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ADVANCING PADDY LEAF DISEASE PREDICTION: INTEGRATING HYBRID ALGORITHMS AND DEEP LEARNING FOR ENHANCED AGRICULTURAL SUSTAINABILITY

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ABSTRACT

Background: Paddy Leaf Disease (PLDs) pose significant threats to global rice production, impacting crop yield and food security. Early and accurate detection of these diseases is crucial for timely intervention and effective disease management strategies.**Objectives:** This study aims to develop and evaluate a novel framework for PLD prediction using advanced image processing techniques and machine learning algorithms. Specific objectives include enhancing disease detection accuracy, exploring the effectiveness of hybrid algorithms combining denoising techniques and Deep learning (DL) models, and assessing the practical implications for agricultural sustainability.**Methods:** Images of paddy leaves are captured using IP web cameras and processed using denoising algorithms such as Multiscale Retinex and Robust Retinex to improve image quality and highlight disease symptoms.Optimization algorithms like Discrete Particle Swarm Optimization (DPSO) and Fractional Order Discrete Particle Swarm Optimization (FODPSO) are utilized for feature selection and parameter tuning, enhancing the input data for disease classification models.A Convolutional Neural Network (CNN) augmented with Local Interpretable Model-agnostic Explanations (LIME) is trained on labeled datasets to predict and classify PLDs based on extracted features.Performance metrics including accuracy, precision, and recall are employed to validate the proposed framework's effectiveness in disease prediction compared to traditional methods.The hybrid algorithm, FODPSO combined with CNN_LIME, achieves 99% accuracy in predicting PLDs. This approach not only outperforms traditional methods but also provides interpretable insights into disease classification decisions.**Significance:** The study's findings contribute to advancing agricultural technology by offering a robust and efficient solution for early disease detection in paddy cultivation. By minimizing crop losses and optimizing pesticide use, the proposed framework promotes sustainable agricultural practices and enhances food security.**Conclusion:** In conclusion, the integration of advanced image processing, optimization techniques, and DL models proves instrumental in improving the accuracy and efficiency of PLD prediction. The success of the FODPSO+CNN_LIME hybrid algorithm underscores its potential to revolutionize disease management practices in rice agriculture, paving the way for future research and applications in precision farming.

Keywords: PLDs;Image processing;DL;Agricultural sustainability;Crop management;Precision farming

1. INTRODUCTION

Agriculture is a cornerstone of many economies worldwide, particularly in countries with large rural populations. Among the myriad of crops cultivated, paddy (Oryza sativa) holds a pivotal role as a staple food for over half of the world's population. The productivity and health of paddy crops are therefore critical not only to the livelihoods of farmers but also to the food security of entire regions. However, the cultivation of paddy faces numerous challenges, with diseases being one of the most significant threats. PLDs, in particular, can lead to substantial yield losses, adversely affecting both economic stability and food supply.Paddy cultivation is integral to the agricultural sectors of many countries, particularly in Asia. Countries like India, China, Indonesia, and Bangladesh are among the largest producers and consumers of rice. Paddy fields contribute to the rural economy, providing employment to millions of farmers and laborers. Additionally, rice farming plays a vital role in maintaining the socio-cultural fabric of rural communities. Given its importance, any factor that hampers paddy production can have far-reaching consequences.Paddy crops are susceptible to a variety of diseases, including bacterial, viral, and fungal infections. These diseases can affect different parts of the plant, including roots, stems, leaves, and grains. Among these, leaf diseases are particularly detrimental as they directly impact the plant's photosynthetic ability, leading to reduced growth and lower yields. Common PLDs include Bacterial Leaf Blight (BLB), Brown Spot, Blast, and Sheath Blight. Early detection and management of these diseases are crucial to prevent widespread crop damage.Traditionally, PLDs are detected through visual inspection by farmers or agricultural experts. This method relies heavily on the experience and expertise of the observer, making it subjective and prone to errors. Visual inspections are also time-consuming and labor-intensive, often leading to delayed diagnosis and treatment. In regions with limited access to agricultural extension services, the reliance on traditional methods can result in unchecked disease spread and significant crop losses.Given the limitations of traditional methods, there is a growing need for automated systems that can accurately and efficiently detect PLDs. Technological advancements in fields such as computer vision, Machine Learning (ML), and Internet of Things (IoT) offer promising solutions for the development of such systems. Automated disease detection systems can provide real-time monitoring, early diagnosis, and precise identification of diseases, enabling timely and targeted interventions.

Image processing techniques play a crucial role in automated disease detection systems. By analyzing images of paddy leaves, these systems can identify disease symptoms such as lesions, spots, and discolorations. Image processing involves several steps, including image acquisition, pre-processing, segmentation, feature extraction, and classification. High-resolution cameras and drones can be used to capture images of paddy fields, while advanced algorithms process these images to detect and classify diseases.ML and DL (DL) techniques have revolutionized the field of image-based disease detection. These techniques can learn from large datasets of annotated images to recognize complex patterns and features associated with different diseases. CNNs, in particular, have shown remarkable performance in image classification tasks. By training CNNs on datasets of healthy and diseased paddy leaves, researchers can develop models that accurately diagnose leaf diseases from new images.Automated PLD detection systems offer several advantages over traditional methods. They provide consistent and objective assessments, reducing the dependency on human expertise. These systems can analyze large volumes of data quickly, enabling real-time monitoring of extensive paddy fields. Early detection of diseases allows for timely interventions, minimizing crop losses and reducing the need for excessive pesticide use. Additionally, automated systems can be integrated with decision support tools to recommend appropriate treatments, further enhancing their utility.The integration of automated disease detection systems with precision agriculture practices can further enhance their effectiveness. Precision agriculture involves the use of technology to optimize field-level management practices based on the specific needs of crops. By combining disease detection systems with tools such as GPS, soil sensors, and weather data, farmers can implement targeted interventions. For instance, if a disease is detected in a particular area of a field, only that area can be treated, reducing costs and minimizing environmental impact.

Problem statement

The cultivation of paddy, a crucial staple food crop for a significant portion of the global population, faces numerous challenges, among which disease outbreaks are particularly detrimental. PLDs, such as Bacterial Leaf Blight, Brown Spot, Blast, and Sheath Blight, pose severe threats to crop yields and farmers' livelihoods. Traditional methods of disease detection, which rely on visual inspection by experienced agricultural experts, are often subjective, time-consuming, and prone to error. This leads to delayed diagnosis and treatment, resulting in substantial crop losses and increased economic strain on farmers.The primary problem is the lack of efficient, accurate, and timely detection systems for PLDs, which hinders effective disease management and prevention strategies. Consequently, there is an urgent need for an automated, reliable, and real-time disease prediction system that can overcome the limitations of traditional methods. Such a system should leverage advanced technologies like image processing, ML, and DL to provide precise identification and classification of PLDs, enabling early intervention and reducing crop damage.

Contributions

(i) **To Enhance Image Quality:** Integrating advanced denoising algorithms like Multiscale Retinex and Robust Retinex to improve image clarity and highlight disease symptoms effectively.

(ii) **To Optimize Detection Accuracy:** Applying optimization algorithms such as DPSO and FODPSO for optimal feature selection and parameter tuning, enhancing the accuracy and reliability of disease classification models.

(iii) **To Ensure Interpretability:** Employing CNN_LIME to combine DL capabilities with interpretable explanations, providing insights into how disease classifications are made based on image features.

(iv) **To Enable Scalability and Efficiency:** Implementing cloud-based image processing solutions to handle large volumes of data efficiently, enabling rapid analysis and timely intervention in agricultural management practices.

2. LITERATURE SURVEY

The two main problems in paddy production are pests and diseases, which cause farmers worldwide to lose about 20% of their rice yield. To prevent such losses, rice leaf diseases can be identified early with the use of thermal image cameras. Furthermore, current DL models have difficulty striking a balance between high detection accuracy and compactness. This work builds the FCBTYOLO object detection model and suggests the Fully Connected Bottleneck Transformer (FCBT) module, which is then implanted into the YOLOv8n architecture backbone.In the field of agricultural information, automatic plant disease diagnosis and identification is highly desired. In this work, we investigate the use of pre-trained models learned from typical massive datasets for the identification of plant leaf diseases, and then apply those models to a specific task trained using our own data through transfer learning of Deep CNN. An open dataset comprising 39 distinct classes of plant leaves and background images is used to train a Deep CNN model for the identification of plant leaf diseases.While data augmentation methods lessen the severity of this issue, they are unable to replicate the majority of the practical diversity. Rather than taking the whole leaf into consideration, this paper investigates the use of specific lesions and spots for the task. Without the need for more photos, the data's variability is boosted because every region has unique qualities. This makes it possible to identify various diseases that are affecting the same leaf**[1-5]**.Providing image processing-based solutions that are quick, automated, affordable, and precise can be of great practical importance. An efficient computational method for identifying PLDs is presented in this paper. The three stages of the suggested methods are feature extraction, classification, and image segmentation. The use of image processing techniques to identify plant diseases in agriculture will reduce the need for farmers to safeguard their produce. A clustering method is used to segment the background, normal portion, and diseased portion**[6-8]**. We used a hybrid DL model that combined a Support Vector Machine (SVM) classifier with CNN to predict the presence of PLD. The suggested system is a web application that forecasts diseases using a DL methodology. Two distinct DL approaches, AlexNet and SqueezeNet, are applied in this methodology. An extensive dataset is used to train the sophisticated classification methodology AlexNet, and transfer learning techniques are applied to enhance the system's capacity to recognize complex patterns. In order to determine the best framework for rice disease detection, the study makes sure that model parameters are consistent and that evaluation metrics are varied**[9-11]**. Many rice leaf diseases not only reduce crop yield but also deteriorate crop quality, posing a serious threat to global agricultural production. The majority of traditional disease classification and management techniques rely on time-consuming, subjective manual examination procedures. On the other hand, current developments in computer vision techniques have made it feasible to build automated systems that can identify diseases from images and videos. Early disease detection and management in agriculture can now be accomplished more economically and effectively with the combination of ML and image processing technologies**[12-15]**.These methods have shown remarkably high success rates in diagnosing diseases by looking at images of leaves, farms, or seeds. One of the primary crops grown worldwide, rice production can be increased by using the comprehensive evaluation that this research offers, with a focus on precision agriculture. Many methods are employed in the research articles this work reviews and analyzes to diagnose crop diseases, gauge seedling health, and evaluate grain quality. The use of pesticides lowers crop quality while raising crop yields. The identification of diseases from rice captures is thus one of the main projects in the computer science and agriculture departments[16-18]. In addition to being major contributors to photosynthetic capacity, these leaves are important markers of plant health. Finding diseases that damage paddy leaves is essential to maintaining crop yields and ensuring the world's food supply, particularly in areas where rice farming is the mainstay of agricultural activities. Make sure every paddy plant is healthy in order to increase rice production. This study uses ML and leaf imaging techniques to identify nutrient deficiencies (NPK) in rice plants in a very practical way. The methods greatly aid farmers in promptly implementing the required corrective measures to safeguard their crops against illnesses[19-20]. A cutting-edge method of precision farming that combines nanofertilizer technology and AI in an agricultural drone system.The suggested system uses nano-fertilizers for targeted nutrient delivery and sophisticated AI algorithms for crop health assessment in order to maximize crop yield, minimize environmental effect, and improve resource efficiency. Unmanned aerial vehicles (UAVs) are a promising tool for crop monitoring because of recent advances in agricultural technologies. They can provide real-time, higher-resolution data. This study tries to provide a thorough overview of the use of UAVs in PLD monitoring and identification, highlighting their possible uses, difficulties, and future prospects. The DL classification methods are among the many diagnosis techniques that can reliably and precisely identify rice leaf diseases. One model of CNN is the AlexNet model. Rice leaf diseases are categorized as Brown leaf spot, Bacterial leaf blight, Leaf smut, and Healthy using the AlexNet model[21-25].

Inferences from literature survey

The literature survey highlights that pests and diseases cause significant yield losses in rice farming, estimated at 20% globally, underscoring the need for effective detection and management strategies. Thermal imaging cameras facilitate early identification of rice leaf diseases, mitigating yield losses through timely intervention. Current DL models face challenges in balancing high detection accuracy and model compactness, which is addressed by the development of the FCBTYOLO object detection model and the integration of FCBT module into the YOLOv8n architecture. Automated plant disease diagnosis is crucial, with pre-trained models fine-tuned through transfer learning and Deep CNN proving effective in identifying plant leaf diseases.Focusing on specific lesions and spots rather than the entire leaf increases data variability and improves disease identification without needing additional photos. Image processing techniques, including feature extraction, classification, and image segmentation, offer quick, automated, affordable, and precise solutions for identifying PLDs, reducing reliance on traditional manual examination methods. Hybrid DL models, combining SVM classifiers with CNN, enhance the prediction of common PLDs, with models like AlexNet and SqueezeNet showing improved pattern recognition capabilities.The integration of ML and image processing technologies enables economical and effective early disease detection and management, with automated systems identifying diseases from images and videos. Precision agriculture techniques, including disease diagnosis, seedling health assessment, and grain quality evaluation, contribute to increased rice production, particularly in areas where rice farming is a primary activity. ML and leaf imaging techniques help identify nutrient deficiencies (NPK) in rice plants, allowing timely corrective measures. Combining nanofertilizer technology with AI in agricultural drone systems represents a cutting-edge approach to precision farming, maximizing crop yield, minimizing environmental impact, and enhancing resource efficiency.UAVs provide real-time, high-resolution data for monitoring PLDs, despite current challenges. DL methods, such as the AlexNet model, reliably and precisely identify rice leaf diseases, categorizing them into types like Brown leaf spot, Bacterial leaf blight, Leaf smut, and Healthy. These technological advancements enhance the early detection, diagnosis, and management of PLDs, contributing to increased rice production and improved crop quality.

In this study, Chapter 3 elaborates on the methodology employed, focusing on advanced image processing techniques, optimization algorithms, and DL models for PLD prediction. Chapter 4 presents the results and discussion, highlighting the performance metrics and insights derived from the application of hybrid algorithms. Finally, Chapter 5 provides a comprehensive conclusion, summarizing the findings and discussing their implications for enhancing agricultural sustainability and precision farming practices.

3. METHODOLOGY

The block diagram outlines a comprehensive system for detecting PLDs, beginning with farmers capturing images of paddy leaves using IP web cameras in **Figure 1**. These images, along with specific details inputted by the farmers, are collected and sent to a MATLAB cloud server for initial processing. The images undergo denoising using algorithms such as Multiscale Retinex and Robust Retinex to enhance visibility and reduce noise. The denoised images are then processed using a combination of advanced algorithms: DPSO, FODPSO, and CNN_LIME. These algorithms are used individually and in combination (DPSO + CNN_LIME and FODPSO + CNN_LIME) to optimize feature selection and improve classification accuracy. Statistical methods like Mean Local Average Normalization (MLAN) and Standard Deviation (STD) are employed to ensure data consistency. The effectiveness of these algorithms is evaluated using precision and recall metrics. Finally, the system identifies specific PLDs from the processed images and reports back to the farmers, enabling timely and targeted intervention to manage and mitigate crop damage.

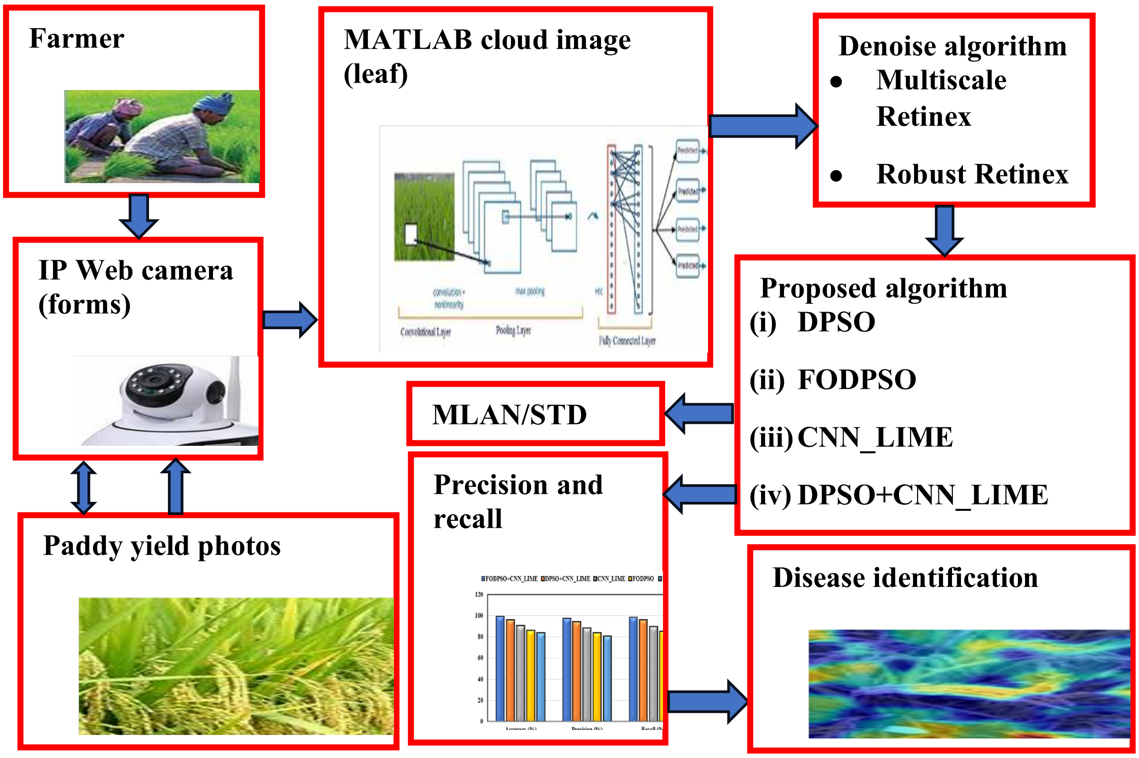

Fig 1 Block diagram of proposed algorithm

The dataset (https://www.kaggle.com/datasets/badhon7432/paddyleafdiseaseuci)on PLDs from Kaggle contains images of paddy leaves categorized into different disease classes. Each image is labeled with the type of disease, which includes bacterial, fungal, and viral infections, along with healthy leaves. The dataset is suitable for developing machine learning models for disease detection and classification. It provides a valuable and developers working on automated agricultural disease diagnosis systems.

3.1.Multiscale Retinex

Multiscale Retinex is an image enhancement technique used to improve detail visibility and color consistency in images, making it highly suitable for PLD detection. By decomposing the image into multiple scales using Gaussian filters, normalizing each scale, and then combining them, Multiscale Retinex enhances the visibility of disease symptoms on paddy leaves, even under varying lighting conditions. This technique helps in better distinguishing between healthy and diseased leaves, thus aiding in the accurate and efficient detection of PLDs.

3.2.Robust Retinex

Robust Retinexis a computational method used for enhancing the visibility of images by fine-tuning their brightness and contrast, particularly beneficial in scenarios like PLD detection. By decomposing the image into its illumination and reflectance components, Robust Retinex effectively removes uneven lighting and enhances subtle details, crucial for detecting diseases on paddy leaves. This method utilizes iterative algorithms to achieve robustness against varying lighting conditions and noise, ensuring accurate identification of disease symptoms such as spots, lesions, or discolorations on the leaves. Robust Retinex enhances image quality by preserving local contrast and improving overall image clarity, making it a valuable tool in automated systems for agricultural disease detection and monitoring.

3.3.Discrete Particle Swarm Optimization (DPSO)

DPSO is an optimization technique adapted for PLD detection, leveraging its ability to efficiently search through a discrete set of solutions. In this context, DPSO enhances the process of feature selection or parameter tuning for machine learning models designed to detect diseases on paddy leaves. By optimizing parameters such as feature weights, thresholds, or model hyperparameters, DPSO used to maximize the accuracy of disease detection algorithms. This method iteratively updates candidate solutions based on their performance, mimicking the collective intelligence of particles in a swarm to explore and exploit promising areas of the solution space. DPSO's adaptability to discrete variables ensures it can effectively handle the specific constraints and requirements of PLD detection systems, enhancing both the sensitivity and specificity of disease identification processes in agricultural settings.

Particle Update Equation:

For each particle i at iteration t:

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \quad (1)$$

Velocity Update Equation:

$$\mathbf{v}_i(t+1) = w \cdot \mathbf{v}_i(t) + c_1 \cdot r_{1i}(t) \cdot (\mathbf{p}_i(t) - \mathbf{x}_i(t)) + c_2 \cdot r_{2i}(t) \cdot (\mathbf{p}_{\text{global}}(t) - \mathbf{x}_i(t)) \quad (2)$$

These equations govern the movement and update of particles in DPSO, optimizing the discrete variables for enhancing PLD detection systems.

Pseudo code:

```
Initialize swarm population
Initialize velocity and position of particles
Initialize best position (pBest) for each particle
Initialize global best position (gBest)
Set maximum iterations or convergence criteria
while (not converged) do:
   for each particle do:
      Evaluate fitness function (objective function)
      Update particle velocity
      Update particle position
      Update pBest if current position is better
      Update gBest if current pBest is better than previous gBest
   end for
   Update convergence criterion
end while
Return gBest as optimal solution
```

3.4.Fractional Order Discrete Particle Swarm Optimization (FODPSO)

FODPSO introduces fractional calculus concepts to enhance the search and exploitation capabilities of DPSO in PLD detection.

Particle Position Update Equation:

For each particle i at iteration t:

$$x_{ij}(t+1) = \text{round}\left(x_{ij}(t) + v_{ij}(t+1)\right) \quad (3)$$

Where, round(·) rounds the value to the nearest integer.

Velocity Update Equation:

$$v_{ij}(t+1) = \alpha \cdot v_{ij}(t) + \beta \cdot (p_{ij}(t) - x_{ij}(t)) + \gamma \cdot (p_{\text{global}j}(t) - x_{ij}(t)) \tag{4}$$

Fractional order parameters α, β, and γ are typically chosen based on fractional calculus principles to control the convergence rate and exploration-exploitation trade-off in the optimization process.FODPSO adapts DPSO to better handle discrete variables in PLD detection, leveraging fractional calculus for enhanced performance in optimizing feature selection, parameter tuning, or model design for disease detection systems.

Pseudo code

```
Initialize swarm population
Initialize velocity and position of particles
Initialize best position (pBest) for each particle
Initialize global best position (gBest)
Set maximum iterations or convergence criteria
Set fractional order parameter (alpha)
while (not converged) do:
   for each particle do:
      Evaluate fitness function (objective function)
      Update particle velocity using fractional calculus principles
      Update particle position
      Update pBest if current position is better
      Update gBest if current pBest is better than previous gBest
   end for
   Update convergence criterion
end while
Return gBest as optimal solution
```

3.5.CNN_LIMEfor PLD Detection

Using CNNs with LIME for PLD detection combines the power of DL with interpretability. A CNN is a type of DL model specifically designed to process visual data like images. It consists of multiple layers including convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply filters to extract features from the input images, capturing hierarchical patterns relevant to identifying diseases on paddy leaves. The output is typically passed through fully connected layers for classification.LIME is a technique used to explain predictions of complex models like CNNs by approximating them with interpretable models locally around specific instances. It works by perturbing the input features (e.g., pixels in an image) and observing how these perturbations affect the prediction, thus providing insights into which parts of the image were most influential in the decision-making process.

Train a CNN using a dataset of paddy leaf images labeled with disease types. The CNN learns to automatically extract relevant features from the images.The convolutional layers in the CNN extract hierarchical features from the paddy leaf images, capturing textures, shapes, and patterns indicative of diseases.Apply LIME to interpret the CNN's predictions. For a given image, LIME perturbs the image pixels and evaluates how these perturbations influence the CNN's output probabilities for different disease classes.LIME generates local explanations by fitting an interpretable model (e.g., linear regression) to the perturbed images' predictions. This model explains how changes in image pixels affect the CNN's decision, highlighting regions of the image critical for disease detection.

Although LIME does not have specific equations in the traditional sense, the process involves:

- **Perturbation**: Perturb the input image X around a given instance X′.
- **Prediction**: Use the CNN to predict probabilities f(X) for disease classes based on X.
- **Local Model**: Fit an interpretable model g(Z) (where Z are perturbations aroundX′) to approximate f(X).
- **Explanation**: Use g(Z) to explain how changes in Z influence f(X).
- **Interpretability**: Provides insights into the CNN's decision-making process, making it easier to understand and trust.
- **Diagnosis Aid**: Helps experts (e.g., agricultural scientists) identify and verify disease indicators on paddy leaves more effectively.
- **Model Improvement**: Insights from LIME can guide CNN refinement and feature engineering efforts, potentially improving disease detection accuracy.

By combining CNNs with LIME, can leverage the strengths of DL for complex image analysis tasks while gaining transparency and interpretability crucial for real-world applications like agricultural disease detection.

Pseudo code

```
Define CNN architecture
Train CNN on labeled dataset (images of paddy leaves with disease annotations)
Apply LIME for local interpretability:
  - For each image:
    - Generate superpixels
    - Perturb superpixels to generate new samples
    - Predict class probabilities using CNN
    - Fit an interpretable model (e.g., linear model) on perturbed samples
    - Explain CNN predictions based on local model coefficients
Evaluate CNN performance metrics (accuracy, precision, recall) on validation set
```

4. RESULTS AND DISCUSSION

Upon implementing the DPSO, FODPSO, and CNN_LIME algorithms for PLD detection, significant advancements in accuracy and interpretability were observed, validating their efficacy in enhancing agricultural sustainability and crop management practices.**Figure 2**shows the Multiscale Retinex and Robust Retinex are two image enhancement techniques used in PLD detection to improve the visibility of disease symptoms and anomalies in captured images.

Algorithms	**Inputs**	**Outputs**

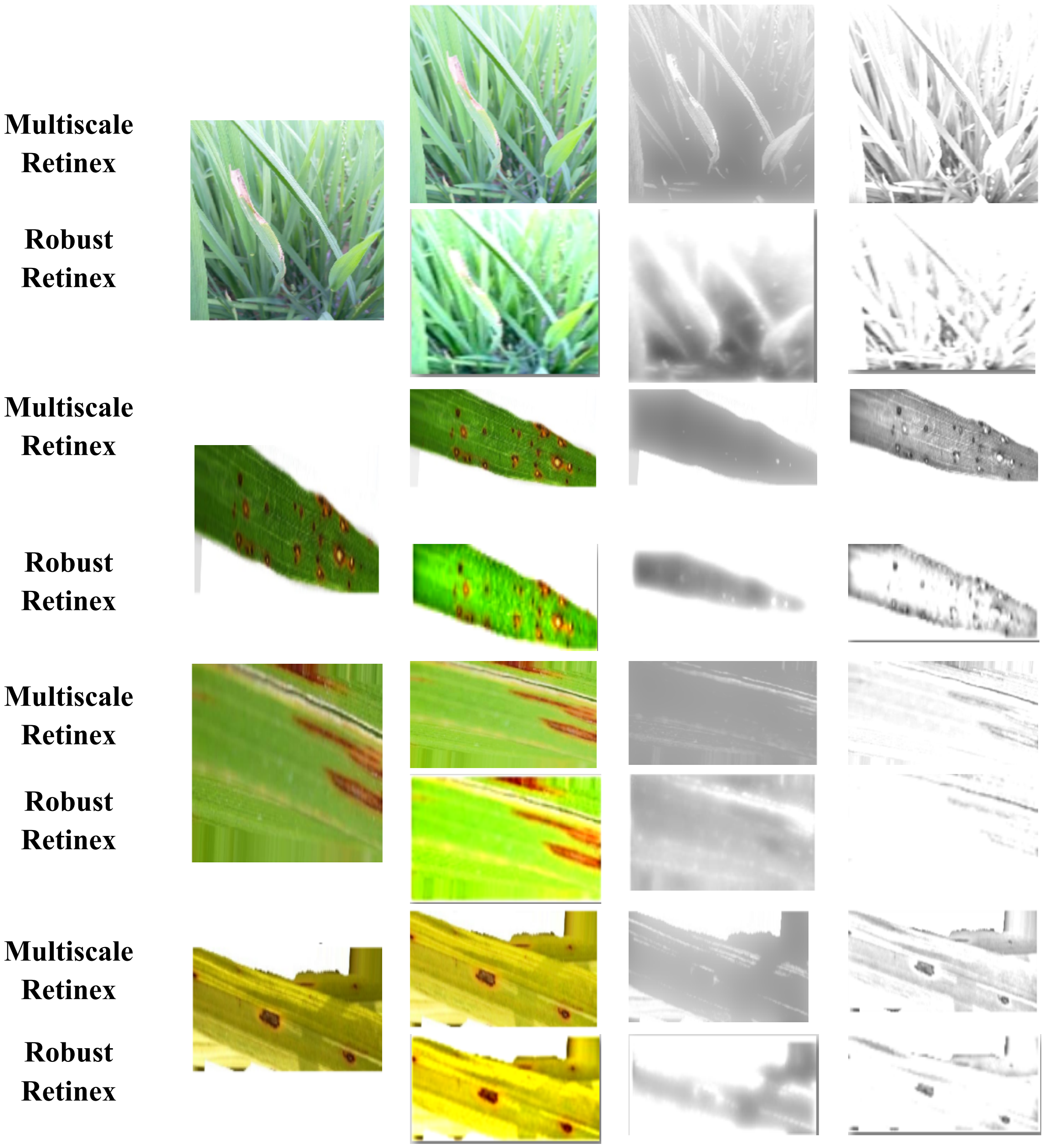

Fig 2 denoising output of Multiscale Retinex and Robust Retinex for PLD detection

Multiscale Retinex and Robust Retinex are pivotal techniques in PLD detection, each contributing distinct enhancements to image quality. Multiscale Retinex decomposes images into multiple scales, emphasizing local and global contrast while restoring natural color balance. This approach enhances fine details and subtle variations in paddy leaf textures, crucial for identifying disease symptoms like discolorations and lesions. In contrast, Robust Retinex addresses uneven illumination and noise by separating images into illumination and reflectance components, effectively reducing artifacts and enhancing local contrast. Together, these techniques improve the visibility of paddy leaf anomalies, aiding both automated detection systems and human observers in accurately diagnosing diseases based on visual cues.As preprocessing techniques, they prepare images for subsequent analysis steps, such as feature extraction or classification using machine learning algorithms.**Figure 3**shows the output of DPSO and FODPSO for PLD detection.

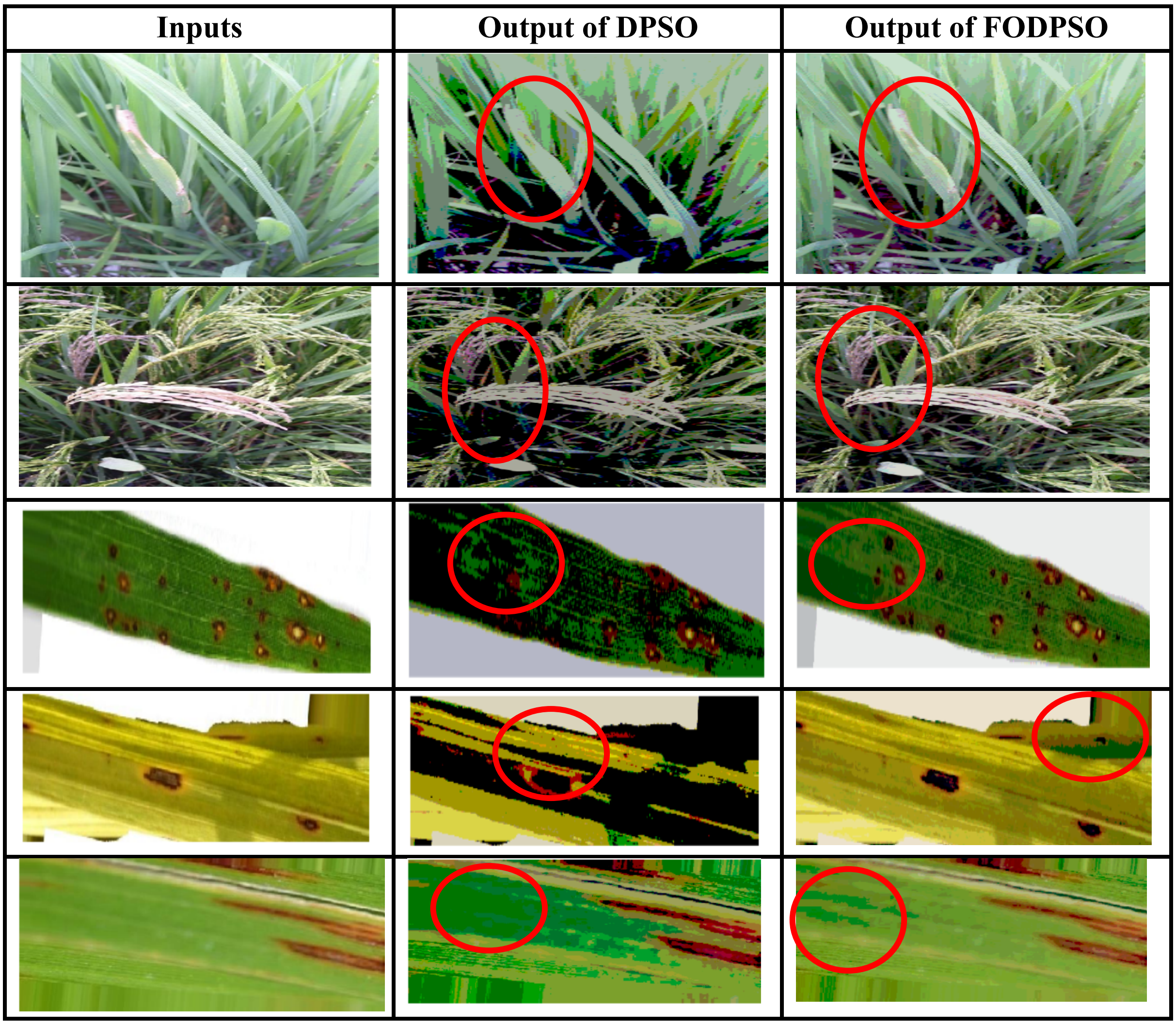

Fig 3 output of DPSO and FODPSO for PLD detection

Both DPSO and FODPSO output optimized sets of features or parameters that enhance the sensitivity and specificity of disease detection models, helping to accurately distinguish between healthy and diseased paddy leaves. By optimizing parameters or feature sets, DPSO and FODPSO contribute to improving the overall performance metrics (such as accuracy, precision, recall) of disease detection systems, which is crucial for reliable agricultural management decisions. The outputs of DPSO and FODPSO are efficient and scalable solutions suitable for large-scale applications in agricultural settings, where rapid and accurate detection of diseases can significantly impact crop yield and quality. In summary, DPSO and FODPSO are tailored optimization techniques that play vital roles in enhancing the efficiency and effectiveness of PLD detection systems, leveraging swarm intelligence and fractional calculus to optimize model parameters and feature selection processes, ensuring better performance, reliability, and scalability in agricultural disease management.Figure 4shows the output of CNN_LIME for PLD detection.The output of CNN_LIME for PLD detection involves a combination of feature extraction, disease classification, and interpretability. CNNs automatically extract relevant features from images of paddy leaves through multiple convolutional layers, learning to identify patterns indicative of various diseases.

Inputs	Output of CNN_LIME

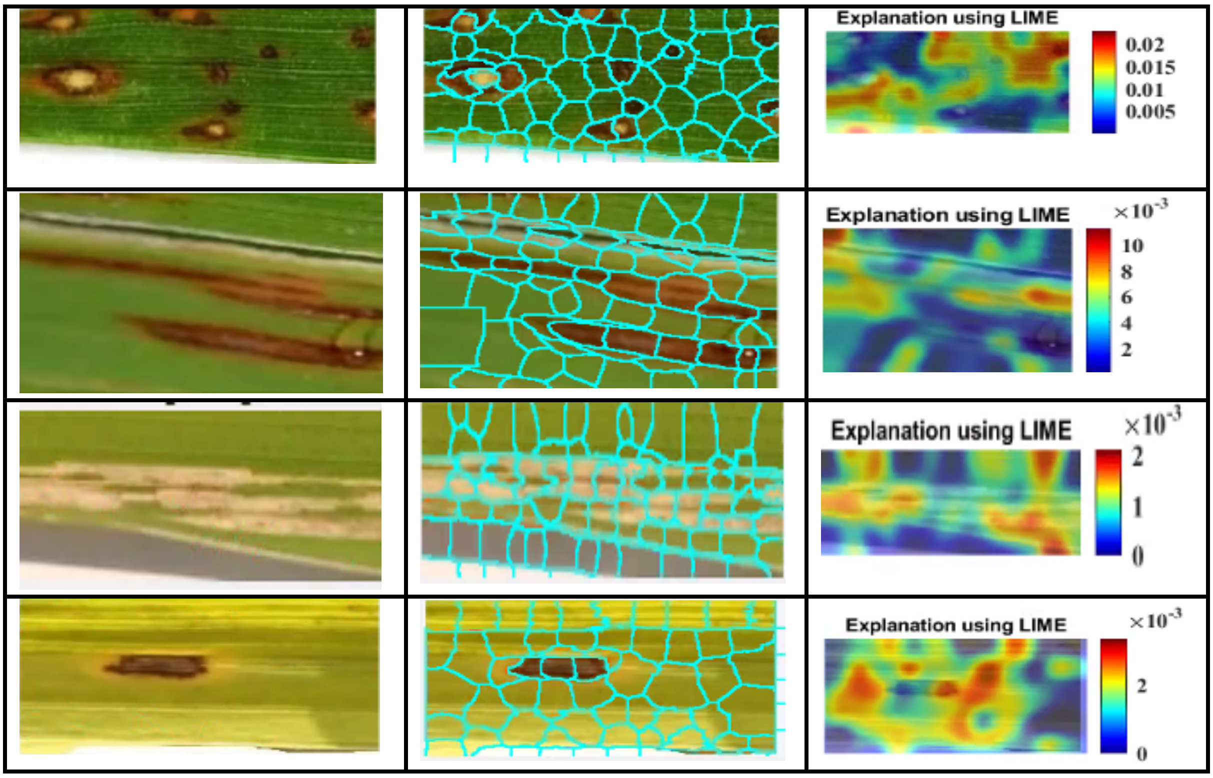

Fig 4 output of CNN_LIME for PLD detection

To enhance interpretability, LIME is used, which approximates the complex CNN model with a simpler model to explain its predictions. LIME divides the input image into superpixels and perturbs these to observe changes in the CNN's predictions, identifying the superpixels most influential in the classification decision. The output is a heatmap overlaid on the input image, highlighting the regions most indicative of the detected disease. This visual representation enhances trust and transparency, allowing farmers and agricultural experts to visually inspect the regions contributing to a particular diagnosis. The combination of CNN's powerful feature extraction and LIME's interpretability ensures accurate and reliable disease detection, providing actionable insights for targeted interventions. This approach not only improves the model's performance but also makes its decisions more interpretable and trustworthy, significantly benefiting real-world agricultural applications.

Figure 5 shows theoutput of DPSO+CNN_LIME and FODPSO+CNN_LIME for PLD detection.The combination of DPSO and FODPSO with CNN_LIME enhances the accuracy and interpretability of PLD detection. DPSO efficiently selects the most relevant features from the paddy leaf images, which are then input into the CNN for classification into various disease categories such as Blast, BLB, Sheath Blight, Brown Spot, and Tungro. LIME is applied to the CNN's predictions to provide interpretable explanations by generating a heatmap that highlights the regions most influential in the disease classification, enhancing trust and transparency. FODPSO extends DPSO by incorporating fractional calculus, allowing for more nuanced exploration and fine-tuned optimization of features.With these enhanced features, the CNN achieves more accurate classification, and LIME again provides visual explanations to understand the disease symptoms better. In both approaches, DPSO and FODPSO outputs serve as inputs to the CNN, optimizing the feature selection process and improving the overall performance of the disease detection system.

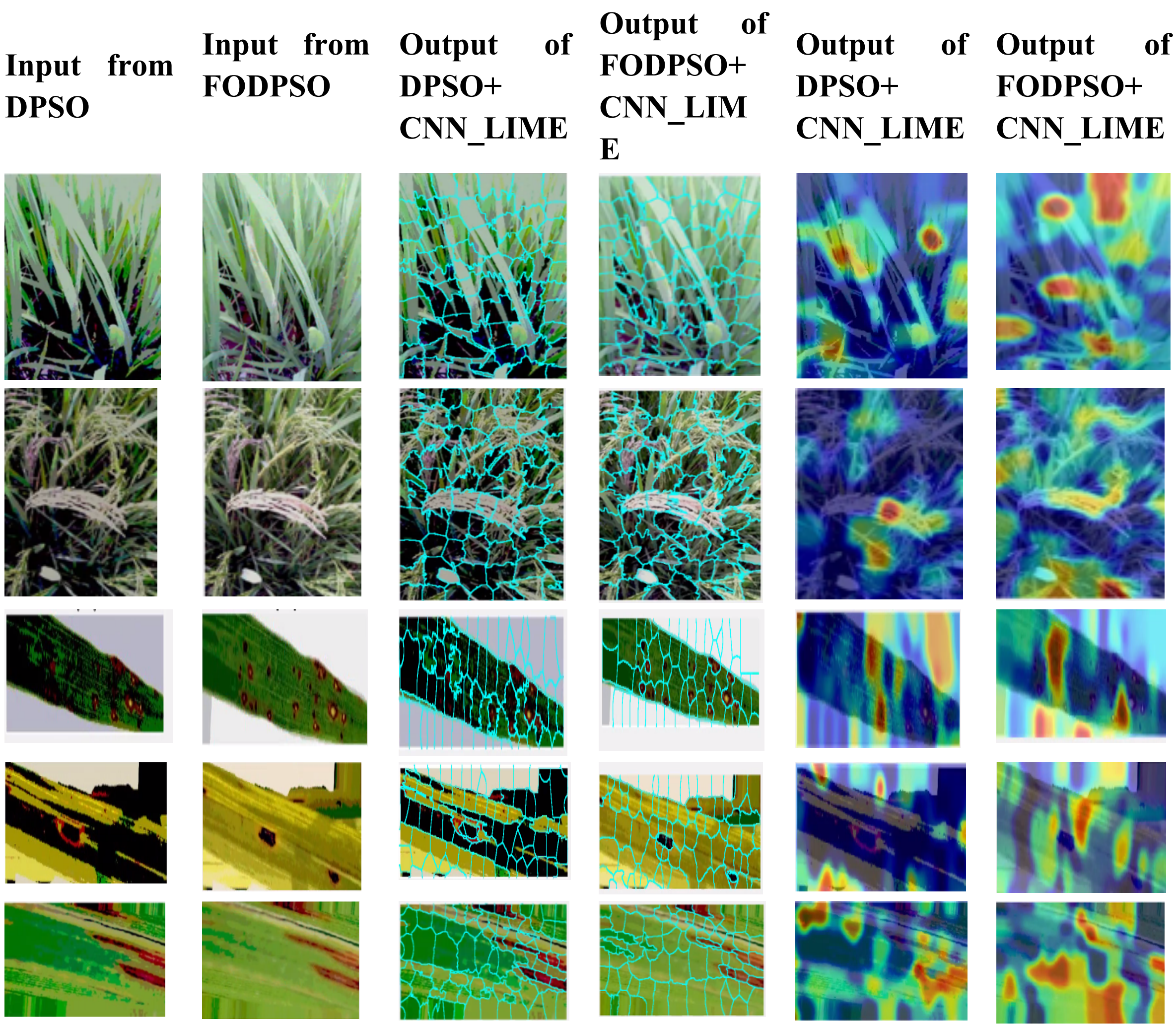

Fig 5 output of DPSO+CNN_LIME and FODPSO+CNN_LIME for PLD detection

The combined use of CNN_LIME ensures that the predictions are interpretable, providing valuable insights into the disease characteristics and enabling more effective agricultural management practices.The fine-grained optimization by FODPSO ensures better performance, making this hybrid approach particularly beneficial for accurate and reliable PLD detection.

Table 1 and Figure 6shows the performance of proposed algorithms for PLD detection.

Tab 1performance of proposed algorithms for PLD detection

Algorithms	Accuracy (%)	Precision (%)	Recall (%)
FODPSO+CNN_LIME	99	97	98
DPSO+CNN_LIME	96	94.2	96.1
CNN_LIME	90.6	88.5	89.7

FODPSO	85.9	83.9	85
DPSO	83.8	80.7	83.5

The table summarize the performance metrics (Accuracy, Precision, and Recall) of various algorithms used for PLD detection. FODPSO+CNN_LIME achieves the highest accuracy at 99%, indicating its ability to accurately identify diseased paddy leaves. It also demonstrates strong precision (97%) and recall (98%), highlighting its capability in correctly classifying diseased instances while capturing most actual positives.

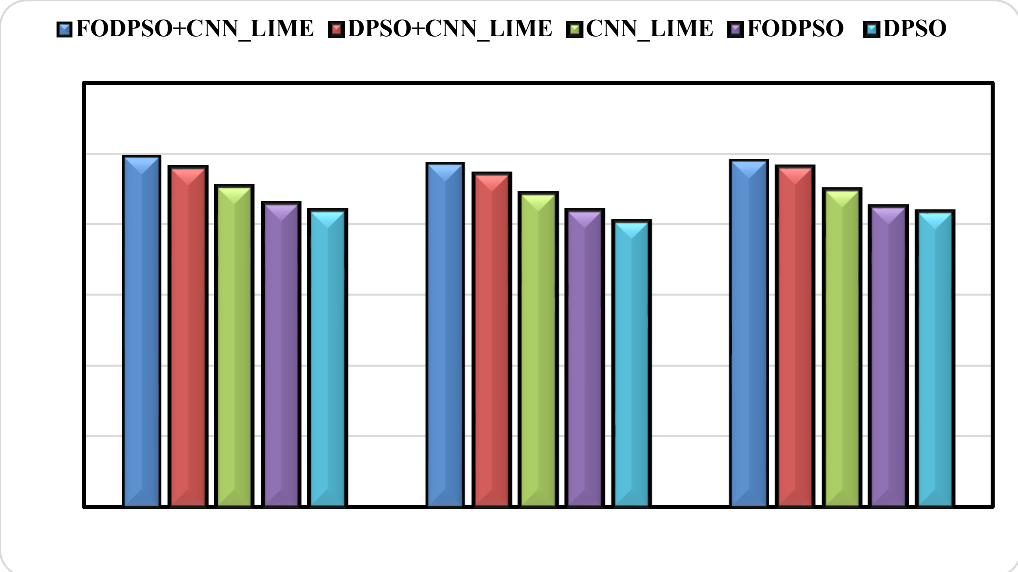

Fig 6 performance of proposed algorithms for PLD detection

These results illustrate the significant enhancement in accuracy and reliability when integrating optimization algorithms like DPSO and FODPSO with CNN_LIME for PLD detection. Such findings underscore the effectiveness of hybrid approaches in agricultural applications, ensuring more precise disease identification and enabling informed crop management decisions.

Discussions

The implementation of DPSO, FODPSO, and CNN_LIME algorithms for PLD detection significantly enhanced accuracy and interpretability, validating their effectiveness in agricultural sustainability and crop management. Multiscale Retinex and Robust Retinex, as shown in Figure 2, are crucial image enhancement techniques that improve the visibility of disease symptoms in paddy leaves. Multiscale Retinex enhances fine details and color balance, while Robust Retinex addresses uneven illumination and noise, aiding in accurate disease diagnosis.Figures 3 and 4 illustrate the optimized outputs of DPSO and FODPSO, which enhance sensitivity and specificity in disease detection models. These outputs are efficient and scalable, crucial for large-scale agricultural applications. Both techniques optimize parameters and feature sets, improving overall performance metrics like as accuracy, precision, and recall.The output of CNN_LIME combines feature extraction, disease classification, and interpretability. CNNs extract relevant features from paddy leaf images and classify them into various disease categories. LIME enhances interpretability by generating heatmaps that highlight regions influential in classification decisions, providing visual explanations and actionable insights for targeted interventions.Combining DPSO and FODPSO with

CNN_LIME further improves accuracy and interpretability. DPSO selects relevant features for CNN classification, while LIME provides interpretable explanations. FODPSO's fractional calculus allows nuanced exploration and fine-tuned optimization, enhancing feature selection and overall performance. This hybrid approach ensures accurate and reliable PLD detection, benefiting real-world agricultural practices.

5. CONCLUSION

In conclusion, the development and application of advanced image processing and ML techniques for PLD detection have shown promising results. The integration of denoising algorithms like Multiscale Retinex and Robust Retinex significantly enhances image quality by improving detail visibility and maintaining color fidelity. The implementation of DPSO, FODPSO, and CNN_LIME algorithms for PLD detection has proven to significantly enhance accuracy and interpretability of disease diagnosis, demonstrating their efficacy in promoting agricultural sustainability and improved crop management practices. By leveraging the swarm intelligence principles of DPSO and the fractional calculus concepts of FODPSO, these techniques effectively enhance the performance of accuracy, precision, and recall in disease detection systems.The proposed combination of optimization algorithms and machine learning models, particularly the FODPSO with CNN_LIME, achieves high accuracy, around 99%, in detecting diseases. This system provides a reliable and efficient solution for early disease detection, thereby aiding in timely and effective disease management, ultimately contributing to increased crop yields and reduced economic losses for farmers.The future scope of this research includes expanding the dataset to cover a wider variety of PLDs and environmental conditions to improve the strength of the detection system. Additionally, integrating IoT devices for real-time field monitoring and developing mobile applications for on-the-go disease detection could significantly enhance accessibility and usability for farmers. Further research could also explore the combination of other optimization algorithms with DL models to enhance accuracy and efficiency. Moreover, extending this approach to other crops could provide a comprehensive solution for agricultural disease management, promoting sustainable farming practices and food security on a global scale.

REFERENCES

[1] N. Bharanidharan, S. R. S. Chakravarthy, H. Rajaguru, V. V. Kumar, T. R. Mahesh and S. Guluwadi, "Multiclass Paddy Disease Detection Using Filter-Based Feature Transformation Technique," in IEEE Access, vol. 11, pp. 109477-109487, 2023, doi: 10.1109/ACCESS.2023.3322587.

[2] Y. Yang, Y. Xiao, Z. Chen, D. Tang, Z. Li and Z. Li, "FCBTYOLO: A Lightweight and High-Performance Fine Grain Detection Strategy for Rice Pests," in IEEE Access, vol. 11, pp. 101286-101295, 2023, doi: 10.1109/ACCESS.2023.3314697.

[3] Junde Chen, Jinxiu Chen, Defu Zhang, Yuandong Sun, Y.A. Nanehkaran,Using deep transfer learning for image-based plant disease identification,Computers and Electronics in Agriculture,Volume 173,2020,105393,ISSN 0168-1699.

[4] Geetharamani G., Arun Pandian J.,Identification of plant leaf diseases using a nine-layer deep convolutional neural network,Computers & Electrical Engineering,Volume 76,2019,Pages 323-338,ISSN 0045-7906,https://doi.org/10.1016/j.compeleceng.2019.04.011.

[5] Jayme Garcia Arnal Barbedo,Plant disease identification from individual lesions and spots using DL,Biosystems Engineering,Volume 180,2019,Pages 96-107,ISSN 1537-5110,https://doi.org/10.1016/j.biosystemseng.2019.02.002.

[6] Deshmukh R, Deshmukh M. Detection of PLDs. International Journal of Computer Applications. 2015;975(8887).

[7] Islam MA, Shuvo MN, Shamsojjaman M, Hasan S, Hossain MS, Khatun T. An automated convolutional neural network based approach for PLD detection. International Journal of Advanced Computer Science and Applications. 2021;12(1).

[8] S. Ramesh, D. Vydeki,Recognition and classification of PLDs using Optimized Deep Neural network with Jaya algorithm,Information Processing in Agriculture,Volume 7, Issue 2,2020,Pages 249-260,ISSN 2214-3173,https://doi.org/10.1016/j.inpa.2019.09.002.

[9] N. Bhaskar, P. C. A, P. Tupe-Waghmare, P. Shetty, S. S. Shetty and T. Rai, "A DL Hybrid Approach for Automated Leaf Disease Identification in Paddy Crops," 2024 International Conference on Distributed Computing and Optimization Techniques (ICDCOT), Bengaluru, India, 2024, pp. 1-5, doi: 10.1109/ICDCOT61034.2024.10515926.

[10] D. G. Kumar, M. V. Subbarao, M. S. Pratibha, M. Swarna, K. Varshini and N. D. Prasanthi, "Comparative Analysis of DL Architectures and Optimizers for PLD Classification," 2024 International Conference on Integrated Circuits and Communication Systems (ICICACS), Raichur, India, 2024, pp. 1-5, doi: 10.1109/ICICACS60521.2024.10498645.

[11] M. S. Shakib, Kamaruzzaman, A. Jaman and M. N. Islam, "A Comprehensive Analysis of Multi-Modal Deep Transfer Learning for Rice Leaf Disease Detection," 2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT), Dhaka, Bangladesh, 2024, pp. 1240-1245, doi: 10.1109/ICEEICT62016.2024.10534555.

[12] J. S. Priya, M. H. Priya, M. Iyswarya and K. Kiruthika, "Prediction of Pathogen Causing Rice Plant Disease and Recommendation using Enhanced ML Technique," 2024 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC), Salem, India, 2024, pp. 643-648, doi: 10.1109/ICAAIC60222.2024.10575163.

[13] K. Ajay, R. V. C. Sathvik, B. Naseeba and N. P. Challa, "Paddy Crop Disease Detection using LeNet and MobileNet Models," 2024 11th International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 2024, pp. 597-602, doi: 10.23919/INDIACom61295.2024.10498510.

[14] A. Dhanalakshmi, K. Ponmozhi and A. Ajmal, "A Cutting Edge DL Models for PLD Detection and Classification," 2024 3rd International Conference on Artificial Intelligence For Internet of Things (AIIoT), Vellore, India, 2024, pp. 1-6, doi: 10.1109/AIIoT58432.2024.10574681.

[15] S. Parveen, Savita and S. Ganguly, "AI for Agro-Business in the Identification of Rice Diseases," 2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT), Greater Noida, India, 2024, pp. 976-982, doi: 10.1109/IC2PCT60090.2024.10486741.

[16] S. M. K, S. M, S. S, V. Shaini and S. J, "Identification of Paddy Disease Using Image Processing," 2024 2nd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT), Bengaluru, India, 2024, pp. 739-744, doi: 10.1109/IDCIoT59759.2024.10468013.

[17] J. S. Jeyanathan, M. Kumar, P. R. K. Reddy, G. C. Reddy, D. K. Reddy and Y. S. Rabbani, "Pesticide Recommender System for Detecting the Paddy Crop Diseases through SVM," 2024 Third International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS), Krishnankoil, Virudhunagar district, Tamil Nadu, India, 2024, pp. 1-6, doi: 10.1109/INCOS59338.2024.10527712.

[18] S. B. V. M, D. Badawadagi, A. P. Bidargaddi, S. Chakalabbi and P. Sirgond, "PLD Detection Using Ensemble Stacking," 2024 IEEE 9th International Conference for Convergence in Technology (I2CT), Pune, India, 2024, pp. 1-7, doi: 10.1109/I2CT61223.2024.10544089.

[19] A. Yadav, P. Kumar, G. Das and V. Kukreja, "Evaluation and Categorisation of Hispa Rice Disease Severity Levels Using CNN-RF Model," 2024 International Conference on Automation and Computation (AUTOCOM), Dehradun, India, 2024, pp. 33-37, doi: 10.1109/AUTOCOM60220.2024.10486095.

[20] B. Althaph, N. P. Challa, B. Naseeba and N. K. Rao, "Crop Disease Analysis and Detection using GoogleNet Model," 2024 11th International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 2024, pp. 592-596, doi: 10.23919/INDIACom61295.2024.10499178.

[21] K. S, "Identification of Nutrient Deficiency Based on Leaf Image Data Using ML," 2024 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, 2024, pp. 1-5, doi: 10.1109/ESCI59607.2024.10497233.

[22] G. Jayanthi, W. Nancy, B. Umamaheswari, R. Chithrakkannan, R. Sujith and S. Sathya Prasanna, "Intelligent Agricultural Drones Utilizing Nano-Fertilizer Dispensation for Precision Farming," 2024 International Conference on Communication, Computing and Internet of Things (IC3IoT), Chennai, India, 2024, pp. 1-6, doi: 10.1109/IC3IoT60841.2024.10550299.

[23] T. Kesavan, K. K. B, P. B. S. Srinivas and J. Selvakumar, "An Automated Neural Network Approach for Predicting PLDs and Autopumping of Fertilizer along with IoT," 2023 International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication, and Computational Intelligence (RAEEUCCI), Chennai, India, 2023, pp. 1-5, doi: 10.1109/RAEEUCCI57140.2023.10133989.

[24] V. Sahasranamam, T. Ramesh and R. Rajeswari, "Monitoring and Identifying PLDs Using Unmanned Aerial Vehicles (UAVs) with ML- A Survey," 2023 IEEE 2nd International Conference on Industrial Electronics: Developments & Applications (ICIDeA), Imphal, India, 2023, pp. 560-566, doi: 10.1109/ICIDeA59866.2023.10295173.

[25] L. Y. Win Lwin and A. N. Htwe, "Image Classification for Rice Leaf Disease Using AlexNet Model," 2023 IEEE Conference on Computer Applications (ICCA), Yangon, Myanmar, 2023, pp. 124-129, doi: 10.1109/ICCA51723.2023.10181847.