for applications involving paddy leaf images. One of its key strengths is its ability to preserve fine details and textures, such as leaf veins and disease spots, which are critical for accurate analysis and disease detection.

3.3 DISEASE CLASSIFICATION

3.3.1 ResNet

Identifying rice leaf diseases through agricultural technology aids in preserving crop health and securing high yields (Mononronjon Dutta et al., 2024). It leverages residual connections, which allow information to bypass layers and alleviate issues like vanishing gradients, enabling deeper and more accurate models. ResNet's ability to effectively extract features and maintain gradient flow through its residual blocks makes it highly suitable for paddy leaf disease classification, enabling accurate identification of different diseases.

3.3.2 InceptionNet

It processes image features at multiple scales through its parallel convolutional filters, making it suitable for capturing diverse patterns. InceptionNet, an advanced convolutional neural network, excels in classifying paddy leaf diseases due to its capacity to extract multi-scale features using its modular design. Its efficiency and flexibility make it well-suited for real-time applications, facilitating prompt and precise disease diagnosis in paddy crops.

3.3.3 EfficientNet

It balances model depth, width, and resolution to deliver optimized performance with fewer computational requirements.EfficientNet is a robust and efficient convolutional neural network (CNN) architecture that excels in classifying paddy leaf diseases by balancing accuracy with computational efficiency. Utilizing its compound scaling method, EfficientNet can accurately detect diseases such as bacterial blight, brown spot, and blast from leaf images. This capability ensures reliable disease identification while maintaining computational efficiency, making it an ideal choice for practical agricultural applications.

3.4 PSEUDO CODE

```
Step 1: Load the dataset
Step 2: Preprocess images
    For each image in paddy_leaf_images:
        - Resize image to input_size (e.g., 224x224)
        - Normalize pixel values: image = image / 255

Step 3: Apply noise removal using the NLM filter
    For each image in paddy_leaf_images:
        - denoised_image = ApplyNLMFilter(image)
        - Append denoised_image to denoised_images
```

Step 4: Split the dataset into training and testing sets (80% training, 20% testing)
Split dataset:
- (train_images, test_images, train_labels, test_labels) = TrainTestSplit(denoised_images, labels, split_ratio=0.8)

Step 5: Initialize classification models (ResNet, InceptionNet, EfficientNet)

Step 6: Train models
For each model in [resnet_model, inception_model, efficientnet_model]:
- model.fit(train_images, train_labels, epochs=num_epochs, batch_size=batch_size)

Step 7: Evaluate model performance
For each model in [resnet_model, inception_model, efficientnet_model]:
- accuracy, precision, recall, f1_score = model.evaluate(test_images, test_labels)

4. RESULTS AND DISCUSSION

4.1 Evaluation Metrics

The evaluation is based on three widely accepted metrics: MSE, PSNR, and SSIM. The results reveal that while the Median Filter efficiently removes salt-and-pepper noise and the Bilateral Filter balances smoothing and edge preservation, the NLM Filter outperforms both in maintaining image quality. By preserving fine details and structural integrity, the NLM Filter is identified as the optimal choice for preprocessing paddy leaf images, paving the way for more reliable disease prediction systems.

The three combinations—**NLM + ResNet**, **NLM + InceptionNet**, and **NLM + EfficientNet**—were evaluated using metrics such as accuracy, precision, recall, and F1 score. Among these, **NLM + ResNet** achieved the highest performance across all criteria, highlighting its strength in learning complex patterns from clean, noise-free images. The synergy between the effective noise removal of NLM and the robust feature extraction of ResNet contributed to this combination's success.

4.1.1 Mean Square Error (MSE)

The MSE measures the average squared difference between the original image and the denoised image. A lower MSE indicates better noise removal with minimal distortion.

$$MSE = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}[I(i,j) - K(i,j)]^2 - - - (6)$$

$I(i,j)$: Pixel value of the original image at position (i,j).
$K(i,j)$: Pixel value of the denoised image at position(i,j)..
M,N: Dimensions of the image.
MSE helps quantify the overall error introduced during denoising.

4.1.2 Peak Signal to Noise Ratio (PSNR)

PSNR quantifies the ratio between the maximum signal power and the noise power. A higher PSNR indicates better denoising quality and preservation of the original image details.

$$PSNR = 10.log_{10}\left(\frac{MAX^2}{MSE}\right) - - - (7)$$

Where:

- MAX: Maximum possible pixel value in the image (e.g., 255 for an 8-bit image).

- MSE: Mean Squared Error between the original and denoised image.

PSNR provides an intuitive measure of how well the signal is preserved relative to noise.

4.1.3 Structure Similarity Index (SSIM)

SSIM assesses the perceptual similarity between the original and denoised images by considering luminance, contrast, and structural information. It ranges from -1 to 1, where 1 indicates perfect similarity.

$$SSIM(I,K) = \frac{(2\mu_I\mu_K + C_1)(2\sigma_{IK} + C_1)}{(\mu_I^2 + \mu_K^2 + C_1)(\sigma_I^2 + \sigma_K^2 + C_2)} - - - (8)$$

Where:

- $\mu_I\mu_K$: Mean intensity values of the original image I and denoised image K.
- σ_I^2,σ_K^2: Variances of I and K.
- σ_{IK}: Covariance between I and K.
- C_1,C_2: Stabilizing constants to avoid division by zero.

SSIM evaluates the perceived image quality by considering structural details, making it particularly useful for preserving leaf textures and disease patterns in paddy images.

4.1.4 Accuracy

In paddy leaf disease classification, accuracy quantifies how well the model can correctly identify both diseased and healthy leaves from the dataset.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} - - - - - - -(9)$$

4.1.5 Precision

Precision is a metric that measures the proportion of correctly identified diseased leaves out of all leaves predicted as diseased.

$$TP = \frac{TP}{TP + FP} - - - - - - - - - - - -(10)$$

4.1.6 Recall

It is a metric that measures the model's ability to correctly identify diseased leaves out of all the actual diseased leaves in the dataset.

$$Recall = \frac{TP}{TP + FN} - - - - - - - - - -(11)$$

4.1.7 F1-Score

The **F1 Score** is a performance metric that combines both **precision** and **recall** into a single value, providing a balanced measure of a model's performance.

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} - - - - - (12)$$

- **TP (True Positives)**: The number of diseased leaves correctly classified as diseased.
- **TN (True Negatives)**: The number of healthy leaves correctly classified as healthy.
- **FP (False Positives)**: The number of healthy leaves incorrectly classified as diseased.
- **FN (False Negatives)**: The number of diseased leaves incorrectly classified as healthy.

4.2 Dataset Description

Paddy Crop and Weeds Digital Image Dataset

This dataset comprises real images of paddy fields captured from different heights and under varying natural lighting conditions. Additionally, it includes images with water and soil

backgrounds removed, along with annotated images that use different colors to represent ground truth for various types of plants (such as paddy, grass, broadleaf weeds, and sedges).
The following Figure 2 represents loading of input image, Figure 3 represents grey scale image, Figure 4 represents filtered image, Figure 5 represents segmented image and Figure 6 represents classified affected area.

Fig 2 Loading Of Input Image

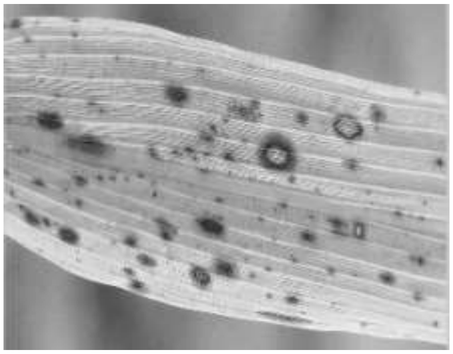

Fig 3 Grey Scale Image

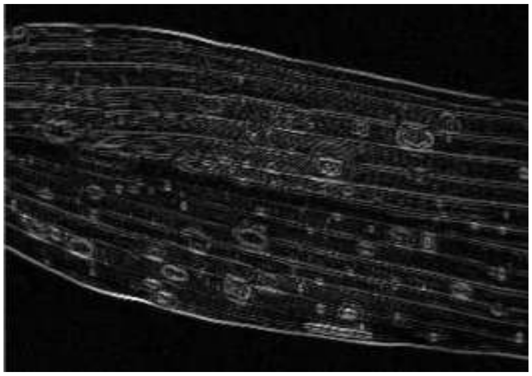

Fig 4 Filtered Image

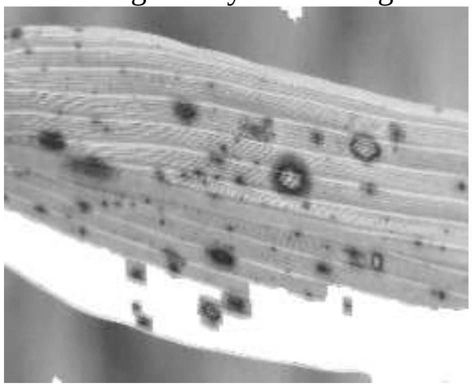

Fig 5 Segmented Image

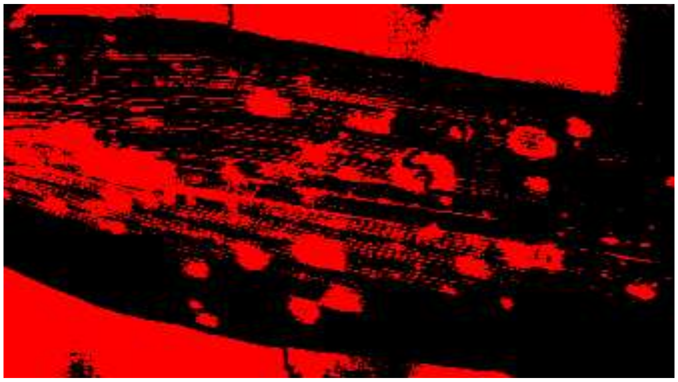

Fig 6 Classified Image

The following Table 1 represent Performance Metrics for Noise Removal Filters on Paddy Crop and Weeds Digital Image Dataset. Figure 7 represents MSE analysis and Figure 8 represents PSNR and SSIM analysis.

Table 1 Performance Metrics for Noise Removal Filters on Paddy Crop and Weeds Digital Image Dataset

DATASET	PERFORMANCE METRICS	FILTERS		
		MEDIAN	BILATERAL	NLM
	MSE	120.45	95.78	45.23

Paddy crop and Weeds Digital Image Dataset	**PSNR**	27.63 dB	29.33 dB	34.57 dB
	SSIM	0.812	0.854	0.928

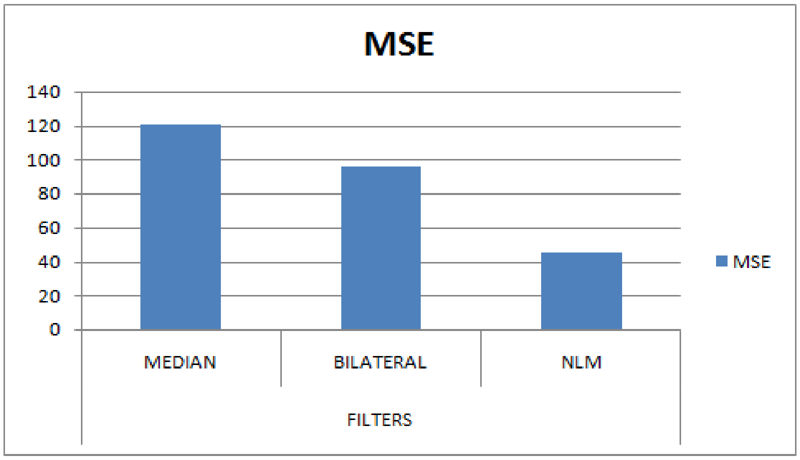

Fig 7 MSE Analysis

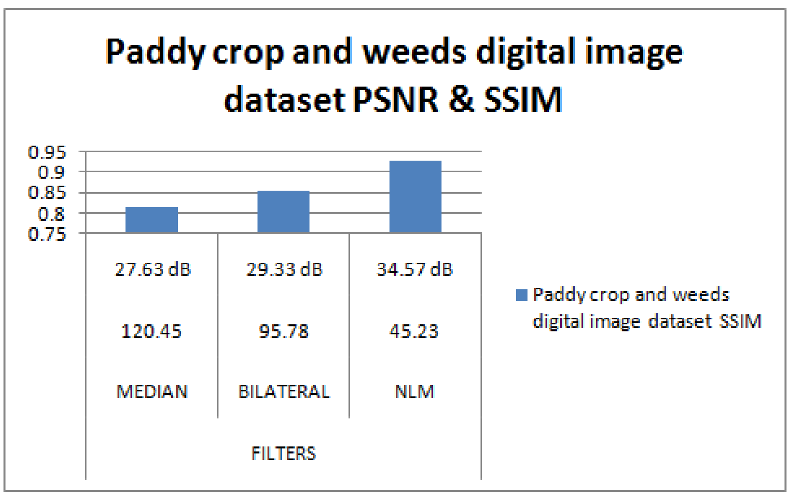

Fig 8 PSNR & SSIM Analysis

The analysis of the Paddy Crop and Weeds Digital Image Dataset focuses on the effectiveness of three filtering techniques—Median, Bilateral, and NLM—based on key performance metrics: MSE, PSNR, and SSIM. Each metric provides insight into the quality of the filtered images in comparison to the original.

MSE quantifies the average squared differences between the pixel values of the original and filtered images. A lower MSE indicates better denoising performance. The MF resulted in the highest MSE value of 120.45, reflecting the least effective noise suppression among the three. The Bilateral Filter (BF) showed improvement with a reduced MSE of 95.78, indicating better preservation of image detail and noise reduction. The NLM filter, known for its advanced denoising capabilities, demonstrated superior performance with the lowest MSE of 45.23, confirming its ability to preserve structural details while minimizing noise.

PSNR assesses the ratio of the maximum signal power to the noise, with higher values indicating better image quality. The MF (Median Filter) achieved a PSNR of 27.63 dB, which, though acceptable, is surpassed by the Bilateral filter with 29.33 dB, indicating clearer denoising and detail preservation. The NLM filter outperformed both, achieving the highest PSNR of 34.57 dB, signifying excellent denoising performance and retention of image fidelity.
SSIM evaluates the structural similarity between the original and filtered images, with values closer to 1 indicating higher similarity. The MF yielded an SSIM of 0.812, showing moderate preservation of structural integrity. TheBilateral filter improved the SSIM to 0.854, highlighting its capability to retain significant structural information. The NLM filter, once again, excelled with the highest SSIM of 0.928, demonstrating superior performance in maintaining structural similarity while removing noise.
NLM filter consistently outperformed the Median and Bilateral filters across all metrics, with the lowest MSE (45.23), the highest PSNR (34.57 dB), and the best SSIM (0.928). These results establish the NLM filter as the most effective technique for denoising and detail preservation in the Paddy Crop and Weeds Digital Image Dataset.
The NLM filter outperforms other noise removal techniques by achieving superior results across key performance metrics. It produces the lowest MSE, indicating minimal deviation between the original and denoised images, which reflects its ability to effectively remove noise while preserving the image's integrity. Additionally, the NLM filter records the highest PSNR, signifying superior noise suppression and better preservation of image quality compared to other methods. Furthermore, its SSIM is the highest, demonstrating its exceptional capability to retain fine details, textures, and structural information essential for tasks such as disease detection in paddy leaf images. These results confirm that NLM is a robust and reliable choice for enhancing the visual and quantitative quality of agricultural images.
Unlike traditional filters that rely on local neighbors, the NLM filter utilizes global information by comparing similar patches across a larger search window. This ensures effective noise reduction while retaining important structural features in the image. Additionally, the NLM filter is highly adaptable, making it suitable for removing various types of noise, including Gaussian, salt-and-pepper, and speckle noise. Its patch-based approach minimizes over-smoothing, which is a common issue with other filters, allowing it to maintain the natural appearance of the image. These advantages make the NLM filter an ideal choice for preprocessing paddy leaf images, enhancing their quality for further analysis and automated disease prediction systems.
The following Table 2 and Figure 9 compares the performance of three DL models—**ResNet**, **InceptionNet**, and **EfficientNet**—when combined with NLM filtering for noise removal. The evaluation is conducted on the **Paddy crop and weeds digital image dataset**, and the models are assessed using four key performance metrics: **Accuracy**, **Precision**, **Recall**, and **F1-Score**.

Table 2 Performance Comparison of Classification Models with NLM Noise Removal for Paddy Leaf Disease Detection

DATASET	**PERFORMANCE METRICS**	**DL Models with NLM Filters**		
		NLM+ResNet	**NLM+IneptionNet**	**NLM+EfficientNet**
Paddy crop and Weeds Digital	**Accuracy**	94.8%	89.3%	91.2%
	Precision	0.95	0.86	0.91
	Recall	0.95	0.89	0.92
	F1-Score	0.95	0.89	0.91

Image Dataset				

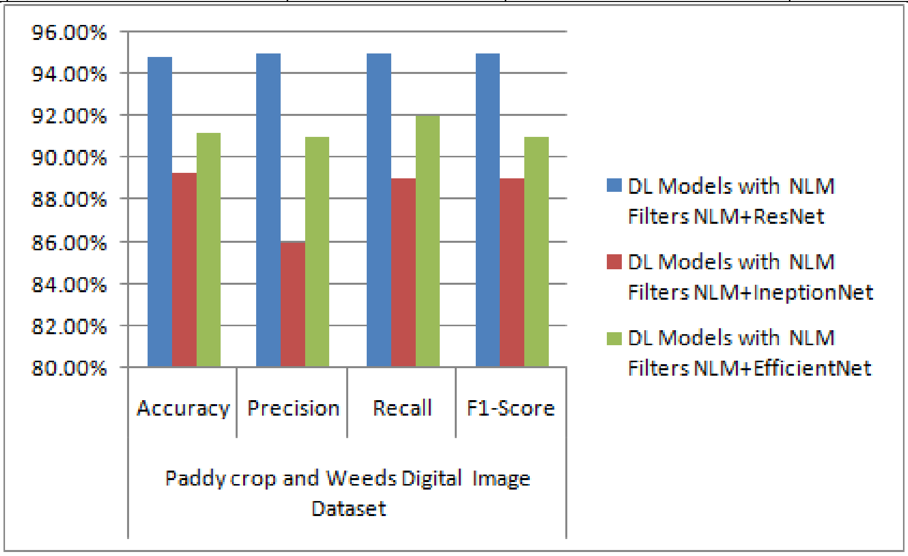

Fig 9 Performance Comparison of Classification Models with NLM Noise Removal for Paddy Leaf Disease Detection

The combination of **NLM + ResNet** achieves the highest accuracy of **94.8%**, indicating that it can effectively classify paddy leaf diseases and healthy leaves with minimal errors. In comparison, **NLM + EfficientNet** achieves an accuracy of **91.2%**, while **NLM + InceptionNet** shows a slightly lower performance with an accuracy of **89.3%**. These results demonstrate that ResNet when paired with the NLM filter for noise removal, provides the most reliable predictions in terms of overall correctness.

Combination **NLM + ResNet** achieves a precision of **0.95**, meaning that 95% of its positive classifications are correct. In contrast, **NLM + EfficientNet** achieves a slightly lower precision of **0.91**, while **NLM + InceptionNet** scores **0.86**. The higher precision of ResNet indicates its superior ability to make accurate positive predictions, reducing the number of incorrectly identified diseased leaves.

In disease classification, recall is critical for ensuring that diseased leaves are not missed. Among the models, **NLM + ResNet** achieves the highest recall at **0.95**, meaning it correctly identifies 95% of the diseased leaves in the dataset. **NLM + EfficientNet** follows with a recall of **0.92**, while **NLM + InceptionNet** achieves **0.89**. The high recall of ResNet highlights its effectiveness in capturing most of the diseased leaves, making it highly suitable for agricultural applications.

The combination **NLM + ResNet** achieves the highest F1-Score of **0.95**, indicating its balanced and reliable performance in identifying both diseased and healthy leaves. **NLM + EfficientNet** achieves a respectable F1-Score of **0.91**, while **NLM + InceptionNet** scores **0.89**.

These results confirm that ResNet, with NLM filtering, provides the best overall performance, excelling in precision and recall simultaneously.

5. CONCLUSION AND FUTURE WORK

In this study, the effectiveness of Median, Bilateral, and NLM filters for noise removal in paddy leaf images was evaluated using the Paddy Crop and Weeds Digital Image Dataset. The results demonstrated that while the Median and Bilateral filters are effective at reducing noise, they often compromise fine details and structural integrity. In contrast, the NLM filter consistently outperformed the others, achieving the lowest MSE, highest PSNR, and highest SSIM. This indicates superior noise reduction while preserving crucial textures and features, such as disease spots and leaf veins, essential for accurate analysis. The findings establish the NLM filter as the optimal choice for preprocessing paddy leaf images, paving the way for enhanced reliability in automated disease detection and agricultural image analysis systems.

Future work will extend this study by exploring advanced noise removal techniques and integrating them with automated disease detection systems for paddy crops. Hybrid filtering approaches that combine the strengths of multiple methods, such as NLM with DL-based denoising networks, could be investigated to achieve even better results in preserving fine details and textures. Additionally, the impact of noise removal on subsequent steps like feature extraction and classification will be studied to understand the end-to-end performance improvements.

To ensure scalability and robustness, future studies will also test the proposed methods on larger and more diverse datasets, including images captured under different environmental conditions, such as varying lighting and weather. Incorporating advanced metrics like perceptual quality indices and real-world validation through expert feedback could further validate the efficacy of noise removal techniques. Furthermore, integrating noise removal techniques into real-time systems for field applications, such as mobile apps or drone-based imaging systems, could make them practical for farmers. Finally, using generative models or self-supervised learning techniques to denoise paddy leaf images without requiring paired training data could offer a novel direction for noise removal research, making it more adaptable and efficient for practical agricultural applications.

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