

Paddy Rice Insect and Disease Detection Using Enhanced YOLOv4

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Abstract

This research endeavors to advance the field of paddy leaf disease detection by proposing an integrated approach that leverages advanced computer vision techniques. The methodology employed comprises several key steps. Initially, a comprehensive dataset of paddy leaf images, encompassing both healthy and diseased leaves, is meticulously curated and annotated. To enhance the robustness and diversity of the dataset, image augmentation techniques, including flipping and rotation, are systematically applied. These augmentations simulate variations in leaf orientation and presentation, facilitating improved generalization of the model. In the pre-processing phase, Contrast Limited Adaptive Histogram Equalization (CLAHE) is deployed to enhance image contrast and emphasize disease-related features. CLAHE amplifies the discriminative capacity of the input data, ensuring that the model can effectively discern subtle disease symptoms. The core of this research lies in the utilization of an Enhanced YOLOv4 (You Only Look Once) model, a state-of-the-art object detection architecture. Enhanced YOLOv4's innate capability to simultaneously locate and classify objects aligns seamlessly with the task of identifying disease-afflicted areas on paddy leaves. The model is systematically trained on the augmented and pre-processed dataset, with iterative fine-tuning carried out until achieving high accuracy on a validation set. To evaluate the performance of the proposed approach, comprehensive testing is conducted on a distinct test dataset. Metrics such as precision, recall, F1-score, and mean average precision (mAP) are meticulously employed to gauge the model's efficacy in disease detection. Ultimately, this research has the potential to significantly advance the field of paddy disease management by enabling early and accurate detection of leaf diseases.

Keywords: Paddy; Leaf Disease Detection; Computer vision; Image Augmentation; CLAHE; Enhanced YOLOv4

1. Introduction

In many countries, agriculture is a significant economic factor. The first human activity that contributed to the advancement and development of humanity was agriculture [1]. Due to the growing population and their increasing need for food to sustain their existence, farming and the food industry are currently the most important industries worldwide [2]. In more than 100 countries, rice is farmed in various socioeconomic and agroecological settings [3]. Countries that produce rice have

developed programmes to increase rice crop productivity. Rice is a major food source around the world, alongside wheat and maize. However, in the field of agriculture, insect pests are regarded as a severe problem that has an impact on crop productivity in this area. Insect pests have a huge negative effect on human nutrition by ultimately lowering crop yield [4]. In some areas, this may result in individuals receiving improper or unsuitable food, or it may cause hunger. Insect pest detection is essential to agricultural pest forecasting [5]. Experts in agriculture typically identify insect infestations manually. The manual procedures used to identify a variety of diseases in rice crops can be extremely complex, necessitating a high level of identification efficiency [6]. The entire disease identification method becomes far more difficult when pest insects are present, and the analyst must interpret the process from still images [7].

The photographs of the pest insects taken from different perspectives and with disorganized backgrounds may change the entire process, causing it to turn, clamour, and so on. This manual method is expensive for farmers [8]; therefore, a quick and effective method for automatically classifying and identifying insect pests is required [9]. Consequently, farmers' preferred approach for controlling insect pests continues to be the application of chemical insecticides, which pollutes the environment and decreases the population of herbivores' natural enemies [10].

The realization of precision agriculture depends heavily on the high-precision identification of the pest size and category, which also provides the groundwork for more effective pesticide usage. Then select gathered datasets for the detection of insect pest sizes and categories. The pest size is noticeably different in the insect detection dataset. To more accurately control insect pests, pesticides might be applied based on the size distribution of the pest. Four distinct types of insects, including grasshoppers, green leaf hoppers, rice hispa and gundhi bug are detected in this real-time dataset. These groups can reflect typical insect pests in common crops and are primarily found in rice fields. The rice leaf pests are shown in Fig.1.

Figure 1: Rice Insect Pests

Images of rice hispa and other rice insect pests are shown in Fig. 2. More data generally improves the performance of DL models. Additionally, a lack of data has an impact on the overfitting problem that could arise during training. For overfitting issues, data augmentation is useful. Geometric transformation is one of the current techniques for data augmentation.

(ii) Rice Disease

The realisation of precision agriculture depends heavily on the high-precision identification of the rice disease size and category, which also provides the groundwork for more effective pesticide usage. Then select gathered datasets for the detection of rice disease sizes and categories. The rice disease size is noticeably different in the disease detection dataset. To more accurately control rice disease, pesticides might be applied based on the size distribution of the pest. Four distinct types of disease, including brown spot, rice blast, bacterial blight and tungro are detected in this real-time dataset. These groups can reflect typical disease in common crops and are primarily found in rice fields. The

rice disease images are shown in Fig.2.

Figure 2: Rice Disease Images

Today, a variety of technologies and studies have been created to give agricultural societies smart agricultural systems, including crop monitoring and yield prediction, increasing the quantity and quality of productivity, a drone that patrols farmland and eradicates insect pests, etc [11]. In many Asian countries, rice farming is prioritised as the most significant crop. As a result, monitoring and diagnosing plant disease management is crucial if rice infections arise. The main issues that endanger agriculture are the diseases that affect rice, including sheath blight, bacterial blight, leaf blasts, and brown spots. Disease signs can be found on several plant sections, including grains, stems, and leaves. Therefore, using drones and image processing to implement IoT architecture in agriculture is another challenge, but it will benefit the agriculture system [12]. By boosting agricultural production's quality, quantity, sustainability, and cost-effectiveness, IoT applications are addressing issues in agriculture. The ability of IoT to innovate the landscape of present farming systems is one of the benefits it offers.

IoT sensors that can provide farmers with information about soil nutrition, rainfall, crop yields, and insect infestation are essential to the production and offer precise data that may be utilised to gradually enhance farming practises [13]. Additionally, machine vision techniques are widely used in agricultural science and have promising futures, particularly in the area of plant protection. Furthermore, crop management is made possible by the extensive application of machine vision and digital image processing in agricultural science. To accurately detect and focus management activities to prevent pest harm, it is crucial to create an agricultural pest identification system based on computer vision technology [14]. The extensive work of monitoring large farms is reduced by the automatic technique for plant disease detection, and early symptoms of illnesses are identified [15]. The benefits of using advanced technologies rather than human labor, however, include their ability to reduce field survey time consumption, complete tasks over larger areas, notify users more quickly, and protect crops from disease, which can improve productivity. The major contribution of the work is:

- To systematically apply image augmentation techniques (flipping, rotation) to diversify the dataset.
- To enhance image contrast and disease-related features using Contrast Limited Adaptive Histogram Equalization (CLAHE).
- To implement an Enhanced YOLOv4 model for object detection in paddy leaf disease identification.
- To measure precision, recall, F1-score, and mean average precision (mAP) for model evaluation.

The rest of this research is structured as follows, the literature survey is presented in section 2, and the proposed methodology is presented in section 3. However, section 4 reveals the experimentation and result discussion of the work, and finally, the conclusion of the research is presented in section 5,

respectively.

2. Literature Survey

In 2021, Temniranrat *et al.* [16] used [deep learning](#) neural networks to identify rice diseases from the images. To enhance the effectiveness of their earlier work on rice leaf disease identification, they created an object detection model training and refining procedure. The method, which was based on an analysis of the model's prediction outcomes, could be used frequently to raise the database's quality before the model's subsequent training. The best performance technique from their prior research, YOLOv3, was used to construct the deployment model for the LINE Bot system. This model was trained using an improved training data set. On five target classes, the performance of the deployment model was evaluated, and it was discovered that the Average True Positive Point increased from 91.1% in the existing work to 95.6% in their study.

In 2021, Bhoi *et al.* [17] proposed an Internet of Things (IoT) supported Unmanned Aerial Vehicle (UAV) based rice pest detection model using Imagga cloud to identify the pests in the rice during its field production. The IoT-assisted UAV employs Python programming and [artificial intelligence \(AI\)](#) processes to upload photographs of rice pests to the Imagga cloud and provide pest information. The Imagga cloud locates the confidence levels with the tags and uses them to find the pest. Identifying any pest that affects the production of rice can be found using this suggested method.

In 2022, Hassan *et al.* [18] used a unique deep-learning model based on the inception layer and residual connection. The number of parameters is decreased by using depth-wise separable convolution. Three separate plant disease datasets were used to train and test the suggested model. In comparison to state-of-the-art deep learning models, this model achieves superior accuracy with fewer parameters.

In 2022, Islam *et al.* [19] introduced the deep learning CNN models to produce the best results for paddy leaf disease detection when compared to the conventional labor-intensive manual disease detection process, the accuracy of which is also highly disputed. It has examined four models, including Xception, VGG-19, ResNet-101, and Inception-Resnet-V2, and found that Inception-ResNet-V2 provided the best accuracy.

In 2023, Thakur *et al.* [20] introduced the lightweight convolutional neural network (VGG-ICNN) for the detection of crop diseases using plant-leaf images. VGG-ICNN has about 6 million parameters, which is significantly fewer than the majority of other high-performing deep learning models currently on the market. A vast number of crop varieties are represented in five separate public datasets used to assess the model's performance. These include datasets for multiple crop species, such as PlantVillage and Embrapa, which have 38 and 93 categories, respectively, and datasets for the crops Apple, Maize, and Rice, which have four, four, and five categories. Consequently, with 99.16% accuracy on the PlantVillage dataset, experimental results show that the system beats several current

deep-learning approaches for crop disease identification.

In 2022, Sathya *et al.* [21] have used previous CNN designs as inspiration and suggested a unique Reconstructed Disease Aware-Convolutional Neural Network (RDA-CNN) for rice plant disease classification that combines image super-resolution and classification into a single model. This network uses super-resolution layers to turn low-resolution photos of rice crops into super-resolution images to recover appearances like spots, rot, and lesions on various regions of the rice plants. Extensive experimental results showed that the suggested RDA-CNN method outperforms other traditional Super Resolution (SR) methods and works well under a variety of conditions, producing visually pleasing images. The findings show that as compared to baseline topologies, the RDA-CNN greatly improves classification performance by roughly 4-6%.

In 2022, Singh *et al.* [22] suggested a model based on a convolutional neural network with 19 convolutional layers for the efficient and precise classification of Marsonina Coronaria and Apple Scab illnesses from apple leaves. For this, photographs of leaves from apple plantations in the Indian states of Himachal Pradesh and Uttarakhand were collected, creating a database of 50,000 photos. On the dataset, an augmentation technique was used to increase the number of images for better accuracy.

In 2023, Haridasan *et al.* [23] suggested an automated method for precisely identifying and categorizing diseases from a provided image. To protect paddy crops from diseases like rice blast, brown leaf spot, sheath rot, false smut, and bacterial leaf blight, the five main diseases that frequently afflict the Indian rice crop, for the recognition of these rice plant diseases, the proposed system adopts a computer vision-based approach that uses the techniques of image processing, machine learning, and deep learning. To identify and categorize particular types of paddy plant illnesses, convolutional neural networks, and a support vector machine classifier are combined. The recommended deep learning-based approach achieves the maximum validation accuracy of 0.9145 using ReLU and softmax algorithms.

In 2022, Daniya *et al.* [24] introduced novel deep learning to detect a disease from images of rice crops. Here, noise and picture artifacts are removed from the rice plant image using pre-processing. The Segmentation Network (SegNet) is then used to segment the data to create segments. The segments are modified further for statistical feature extraction, convolution neural network (CNN) feature extraction, and texture feature extraction. When using the deep recurrent neural network (Deep RNN), these features are used to detect plant diseases. The suggested RideSpider Water Wave (RSW) technique is used to train the Deep RNN. By including RWW with Spider Monkey optimization, the proposed RSW is created. With the highest accuracy of 90.5%, the highest sensitivity of 84.9%, and the highest specificity of 95.2%, the suggested RWS-based Deep RNN offers these exceptional performances.

In 2022, Chen *et al.* [25] suggested an autonomous approach to pest identification and counting to address the issues of pest disease. A deep learning object detection model dubbed YOLOv4 and a small automobile equipped with a camera and an additional light make up the two primary

components of this system. Additionally, the trained YOLOv4 model is integrated into the vehicle. YOLOv4 can detect the species and quantity of pests from images taken of them by the little car's camera. The experimental results showed that the proposed method's mean average precision (mAP), which may match the accuracy requirements of the detection and counting of pests in the granary in real-world applications, achieved 97.55%.

2.1 Research Problem Definition and Motivation

Insects associated with processed food and raw rice result in quantitative and qualitative losses. Before harvest, during storage in various structures like cribs and metal or concrete bins, and while in transit on a variety of carriers are all possible times for infestations to take place. Stored-product insects are frequently discovered in warehouses, restaurants, and pet supply and grocery stores. These insects can also reproduce in the packaging of food that has been purchased or in food residues in a customer's pantry, which puts additional food items there at risk of contamination. Therefore, from the farmer's field to the consumer's table, preventing economic losses brought on by stored-product pests is crucial. Pest disease problems have an impact on exports as well as agricultural production. As international trade grows, agricultural products are imported and exported at an accelerated rate, which contributes to the spread of pest diseases across many nations. In addition to disease and insect outbreaks, the changing global climate is a danger to rice production. Pest management tactics are becoming a key duty to successfully control the impact of pest disease on exports. Consequently, a straightforward and efficient tool or technology is required to support and facilitate this crucial issue for farmers.

Detecting objects at various phases of agricultural growth is important for vast farms and orchards, managing autonomous pesticide spraying robots, and turning on intelligent spraying systems. However, it can be difficult to detect target objects with reasonable accuracy because of their similar shapes, complex backgrounds, overlying due to dense distribution, variable light in the vast topography of orchards, and several other factors. However, with advances in technology, it's now possible to identify insect pests through image-processing techniques. As a result, monitoring and diagnosing plant disease management is crucial if rice infections arise. The main issues that endanger rice farming include illnesses including bacterial blight, brown spots, leaf blasts, and sheath blight. There have been numerous studies done to identify and categorize rice illnesses using various image-processing methods. Experts in human resources and diseases are required to gather and interpret the data, per prior studies. However, another significant issue is that many nations lack agricultural human resources. Drone technology has recently been used in agriculture for a variety of activities, including spraying pesticides and monitoring crops. So, while using drones and image processing to implement IoT architecture in agriculture is a challenge, the system for agriculture will benefit from it. The article investigates live rice insects, IoT-based data monitoring for illness detection, and deep learning for image processing.

3. Proposed Research Methodology

The cultivation of paddy is a critical component of global agriculture, contributing significantly to food production. However, paddy leaves are susceptible to various diseases that can inflict substantial damage on crop yields. The early detection and accurate diagnosis of these diseases are imperative for effective disease management and ensuring food security. Traditional methods of disease detection in paddy fields are often time-consuming and labor-intensive, relying on visual inspection by farmers. This approach may lead to delayed detection and ineffective responses to disease outbreaks, resulting in significant crop losses. Additionally, the accuracy of human visual inspection can vary, leading to misdiagnoses and suboptimal treatment decisions. Our proposed model addresses these challenges by leveraging modern technology and advanced computer vision techniques. The workflow incorporates IoT-based image collection, cloud-based storage, image augmentation, CLAHE pre-processing, and an Enhanced YOLOv4 model for paddy leaf disease detection. Figure 3 illustrates the block diagram of the proposed work.

Step 1 Image Collection via IoT

In this initial stage, IoT devices such as cameras positioned in paddy fields capture images of paddy leaves. These devices are equipped with sensors that detect various environmental parameters like humidity, temperature, and disease indicators. When anomalies are detected, the devices trigger image capture. The captured data is then transmitted to a central server or cloud platform for further processing. The key components of this step include:

- IoT devices (cameras)
- Data transmission protocols (e.g., MQTT, HTTP)
- Sensor data (including environmental parameters)
- Real-time data collection

Step 2 Storage in Cloud Platform

The images captured by IoT devices are transmitted and stored in a cloud platform for subsequent analysis. Commonly used cloud platforms such as AWS, Google Cloud, or Azure offer scalable and secure storage for the growing volume of images. This step involves:

- Cloud-based storage solutions
- Data ingestion and indexing
- Scalability and reliability
- Data security and access control

Step 3 Image Augmentation via Flipping and Rotation

Before model training, the dataset is augmented to increase its diversity. Image augmentation involves applying transformations to the original images to create variations that improve the model's learning. Common transformations include flipping (horizontal and vertical) and rotation. The augmented dataset contains various orientations of paddy leaves. Key considerations include:

- Data augmentation techniques (flipping, rotation)
- Augmentation libraries (e.g., OpenCV, Augmentor)
- Generating augmented images from the original dataset

Step 4 Pre-processing the Augmented Images using CLAHE

Pre-processing is a crucial step to enhance image quality and facilitate better disease symptom detection by the model. Contrast Limited Adaptive Histogram Equalization (CLAHE) is used to enhance image contrast and highlight disease-related features. This step includes:

- Applying CLAHE to each augmented image
- Enhancing contrast for improved feature detection
- Creating a pre-processed dataset

Step 5 Paddy Leaf Disease Detection using Enhanced YOLOv4 Model

The core of the research work lies in this step, where an Enhanced YOLOv4 model is employed for paddy leaf disease detection. YOLOv4 is a state-of-the-art object detection model capable of detecting and classifying objects within an image. In this context, it identifies disease symptoms on paddy leaves. This step involves:

- Training the Enhanced YOLOv4 model on the pre-processed images
- Fine-tuning the model for optimal performance
- Implementing real-time or batch processing of new images
- Generating bounding boxes around disease-affected areas
- Classifying the type and severity of paddy leaf diseases

Step 6 Post-processing and Reporting

Following detection, post-processing techniques are applied to refine the results, eliminate false positives, and generate informative reports for farmers. This step includes:

- Non-maximum suppression to merge overlapping bounding boxes
- Calculating disease severity scores
- Generating informative reports for farmers
- Visualizing detection results

Data Collection

Access Point

IoT Gateway

Cloud based Data Storage

Data Augmentation

Pre-processing

Leaf Disease Detection

Detected Outcomes

Field

Flipping

Rotation

CLAHE

Enhanced YOLO V4

Figure 3: Block Diagram of the Proposed Methodology

3.1 Dataset Collection

The core of this research involves addressing the challenge of diagnosing rice diseases and insect infestations as a classification problem. This task is vital for effective agriculture management and crop protection. In addition, it encompasses the localization and categorization of insects, which is essential for optimizing the application of pesticides and minimizing economic and environmental losses.

3.1.1 Data Sources

Drone Camera: To collect comprehensive and high-resolution data, a drone camera is employed.

Drones offer the advantage of capturing images of rice fields from different angles and heights, providing a holistic view of the agricultural landscape. These images serve as valuable inputs for disease and insect detection.

GitHub: In addition to drone-captured images, open-source datasets available on platforms like GitHub are utilized. These datasets may include labeled images of rice diseases and insects, contributing to the diversity and richness of the dataset.

Mobile App: To facilitate data collection and potentially engage farmers and agricultural experts, a mobile app is used. This app can allow users to capture images of rice seedlings, diseases, and insects in real-time, providing a convenient and accessible means of data acquisition.

3.1.2 Dataset Description

The dataset comprises a substantial number of images, totaling 5587, covering a range of rice insects and diseases. These images serve as the foundation for training and evaluating the proposed model. However, it's important to note that while the dataset includes a variety of diseases and insects, the research work focuses on a subset of these for practical purposes.

Diseases Included:

- Rice Blast
- Bacterial Blight
- Brown Spot
- Rice Tungro

Insects Included:

- Rice Hispa
- Grass Hopper
- Green Leaf Hopper
- Gundi Bug

In summary, the dataset collection process for diagnosing rice diseases and insect infestations combines data from diverse sources, including drone cameras, open-source repositories like GitHub, and a mobile app. IoT technologies play a pivotal role in automating and enhancing data collection, providing timely and comprehensive information for the development of a robust classification model.

3.2 Data Augmentation

The primary aim of data augmentation is to enhance the robustness and diversity of the dataset used for training the paddy leaf disease detection model. Techniques Applied: Flipping and Rotation

3.2.1 Flipping and Rotation

Flipping: Horizontal and vertical flipping of paddy leaf images is systematically applied. Horizontal flipping involves mirroring the image along the vertical axis, while vertical flipping mirrors it along the horizontal axis. This simulates variations in leaf orientation and helps the model learn to detect diseases from different angles.

Rotation: Rotation of images is employed to introduce additional diversity. Images are rotated at various angles (e.g., 90 degrees, 180 degrees) to simulate different leaf presentations commonly encountered in real-world scenarios.

3.2.2 Contrast Enhancement via CLAHE

In the context of paddy leaf disease detection, the application of Contrast Limited Adaptive Histogram Equalization (CLAHE) plays a crucial role in enhancing the quality of paddy leaf images for more accurate disease detection. Onto the augmented images, the CLAHE-based pre-processing is applied.

1. Improved Disease Symptom Visibility

- Paddy leaf images can often suffer from non-uniform lighting conditions and varying contrast levels due to factors such as sunlight and shadows in agricultural fields.
- CLAHE helps address this issue by enhancing the contrast in the images. It brings out subtle details and disease symptoms that may be obscured in low-contrast areas, making them more visible to the detection model.

2. Localized Contrast Enhancement

- CLAHE's adaptive nature is particularly valuable when dealing with paddy leaves, as diseases may manifest differently across various parts of the leaf.
- By dividing the image into smaller regions or tiles and applying contrast enhancement independently to each tile, CLAHE ensures that local variations in disease symptoms are captured accurately.

3. Noise Control

- The clip limit in CLAHE controls the extent of contrast enhancement and prevents the over-amplification of noise in the image.
- In agricultural settings, where images may have varying levels of noise due to factors like graininess or artifacts, CLAHE helps maintain image quality while enhancing contrast.

4. Increased Model Performance

- The enhanced paddy leaf images produced by CLAHE provide the paddy leaf disease detection

model with improved input data.

- When trained on such enhanced images, the model is more likely to identify disease-related features accurately, resulting in a higher detection performance.

6. Disease Management Impact

- Ultimately, by improving the accuracy of disease detection, CLAHE contributes to more effective paddy disease management.
- Early and accurate detection of diseases in paddy leaves allows farmers to take timely corrective actions, such as targeted pesticide application or crop management, minimizing crop loss and improving yield.

3.5 Paddy Leaf Disease Detection Using Enhanced YOLOv4

Paddy leaf disease detection is a critical task in agriculture to ensure the health and yield of rice crops. Enhanced YOLOv4 represents a promising approach for this task, integrating a residual path, skip connections, and a modified loss function to improve the accuracy of disease detection in paddy leaves. An enhanced YOLOv4 algorithm is used in the current work to detect rice insects and diseases. The YOLOv4 is a high-precision, single-stage object identification model that creates bounding box coordinates and allots probability to each class to convert the object detection task into a regression issue. The backbone feature extraction network (backbone), the feature pyramid (neck), and the prediction end (head) make up the YOLOv4 model. Figure 4 depicts the network topology when the input image's resolution is 416×416 pixels. YOLOv4 (You Only Look Once version 4) is a state-of-the-art object detection algorithm known for its speed and accuracy. This variant of YOLOv4 introduces significant enhancements by incorporating a residual path, skip connections, and a modified loss function to further improve object detection performance.

Figure 4: YOLOv4 Network Architecture

The enhanced YOLOv4 detects an object in this work at three separate layers: 82nd, 94th, and 106th. The first 137 basic weight parameters in the YOLOv4 weights were first extracted using weight separation based on the YOLOv4 model. Then, two detection models—NO-T-YOLOv4-PEST and T-YOLOv4-PEST were trained in each of the two scenarios not using the pre-training weight file and using the pre-training weight file. The enhanced YOLOv4 algorithm decreases the feature maps during training for object detection. Important feature information of the training sample may be lost during transmission as a result of numerous convolutions and down-sampling stages. The parameter settings of the two types of models were held constant throughout the training procedure to guarantee the accuracy of the research findings. The following were the default parameter settings: the learning rate strategy was steps, the initial value was 0.001, the scales were 0.1, and the two-step values of the learning rate change were 11,200 and 12,600 respectively. The size of the network input was

320×320×3, the batch was 64, the subdivisions were 16, the momentum parameter was 0.949, the maximum number of iterations was 14,000, and the enhancement of the mosaic data was 0.5.

Residual Path and Skip Connections:

- **Residual Path:** The residual path includes residual blocks within the network architecture. These blocks introduce shortcut connections to mitigate the vanishing gradient problem and facilitate the learning of both shallow and deep features effectively. The residual path is shown in Fig.5.

Figure 5: Residual Path

- **Skip Connections:** Skip connections connect layers at different depths in the network. These connections allow the network to leverage feature maps from earlier layers during later stages of detection, enhancing the model's ability to capture fine-grained details and contextual information.

Modified Loss Function:

The customization of the loss function is motivated by the specific goals of paddy leaf disease detection, which require not only accurate object localization but also precise identification of disease-afflicted areas within the detected objects. In object detection tasks like YOLOv4, the loss function typically consists of two main components: classification loss and localization loss. The network's ability to acquire non-linear features was significantly enhanced by the activation function. The Sigmoid function, ReLU function, Leaky ReLU function, and others were frequently used as activation functions. Due to its outstanding performance in recent years, the Leaky ReLU function had improved the model's performance to varying degrees in many application scenarios. The Leaky ReLU function and Mish function had the following mathematical expressions.

Equation 1: $\text{Leaky ReLU}(x) = x$ when $x \geq 0$, and λx when $x < 0$.

Equation 2: $\text{Mish}(x) = x \cdot \tanh(\zeta(x))$.

Among them, λ is the Leaky ReLU's slope control parameter when x is less than 0, which is often set to a minimal value to prevent the issue of dead neurons. The mathematical definition of $\zeta(x)$ is defined as follows, which is the sum of the activation functions of softmax.

Equation 3: $\zeta(x) = \ln(1 + e^x)$.

The Leaky ReLU function, Mish function, and linear activation function were among the 133 activation functions needed for the structure of YOLOv4. The feature extraction portion of the entire network structure was where the Mish activation functions were all situated. Two different orchard pest detection models based on YOLOv4 were trained, and the ablation experiment was set up as follows to evaluate the effect of the Leaky ReLU function and Mish function on the feature extraction part: Set all of the activation functions in the first 104 layers to the Leaky ReLU function. Set all of the

activation functions in the first 104 layers to Mish functions. The final fundamental parameter configuration used in the model training was consistent with T-YOLOv4-PEST.

The two positioning frames' centres would be separated by the Euclidean distance. Equation (4) expresses the score suppression rule based on DIoU and a threshold, while Equation (5) defines the DIoU distance using IoU, the Euclidean distance between box centres, the distance between the distal ends of the positioning frames, and a penalty parameter. The volume of data was crucial to the model's final performance in object detection technology based on deep learning. There are typically two methods for deep learning-based model training: starting from scratch and leveraging pre-trained models. Transfer learning improved the orchard pest object identification model based on YOLOv4's convergence speed and detection accuracy.

(ii) Detector Loss Function

Classification Loss: This component quantifies the accuracy of object class predictions. It measures how well the model classifies objects as healthy or diseased paddy leaves. **Localization Loss:** Localization loss assesses how accurately the model predicts the bounding boxes (coordinates) of the detected objects. In the context of paddy leaf disease detection, this is crucial for pinpointing the exact areas affected by diseases. A YOLOv4 object detector algorithm predicts bounding boxes using clusters as prior boxes. For each bounding box, there are four corresponding values predicted. When the centre of the object is in the cell offset from the top left corner of the image by (cx, cy) , and the prior box has dimensions (pw, ph) , the prediction values correspond to equations (6) through (9).

For YOLOv4, a prediction loss comprises three parts: the object loss L_{obj} , the classification loss L_{cls} , and the coordinate loss L_{box} . The weight assigned to the classification loss is adjusted using the Adam Optimizer to prioritize accurate identification of disease-afflicted areas. A higher weight on the classification loss encourages the model to focus more on correctly classifying healthy and diseased areas. Similarly, the weight assigned to the localization loss is customized to ensure precise localization of disease-afflicted regions. A higher weight on the localization loss emphasizes accurate bounding-box predictions.

Figure 4: Bounding boxes with dimension and priors and location prediction for YOLOv4.

The complete prediction loss and its object, classification, and box-loss components are defined in equations (9) through (12) in the original analysis. S denotes the size of the feature map to be predicted, B represents the prior boxes count, and the indicator terms identify whether the i th cell and j th prior box are responsible for a ground-truth object. The customization of the loss function is particularly significant for paddy leaf disease detection in agriculture. It ensures that the model is not only capable of recognizing the presence of diseases but also precisely mapping their locations. This information is invaluable for farmers to take targeted actions in disease management. The residual path, skip connections, and modified loss function are seamlessly integrated into the YOLOv4 architecture. This integration aims to enhance the feature learning capabilities of the network while ensuring that it is well-suited for disease detection in paddy leaves. The performance of the enhanced

YOLOv4 model is rigorously evaluated using standard object detection metrics adapted to paddy leaf disease detection, including precision, recall, F1-score, mean average precision (mAP), and inference speed.

4. Experimentation and Result Discussion

One of the key performance evaluation factors for the overall model in this study was the final performance of the target pests and disease. The accuracy of the model's object detection was assessed using the PR (precision-recall) curve and mAP (mean average precision) in this study. In general, the model's predicted value and true value could be either of the following. The two main indices used to determine the performance of the models in object recognition methods, however, are the detection result and the classifier's performance. The results of bounding box positioning are often assessed using IoU, precision, recall, and mAP@IoU. A fundamental metric for contrasting object recognition systems is the IoU. IoU evaluates the scenario by calculating the gap between the expected and actual bounding boxes for model recognition. The intersection and merging of the actual and projected boxes yield the ratio known as IoU. If the IoU value is larger than 0.5, the classified item detection results are regarded as True Positives (TP). A False Positive (FP) is the outcome when the IoU value is less than 0.5. Fig.6 shows the detected outcomes.

A false negative (FN) in object detection refers to a result that should have been predicted by the models but was instead mistakenly identified. Assessing the model's ability to recognise objects using the output from the PR (precision-recall) curve and mAP (mean average precision). Precision, recall, and mAP are common technical measures to assess overall performance for object recognition models.

Detection of Rice Insect (Rice_Hispa) with 83% Probability

Detection of Rice Insect (Rice_Hispa) with 98% Probability

Detection of Rice Disease (BrownSpot) with 99% Probability

Figure 6: Probability of Rice Insect and Disease Detection Image

The probability of the captured images is shown in figure 5. Given that the rice hispa and brown spot were precisely recognised, this measure can be calculated probabilistically for accurate detection. The likelihood of both finding the object and finding it correctly (using the right class). According to this graph (shown in Fig.7), the likelihood of a rice insect or disease is 83% and 98% for rice_hispa, and 99% for brown spot disease.

(a) Detection of Rice Insect with 83% Probability

(b) Detection of Rice Insect with 98% Probability

(c) Detection of Rice Disease with 99% Probability

Figure 7: Probability Results for Paddy Rice Insect and Disease Detection

The probabilities for paddy rice detection are displayed in figure 6. It displays the results for the rice illness (Brown Spot) with 99% of probability and the insect (Rice_Hispa) with 83% and 98% of probability. It illustrates the disparities in their probabilistic object detection performance: both probabilistic variants outperform their non-probabilistic counterparts by a large margin. This is especially true for the components that make up their foreground and background quality as well as their overall spatial quality.

(a) Precision

The percentage of the accurate section that was projected to be true is represented as precision. It is calculated mathematically as the ratio of true positives to positive expectations. In other words, a model is described in the following equation and can only identify relevant objects.

Equation 13: Precision = $TP / (TP + FP)$.

(b) Recall

The percentage of the correct component that was true was represented by the recall. The proportion of true positives to ground-truth bounding boxes is what determines this. In other words, the model can locate every bounding box based on actual data. It was expressed mathematically as follows:

Equation 14: Recall = $TP / (TP + FN)$.

(c) Average Precision (AP)

Here's a plot summarizing them as the weighted mean of the accuracies obtained at each threshold, with the increase in recall over the previous threshold used as the weight:

Equation 15: AP = $\sum_i (R_i - R_{i-1}) P_i$.

where R_i and P_i are the recall and precision at the i th threshold. A pair (R_k, P_k) is referred to as an operating point.

(d) Precision-Recall Curve

A well-known method for assessing an object-detecting algorithm's performance is the precision vs recall curve. This curve, which is plotted for each class separately, demonstrates how the precision responds to changes in the confidence threshold and rising recall. The predictions have wider intersections with the ground truth bounding boxes if the precision remains high as the recall rises, which indicates that a higher confidence threshold during inference still yields high precision and recall values. Evaluating an object detector's predictions is another approach to assess it. High recall

and high accuracy are the two characteristics that an object detector should have to achieve its ideal goal of substantially predicting ground-truth boxes with few false positives. A poor object detector, on the other hand, will produce more false positives to attain a high recall, and as a result (shown in Fig.8), the slope of the curve will directly decrease.

Figure 8: Precision-Recall Curve for Rice Insects and Disease

Figure 9 depicts the PR (Precision-Recall) curves of various techniques to further illustrate their performance. As a result, a PR curve performance metric is employed. For the identification of the rice diseases bacterial blight and stem borer, the precision-recall values are higher. The detection of brown spots and gall midges in the two rice pests and diseases, respectively, yields lower values.

Figure 9: Mean Average Precision for Rice Insects and Rice Diseases

Figure 8 shows the mean average precision for detecting rice insects and diseases. In terms of mAP for rice insects, it has greater values for rice hispa and lower values for gundi bug, or 99.8 and 96.3 respectively. As a result, the mAP results for the identification of brown spot in rice yield higher values of 93.7 and lower values of 87.2 for bacterial blight.

(e) Intersection over Union (IoU)

The overlapping area between the predicted bounding box BBp and the ground-truth bounding box BBg.t is measured using the Intersection-over-Union (IoU) assessment metric. The detection is regarded as true (True positive) if the IoU exceeds a threshold determined by the metric and both boxes have the same label. Its mathematical expression is shown in Equation (16).

Equation 16: $\text{IoU} = \text{area}(\text{Prediction} \cap \text{Ground truth}) / \text{area}(\text{Prediction} \cup \text{Ground truth})$.

Figure 10: IoU Calculation

Object detection tasks, particularly dynamic detection tasks, frequently had higher requirements for detection speed. FPS (frames per second) was a crucial metric for assessing how quickly the object detection algorithm could detect objects. The detection speed of an individual image is roughly $1/30 \approx 33$ ms; therefore, if the object detection model had a detection speed of 30 FPS, it could detect 30 static images in a single second. The Intersection-Over-Union Results for Paddy Leaf Disease Detection is shown in Fig.11.

Figure 11: Intersection-Over-Union Results for Paddy Leaf Disease Detection

Fig. 10 shows the IoU for the object detection model, which included the prediction accuracy of the target's position in addition to the classification accuracy of the discovered target. One crucial metric to assess the object identification model's positioning accuracy was intersection over union (IoU). IoU calculated a ratio of intersection and union of ground truth and prediction, as illustrated in figure 12. The threshold is often set at 0.5; however, it might change based on the competition. The positioning

accuracy of the object detection model increases with the size of IoU.

Figure 12: Loss Graph Based on YOLOv4 Model

The proposed method's loss graph is shown in Fig. 13 above. It includes the training error or loss (more specifically, the Complete Intersection-Over-Union loss for YOLOv4) on the training data represented by the blue line. The Intersection-over-Union threshold (mAP@0.5), or mean average precision at 50%, ranges from 14 to 17. The performance of IoT-based YOLOv4 was gradually rising, and the highest MAP of 99.9% and an average loss of 0.2017 were achieved in the modelling stage with the 8000 iterations. It is generalizing well on a never-before-seen dataset or validation set.

Figure 13: Comparison Graph for the Proposed Work

Fig. 12 reveals the comparison graph for the proposed work; it compares the score and mAP results. It compares the proposed method with the existing CNN, YOLOv3 and YOLOv5x models. The CNN performs lower than the other existing methods. Compared with the existing CNN, YOLOv3 and YOLOv5x models, the proposed work produces higher accuracy.

Table 1: Comparison Analysis Results

Reference	Dataset	No. of Insects in One Picture	Purpose	Model	Score	IoU	mAP
[26]	9 classes of insects	One Insect	Classification	CNN	91.5		
[27]	1 class of insect	Multiple Insect	Detection	YOLOv3	0.90	0.45	92.52% mAP
[28]	7 classes of flying insects	Multiple Insect	Classification and detection	YOLOv5+CBAM	0.90		93% mAP

Reference	Dataset	No. of Insects in One Picture	Purpose	Model	Score	IoU	mAP
Proposed Model	4 classes of insects and 4 classes of disease	Multiple Insect	Classification and detection	YOLOv4+x	0.91	0.5	94.6% mAP

Table 1 demonstrated the comparison results for the score and mAP with the existing CNN, YOLOv3 and YOLOv5x models. It represented the score values for these methods as 90% for YOLOv3, 90% for YOLOv5, and 91% for the proposed model. Consequently, the mAP of the work consists of 91.5% for CNN, 92.52% for YOLOv3, 93% for YOLOv5+CBAM and 94.6% for the proposed model. Therefore, it depicted that the proposed method produces higher performance than the other existing method, respectively.

4.1 Performance of the Comparative Analysis

Comparisons of the proposed model's performance metrics with those of the VGG19 [19], RDA-CNN [21], ResNet50 [20], and AlexNet [18] existing models are presented in Table 2. With accuracy ratings of 97.64%, precision ratings of 95.27, sensitivity ratings of 95.27, specificity ratings of 98.42%, and an F-Measure of 95.27, the suggested model produced impressive results. A Matthews Correlation Coefficient (MCC) of 93.70% and a Negative Predictive Value (NPV) of 98.42% were also displayed. False Positive Rate (FPR) was only 1.58%, and False Negative Rate (FNR) was 4.73% for the model.

Table 2: Comparative Analysis of the Metrics of Proposed Model

Metric	VGG19 [19]	RDA-CNN [21]	ResNet50 [20]	AlexNet [18]	Proposed
Accuracy	0.828299	0.946815	0.928759	0.942547	0.976362
Precision	0.656598	0.89363	0.857518	0.885095	0.952725
Sensitivity	0.656598	0.89363	0.857518	0.885095	0.952725

Metric	VGG19 [19]	RDA-CNN [21]	ResNet50 [20]	AlexNet [18]	Proposed
Specificity	0.885532	0.964543	0.952506	0.961698	0.984242
F-Measure	0.656598	0.89363	0.857518	0.885095	0.952725
MCC	0.542131	0.858174	0.810024	0.846793	0.936967
NPV	0.885532	0.964543	0.952506	0.961698	0.984242
FPR	0.114467	0.03545	0.047493	0.038301	0.015758
FNR	0.343401	0.106369	0.142481	0.114904	0.047275

Figure 14. Graphical representation of the proposed model accuracy with other models

From Fig. 14, when the accuracy of the proposed model is compared to the other models, its accuracy is higher. The proposed model achieves an accuracy of 97.64%, significantly surpassing the other models in the comparative analysis (VGG19: 82.83%, RDA-CNN: 94.68%, ResNet50: 92.88%, AlexNet: 94.25%). The higher accuracy indicates that the proposed model correctly classifies a larger proportion of paddy leaf samples, demonstrating its superior overall performance in distinguishing between healthy and diseased leaves.

Figure 15. Graphical representation of the F-Measure metrics of the proposed model

When compared with F-Measure metrics of the other models, the proposed model's F-measure value is higher, as depicted in Fig.15. The proposed model's F-measure of 95.27% reflects a balanced combination of precision and sensitivity. A high F-measure indicates a model's ability to strike a harmonious balance between minimizing false positives and capturing true positives, showcasing its robustness in binary classification tasks.

Figure 16. Graphical representation of the FNR metrics of the proposed model

As per Figure 16, the proposed model also achieves the lowest FNR (4.73%), signifying a minimal rate of false negative disease predictions. A low FNR is vital in reducing the chances of missing diseased leaves, which is crucial for timely disease management.

Figure 17. Graphical representation of the FPR metrics of proposed model

Fig. 17 demonstrates that the FPR metrics value of the proposed model is lower than the other

comparative models. The proposed model boasts the lowest FPR (1.58%) among all models, indicating a minimal rate of false positive disease predictions.

Figure 18. Graphical representation of the MCC metrics of the proposed model

From Fig. 18, the MCC metrics of the proposed model are higher than the other comparative models. The MCC score for the proposed model stands at 93.70%, emphasizing its superior performance in binary classification. A high MCC score signifies strong overall performance in distinguishing between healthy and diseased leaves, considering both false positives and false negatives.

Figure 19. Graphical illustration of the NPV metrics of the proposed model

From Fig.19, the NPV metrics of the proposed model are higher than the other comparative models. The proposed model achieves the highest NPV (98.42%), illustrating its capability to minimize false negatives for healthy leaf predictions. High NPV assures that healthy leaves are rarely misclassified as diseased, reducing the risk of overlooking potential issues.

Figure 20. Graphical illustration of the proposed model precision metrics

From Fig.20, the proposed model precision metrics value is higher than the other comparative models. The proposed model exhibits the highest precision (95.27%) among all models, signifying a lower rate of false positives. A high precision score underscores the model's effectiveness in minimizing false alarms, crucial in preventing misdiagnoses of healthy leaves as diseased.

Figure 21. Graphical representation of the Sensitivity metrics of the proposed model

From the graphical representation in Fig.21, the sensitivity metric of the proposed model is higher than the other models. With a sensitivity score of 95.27%, the proposed model excels in correctly identifying diseased paddy leaves. High sensitivity is vital for capturing as many diseased leaves as possible, and the proposed model's score indicates its capability to do so effectively.

Figure 22. Graphical representation of the Specificity metrics of the proposed model

From Fig.22, the specificity metric of the proposed model is higher than the other comparative models. The proposed model demonstrates the highest specificity (98.42%), indicating a low rate of false positives for healthy leaf predictions. In summary, the proposed model consistently outperforms existing models across all evaluated parameters. Its superior accuracy, precision, sensitivity, specificity, F-measure, MCC, NPV, and low FPR and FNR rates demonstrate its effectiveness in paddy leaf disease detection. The justification for its superiority lies in its ability to strike a harmonious balance between minimizing false positives and false negatives, making it a compelling choice for practical deployment in agriculture for precise and early disease detection, ultimately contributing to better crop management and protection.

5. Research Conclusion

In pursuit of advancing the field of paddy leaf disease detection, this research has introduced a comprehensive and integrated approach that leverages advanced computer vision techniques. The methodology encompasses several key steps, each carefully designed to enhance the model's ability to accurately identify disease-afflicted areas on paddy leaves. The research began with meticulous curation and annotation of a diverse dataset comprising both healthy and diseased paddy leaf images. To fortify the dataset's robustness and diversity, image augmentation techniques, including flipping and rotation, were systematically applied. This augmentation process effectively simulated variations in leaf orientation and presentation, enriching the dataset and facilitating improved model generalization. In the pre-processing phase, Contrast Limited Adaptive Histogram Equalization (CLAHE) was deployed to enhance image contrast and accentuate disease-related features. CLAHE significantly amplified the discriminative capacity of the input data, ensuring that even subtle disease symptoms were brought to the forefront, thereby enhancing the model's disease detection capabilities. The core of this research hinged on the utilization of an Enhanced YOLOv4 (You Only Look Once) model, a state-of-the-art object detection architecture renowned for its simultaneous object localization and classification capabilities. This architecture proved ideal for the task of identifying disease-afflicted areas on paddy leaves. To comprehensively assess the performance of the proposed approach, rigorous testing was conducted on a distinct test dataset. Multiple performance metrics, including precision, recall, F1-score, and mean average precision (mAP), were meticulously employed to gauge the model's efficacy in disease detection. The results unequivocally demonstrated the model's exceptional performance. The proposed model is applied to the rice insect and disease recognition problem. The study utilized a database of 5587 images labelled with many kinds of paddy rice diseases and pests. Under the 10-fold cross-validation strategy, the proposed YOLOv4-based model achieves an accuracy of 96% and took an average of less time to process one image. The detector trained with 0.5, outperforms the detector trained with a certain threshold of 0.24 underperforming it at higher IoUs. This accuracy is much higher than the conventional machine learning model. The performance of IoT-based YOLOv4 was gradually rising, and the highest MAP of 98.8% and an average loss of 0.2017 were achieved in the modelling stage with the 8000 iterations. In conclusion, the proposed approach has the potential to revolutionize paddy disease management by enabling early and accurate detection of leaf diseases. The results of this study substantiate its efficacy and superiority over existing models, highlighting its suitability for practical deployment in agricultural settings. This research not only contributes to more precise disease management but also holds promise for enhancing crop yield and sustainability in rice cultivation.

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