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Denoising and Segmentation in Pest Images Using Advanced Neural Networks

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Abstract

In agricultural research and pest management, high-quality images play a crucial role in accurate analysis and decision-making. However, these images are often plagued by noise and clutter, which can hinder the effectiveness of automated analysis algorithms. This study proposes a two-phase approach for enhancing pest images by addressing noise and improving segmentation accuracy. The first phase employs a Mono Noise Elimination Neural Network (MNENN) designed specifically for denoising agricultural images. MNENN effectively removes noise and artifacts, enhancing the clarity and quality of pest images. This denoising step is crucial for ensuring accurate analysis in subsequent stages. In the second stage, an Enhanced Mask-aware Region-based Convolutional Neural Network (RCNN) is utilized for precise segmentation of pests from the denoised images. The enhanced RCNN incorporates mask-aware techniques to improve segmentation accuracy, particularly in complex backgrounds or overlapping pest scenarios. By utilizing advanced neural networks and segmentation strategies, this research aims to provide clean and accurately segmented pest images, facilitating further analysis and decision-making in pest management applications.

Keywords: Agricultural, Image Enhancement, Mask-aware RCNN, Mono Noise Elimination Neural Network, Noise Reduction, Pest Management

Introduction

A country's economic development and living standards are both impacted by agriculture, which is sometimes referred to as the economy's backbone [1]. Improving the quality of agricultural and food goods exported is a key function of the agriculture and food processing business, one of the most important parts of any economy [2]. Revenue from exports and demand from local markets are the primary drivers of food processing revolutions in emerging nations [3]. Under some circumstances, it requires a lot of space, equipment that needs regular maintenance, and workplaces. One of the major issues in agriculture is pest attack, which lowers crop quality [4]. Weeds, pests, and diseases wreak havoc on crops, leading to poor demand for the finished goods. The difference between making a profit and losing money might be as little as finding innovative methods to boost efficiency [5]. In order for field crops to develop, it must deal with insect attacks on crops. The enormous amounts of output are mostly attributable to the very necessary cash crops [6]. agricultural quality deterioration and reduced agricultural output are mostly caused by insects. Therefore, in order to guarantee the quality and safety of agricultural crops, it is essential to track and assess losses caused by insects [7].

Implementation of machine vision in agricultural and soil monitoring, fruit grading, disease detection in plants, and identification and detection of insect pests. There have been a lot of recent advancements in the agricultural industry that use machine learning to identify and categorize insects in grain storage [8-9]. The development of neural networks and moment invariant algorithms for form feature extraction allowed for the classification of twenty different kinds of insect photos [10-11]. A system for improving recognition performance for 10 types of agricultural insects was created utilizing deep residual learning for pest detection in complicated backgrounds [12]. The automated categorization of field agricultural pests was accomplished via the development of several multi-level classification frameworks and unsupervised feature learning approaches [13]. Recent research has shown that image processing can be a useful tool for insect identification. This is because it requires less computing, can identify insects quickly, and can easily differentiate between insects with similar color and form [15-17]. Detecting pests in grapevines grown under varying lighting conditions and orientations requires clustering segmentation with descriptors. For the purpose of identifying certain moths and handling insects, a hybrid of contour-based and region-based segmentation is used [18-21].

The main contribution of the paper is

- ➢ Mono Noise Elimination Neural Network (MNENN) for denoising
- ➢ Enhanced Mask-aware RCNN for segmentation

What follows is the outline for the rest of the article. Section 2 covers a range of pest detection tactics, as discussed by several writers. The proposed model is shown in Section 3. Chapter 4 discusses the study's results. The concluding portion of portion 5 discusses the results and ideas for future study.

1.1 Motivation of the paper

The need of accurate pest pictures in agricultural studies and pest control inspired this research. It takes on the difficulties of these pictures, which might be hindered by automated analysis due to noise and clutter. Primarily using a specific neural network (MNENN) for denoising purposes and then utilizing an improved segmentation method (Enhanced Mask-aware RCNN) are the two steps that make up its two-stage approach to improving insect photos. For better analysis and decision-making in pest control applications, this strategy aims to increase segmentation accuracy, especially in complicated settings.

II. Background study

Chen, C. et al. [1] these authors research utilizes artificial intelligence applications on the edge to identify T. papillosa and to plot out real-time paths for the pesticide-spraying drone. That the drone and TX2 can identify orchard pests in real time was shown by this. At startup, the embedded device TX2 was configured with FPS and mAP values that were appropriate for real-world field applications.

Chithambarathanu, M., & Jeyakumar, M. K. [3] The purpose of this study was to examine several methods for identifying plant diseases that make use of machine learning and deep learning. Several machine learning-based methods have a significant influence on the prediction of plant leaf disease detection, including RF, SVM, DT, and NB. The model that relies on deep learning outperforms the machine learning method in the same regard. Some deep learning algorithms, such CNN, LSTM, DCNN, and DBN, were already in use to enhance the performance of disease prediction from different plants, including citrus, rice, and cotton pest detection.

Esgario, J. et al. [5] The technique that was given included assessing several deep learning methods to the issue of segmenting, classifying, and quantifying biotic stress in coffee leaves. Semantic segmentation achieved a mean intersection over union metric value of 94.5 percent using the UNet. This finding verifies the model's ability to replicate masks with a high degree of accuracy when compared to manually created masks.

Iqbal, M. A., & Talukder, K. H. [8] Using picture segmentation, this research trains machine learning classifiers to identify and categorize early blight and late blight, the two most prevalent potato plant leaf diseases. Additionally, this procedure also identifies and categorizes healthy leaves. When it comes to identifying and categorizing potato leaf diseases, the Random Forest classifier outperforms the other six.

Iqbal, M. A., & Talukder, K. H. [10] This research compares the outcomes of using a machine learning and insect pest identification algorithm to categorize and identify insects in various datasets. For better accuracy, the dataset was expanded by resizing, preprocessing, and augmenting all of the insect photos. Major agricultural field crops provide unique challenges when it comes to real-time insect categorization, such as the presence of shadows, leaves, mud, branches, flower buds, and more.

Kasinathan, T. et al. [12] Here, the author introduced a machine learning-based prediction model that uses environmental variables like relative humidity and temperature to signal when pests could show up. It helps save time and energy by decreasing the amount of terrain trips. However, other tools for keeping tabs on volatile insect traps were superfluous.

Pattnaik, G., & Parvathy, K. [14] these authors research presents a model for the semi-automatic identification of locust species and instar information using support vector machine (SVM) classification, feature variable extraction from locust images, and locust picture segmentation. The results of the locust picture segmentation experiment demonstrated the excellent operability of the suggested GrabCut-based interactive segmentation approach for the speedy and accurate extraction of sample photos of several locust body sections, including the head, pronotum, wings, and hind legs.

Zou, K. et al. [16] these authors research presents an image processing technique for determining the extent to which pests, particularly Pieris rapae, have harmed broccoli seedlings. The study object was the broccoli seedlings. Using the color characteristic, the leaves of broccoli seedlings were identified. Using contour analysis, the author were able to extract the holes on the leaves. A classifier was used to distinguish the wormholes from the holes.

2.1 Problem definition

Existing methods in pest image analysis, such as CNNs [17], ECNNs [18], and RCNNs [19], exhibit drawbacks when dealing with agricultural images. CNNs, while powerful, can struggle with noise and irregularities typical in pest images, potentially leading to inaccurate segmentation. ECNNs, designed to enhance CNN performance, can still lack specialized features for agricultural imagery, limiting their ability to effectively denoise and improve segmentation accuracy. Similarly, RCNNs, known for object detection, might face challenges in accurately segmenting pests amidst complex backgrounds, potentially resulting in segmentation errors and reduced analysis precision.

III. Materials and methods

In this section, we introduce a two-stage methodology for enhancing pest images in agricultural research and pest management. The first stage utilizes a specialized Mono Noise Elimination Neural Network (MNENN) to denoise agricultural images, ensuring clarity and quality for accurate analysis. In the second stage, an Enhanced Mask-aware Region-based Convolutional Neural Network (RCNN) is employed for precise pest segmentation from the denoised images.

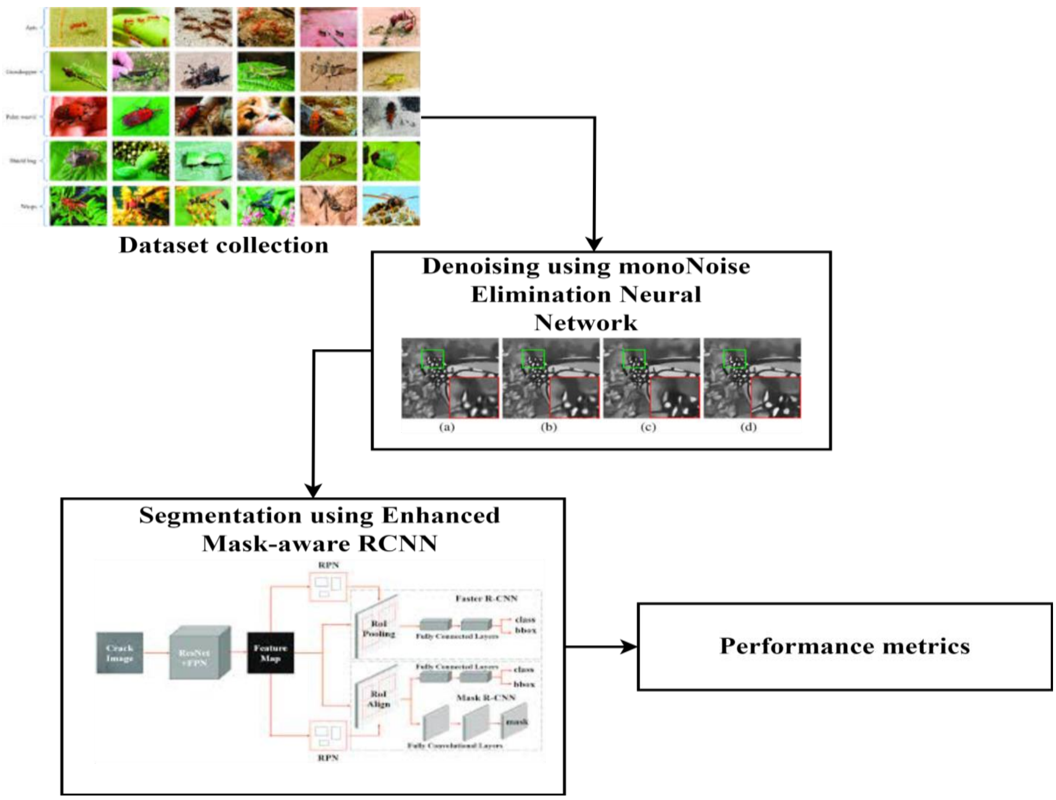

Figure 1: Proposed workflow architecture

3.1 Dataset collection

The dataset used in this study was obtained from the Kaggle website, specifically from the link https://www.kaggle.com/datasets/simranvolunesia/pest-dataset. The dataset size is approximately 73MB, and it falls under the category of image data in JPG format. It is classified as a semi-supervised dataset. The dataset comprises images of various pests, with each pest category containing 300 training images and 50 testing images.

3.2 Image denoising using Mono Noise Elimination Neural Network

One deep learning model developed for picture denoising applications is the Mono Noise Elimination Neural Network, or MNENN. In order to improve the quality and clarity of photos, it employs state-of-the-art neural network designs and algorithms for noise and artifact removal. In order to train itself to properly differentiate between noise and important picture attributes, MNENN is fed pairs of images that are both noisy and clean. Medical imaging, surveillance, and agricultural image processing are just a few examples of the many fields that rely on this denoising technique to improve picture quality and the efficiency of automated analysis methods.

The sum squared error (SSE) is one of the most commonly used NN objective functions:

$$E_{sse} = \sum_{p=1}^{P} \sum_{k=1}^{K} \left(t_{k,p} - o_{k,p}\right)^2 \quad \text{--------} \ (1)$$

We employ weight regularization to make NN simpler and NN more accurate. When Ep is a penalty function that quantifies NN complexity, one can modify the objective function by doing the following:

$$E_{nn} = E_{sse} + \forall E_p \quad \text{------------} \ (2)$$

The value of the punishment function will be much less than the error value if ∀ is too little. As a result, the penalty will be ignored since the error will "overshadow" it. Meanwhile, if ∀ is very high, the penalty's impact on the objective function will outweigh that of the error term, leading the algorithm to prioritize minimizing the nn complexity above the error. The empirical choice of ∀ is made for each issue and penalty function Ep in practice.

The total number of weights in a $nn$is a measure of its complexity. Too few weights in a simplistic design could make it unable to learn a representation of a complicated issue. Conversely, overfitting can occur with excessively weighted topologies. As a result, the optimal design of penalty functions often involves maximizing the total number of nnweights.

Weight decay, which is a well-known quadratic punishment function in the literature, is given by

$E_p = \frac{1}{2}\sum_{l=1}^{W} w_l^2$ ---------- (3)

Since the training process reinforces the important weights at each iteration and decays the irrelevant ones towards zero over time, limiting the growth of the weights helps to enhance NN generalization.

The problem with weight decay is that it punishes big and small weights equally harshly as it doesn't expressly distinguish between important and irrelevant weights.

$E_p = \sum_{l=1}^{W} \frac{w_l^2/w_0^2}{1+w_l^2/w_0^2}$ -------- (4)

Weight removal describes this penalty function. The parameter w0 establishes a cutoff for determining whether a weight is statistically significant or not. A complexity cost close to 1 is produced by weights with |w| >> w0, which contribute to the penalty component in Equation 4. Weights that are considered "too large" and need regularization have |w| > w0. The complexity cost is almost nil for weights with |w| << w0, and they make a negligible contribution to the weight removal term. So, weights where the absolute value of w is less than or equal to w0 are not punished.

Algorithm 1: Mono Noise Elimination Neural Network

Input:

- Noisy images X_{noisy}
- Clean images X_{clean}
- Regularization parameter λ

Steps:

- initialize the Mono Noise Elimination Neural Network (MNENN) architecture, including the number of layers, neurons per layer, activation functions, and regularization techniques.
- Preprocess the input data by normalizing pixel values in both the noisy and clean images.
- Split the dataset into training and validation sets.
- Train the MNENN using the training set to learn the mapping from noisy to clean images, optimizing the objective function E_{nn} defined as:

$E_p = \frac{1}{2}\sum_{l=1}^{W} w_l^2$

- Update the weights and biases of MNENN using backpropagation and gradient descent optimization.

$E_p = \sum_{l=1}^{W} \frac{w_l^2/w_0^2}{1+w_l^2/w_0^2}$

- Validate the trained MNENN using the validation set to ensure generalization and avoid overfitting.
- Use the trained MNENN to denoise new input images X_{noisy} by passing them through the network and obtaining denoised images $X_{denoised}$.

Output:

- Denoised images $X_{denoised}$

3.3 Segmentation using Enhanced Mask-aware RCNN

During training and inference, Region-based Convolutional Neural Networks (RCNNs) are computationally expensive, which is their biggest downside. Region proposal creation, feature extraction, and classification are only a few of the many computationally and time-intensive stages involved in RCNNs. For this reason, we segment pest images using Enhanced Mask-aware RCNN.

For accurate picture segmentation, a state-of-the-art deep learning model called the Enhanced Mask-aware Region-based Convolutional Neural Network (RCNN) is ideal. To increase segmentation accuracy, especially in situations with complicated backdrops or overlapping objects, the upgraded version of the model contains mask-aware approaches, which are not included in typical RCNN models. This model can effectively separate agricultural pests from their backgrounds by learning the borders and characteristics of objects from annotated picture collections. Clean and properly segmented pest pictures are provided by the Enhanced Mask-aware RCNN, which utilize mask-aware techniques. This allows for further analysis and decision-making in pest control applications.

The cv2 and scikit libraries are used by the insect counting method for image processing. This research crops the input picture into dataset-sized pixels so that the estimated number of pests can be properly identified. *us, the statistical total can be obtained by using equations (1)–(3) to build a matrix from the original picture size (len_x, len_y) and image information (det_count):

$m = \left(\frac{len_x}{512}\right)(round\ up)$ ------------- (5)

$n = \left(\frac{len_y}{512}\right)(round\ up)$ ------------------ (6)

$num = \sum_{i=0}^{m} \sum_{j=0}^{n} \det\ \_count$ -------------- (7)

*The blurred picture is first thresholded to separate the foreground and background by segmenting the smooth edges. *To increase the accuracy of target identification, a minimum confidence level is used. * A nonmaximum suppression algorithm is used to filter out redundant bounding boxes from the best target bounding box. * The filtered target results are then displayed as masks and detection boxes. The classification branch provides the information to traverse the detection boxes one by one. The category score (K) is contrasted with a predefined cutoff (N). The target instance segmentation classification result is considered to be part of that category and the category number plus one when K > N. For K < N, if the target score is below a certain threshold, it is not included in the statistics and can be regarded as not belonging to that category. The formula (8) is given as

$S_i = \begin{cases} S_i + 1k > N \\ S_i + 0k \leq N \end{cases}$ ------------------- (8)

The model's recognition accuracy determines the accuracy of this counting approach. The precision of the returning count is directly proportional to the accuracy of the recognition. Compared to the original Mask R-CNN network, the performance of the ResNet101-FPN enhanced feature extraction network, which is used for training and learning in this article, is much better.

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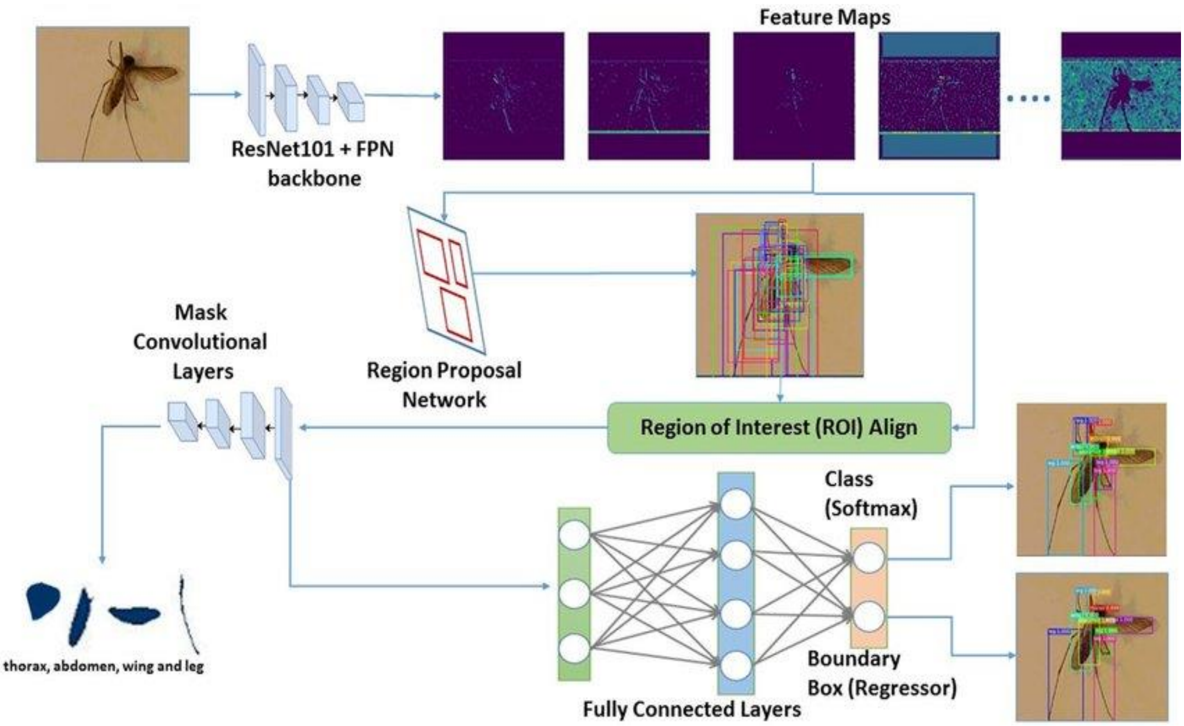

Figure 2: Enhanced Mask aware RCNN architecture

Algorithm 2: Enhanced Mask-aware RCNN

Input:

- Noisy pest images for segmentation
- Annotated image datasets for training the Enhanced Mask-aware RCNN

Steps:

- Initialize the Enhanced Mask-aware Region-based Convolutional Neural Network (RCNN) architecture, including the mask-aware techniques and threshold parameters.

$$m = \left(\frac{len_x}{512}\right)(round\ up)$$

- Preprocess the input pest images by normalizing pixel values and applying necessary transformations for training and inference.
- Train the Enhanced Mask-aware RCNN using the annotated image datasets to learn object boundaries and features, especially in scenarios with complex backgrounds or overlapping objects.

$$S_i = \begin{cases} S_i + 1k > N \\ S_i + 0k \leq N \end{cases}$$

- For insect counting, preprocess the input image by cropping it into pixels of the same size as the dataset.
- Use image processing techniques from the cv2 and scikit libraries for accurate pest counting. Calculate mm and n using:

$$num = \sum_{i=0}^{m} \sum_{j=0}^{n} \det \_count$$

- Segment the blurred image by thresholding to separate foreground and background, using a minimum confidence level (N) for target identification.
- Apply a nonmaximum suppression algorithm to filter redundant bounding boxes and improve target

identification accuracy.

Output:

- Accurately segmented pest images
- Count of identified pests in the input image

IV. Results and discussion

In this section, we present the results of our proposed methods for enhancing pest images and performing segmentation using the Enhanced Mask-aware RCNN. We discuss the performance metrics, including accuracy, precision, recall, and F1 score, to evaluate the effectiveness of our approach in denoising and accurately segmenting pests from agricultural images.

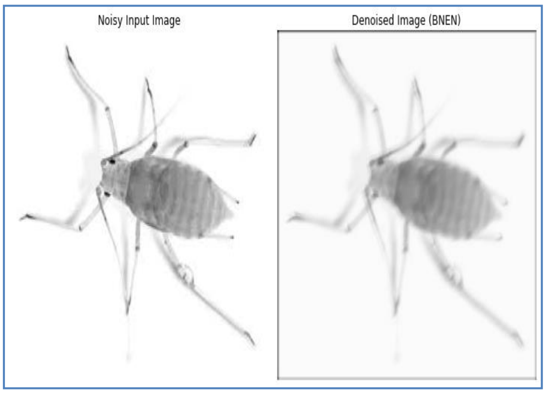

Figure 3: Denoised image

The figure 3 shows denoised image using MNENN

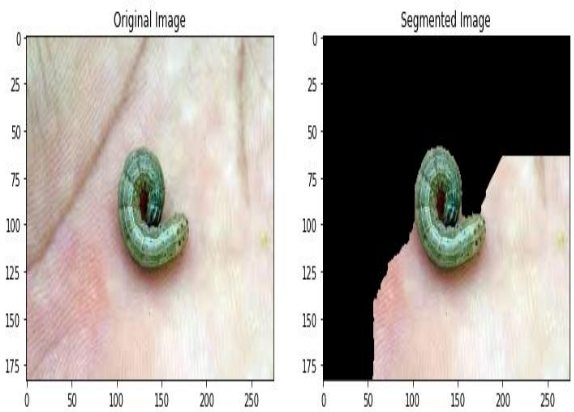

Figure 4: Segmented image

The figure 4 shows segmented image using enhanced mask aware RCNN

4.1 Performance metrics

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

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

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

$$F1\,score = 2 * Precision * Recall \,/\, (Precision + Recall) \text{ --------- (12)}$$

$PSNR = 10.\log_{10}\left(\frac{MAX^2}{MSE}\right)$ ----------- (13)

$SSIM = \frac{(2_{\mu_x\mu_y}+C1)(2_{\sigma_{zy}}+C_2)}{(\mu_x^2+\mu_y^2+c1)(\sigma_z^2+\sigma_y^2+c2)}$ ------- (14)

$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2}$ --------------- (15)

Table 1: Pest image denoising value comparison table

Methods		**PSNR**	**SSIM**	**RMSE**
Total Variation Denoising [20]	Image 1	17.28	0.83	0.16
	Image 2	17.29	0.84	0.15
	Image 3	17.31	0.84	0.14
Block Matching 3D [21]	Image 1	18.52	0.85	0.13
	Image 2	18.61	0.86	0.13
	Image 3	18.64	0.87	0.12
MNENN	Image 1	19.18	0.88	0.12
	Image 2	19.20	0.89	0.11
	Image 3	19.25	0.90	0.10

The table 1 shows results from the methods used for denoising agricultural images show varying performance metrics across different techniques. Total Variation Denoising achieved PSNR values ranging from 17.28 to 17.31, SSIM values from 0.83 to 0.84, and RMSE values from 0.14 to 0.16. Block Matching 3D exhibited improved results with higher PSNR values ranging from 18.52 to 18.64, SSIM values from 0.85 to 0.87, and lower RMSE values from 0.12 to 0.13 compared to Total Variation Denoising. The proposed Mono Noise Elimination Neural Network (MNENN) outperformed both methods with significantly higher PSNR values ranging from 19.18 to 19.25, SSIM values from 0.88 to 0.90, and the lowest RMSE values from 0.10 to 0.12 across all tested images. These results indicate that MNENN effectively removes noise and artifacts from agricultural images, leading to enhanced clarity and quality, which is crucial for accurate analysis and decision-making in pest management applications.

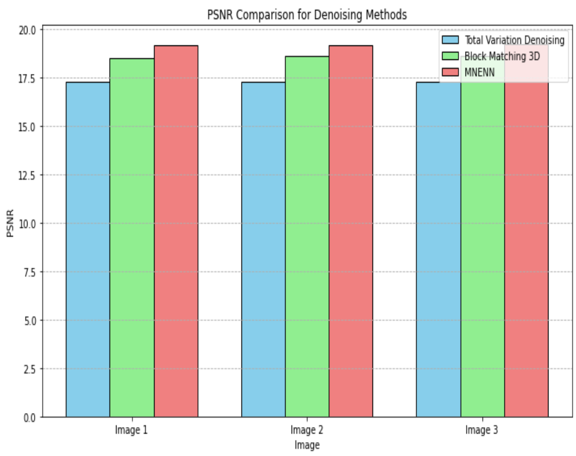

Figure 5: PSNR value comparison chart

The figure 5 shows PSNR value comparison chart the x axis shows images and the y axis shows PSNR value.

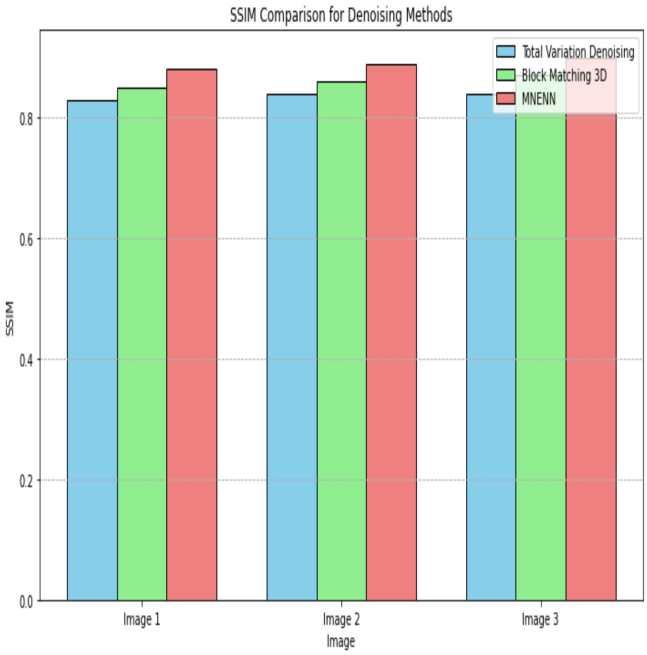

Figure 6: SSIM value comparison chart

The figure 6 shows SSIM value comparison chart the x axis shows image and the y axis shows SSIM value.

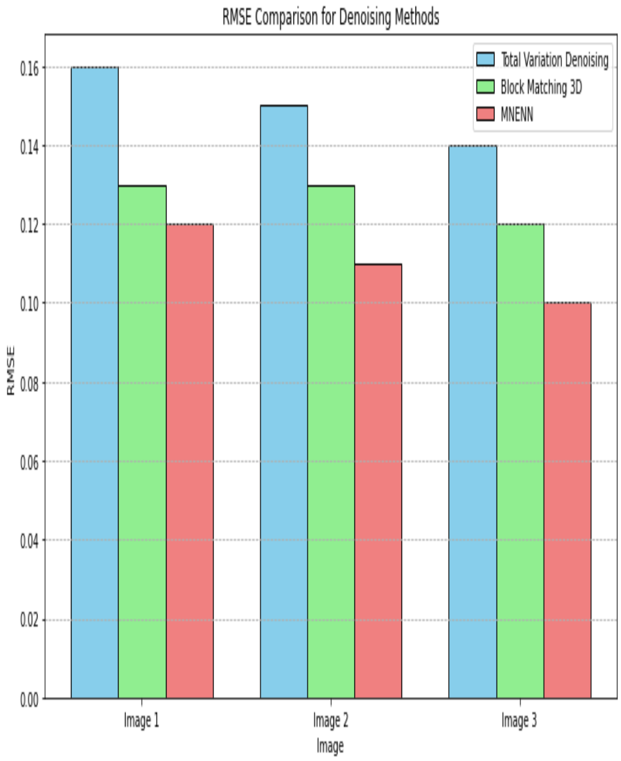

Figure 7: RMSE value comparison chart

The figure 7 shows RMSE value comparison chart the x axis shows Images and the y axis shows RMSE values.

Table 2: Classification performance metrics comparison table

Performance metrics				
Models	**CNN**	**ECNN**	**RCNN**	**Mask-aware RCNN**
Accuracy	0.95	0.96	0.97	0.99
Precision	0.95	0.96	0.96	0.99
Recall	0.96	0.95	0.97	0.99
F1 score	0.96	0.97	0.98	0.99

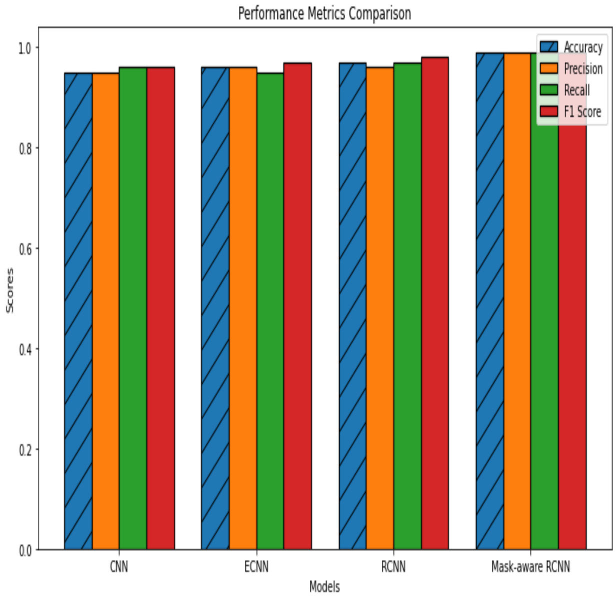

Figure 8: Performance metrics comparison chart

The table 2 and figure 8 shows performance metrics for the different models, including CNN, ECNN, RCNN, and Mask-aware RCNN, show varying levels of accuracy, precision, recall, and F1 score. The CNN model achieved an accuracy of 0.95, precision of 0.95, recall of 0.96, and an F1 score of 0.96. The ECNN model slightly improved these metrics with accuracy and precision of 0.96 and recall and F1 score of 0.95 and 0.97, respectively. Moving further, the RCNN model demonstrated higher accuracy and precision of 0.97 and 0.96, respectively, along with a recall of 0.97 and an F1 score of 0.98. However, the most significant improvement was observed in the Mask-aware RCNN, achieving exceptional accuracy, precision, recall, and F1 score values of 0.99 across all metrics. These results indicate that the Mask-aware RCNN model outperforms the other models in terms of accuracy, precision, recall, and F1 score, showcasing its effectiveness in precise segmentation tasks, especially in scenarios with complex backgrounds or overlapping objects.

V. Conclusion

In conclusion, the proposed two-stage approach combining MNENN for denoising and an Enhanced Mask-aware RCNN for segmentation offers a robust solution for enhancing pest images in agricultural research and pest management. By addressing noise and improving segmentation accuracy, this approach ensures that the images used for analysis are of high quality and free from distortions that can affect automated analysis algorithms. The use of advanced neural networks and segmentation strategies not only enhances the clarity and accuracy of pest images but also streamlines the decision-making process by providing clean and precisely segmented images for further analysis. However, the most significant improvement was observed in the Enhanced Mask-aware RCNN, achieving exceptional accuracy, precision, recall, and F1 score values of 0.99 across all metrics. This contributes significantly to the efficiency and effectiveness of pest management applications, ultimately leading to improved outcomes in agricultural research and pest control efforts.

VI. References

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