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Research Article

Feature-Augmented Convolutional Neural Network Optimisation for Wheat Yellow Rust Identification

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ABSTRACT

Nowadays, yellow rust is a type of condition having a huge domain triggering excessive adverse effects on wheat. Manually addressing wheat yellow rust using the standard approach is not highly effective. In order to enhance this condition, a Deep Learning (DL)-based method was applied in this analysis to identify wheat yellow rust from the Yellow Rust-19 dataset leaf images. The solution offered was constructed using the Optimized Feature-Augmented Convolutional Neural Network (OFAC-Net) model to classify R (Minor infection), MR (Small and Medium Infection), MR-MS (Moderate Resistance and Susceptible), MS (Medium Infection), and S (Major signs of infection), aiming to improve the efficiency of detecting and classifying yellow rust in wheat leaf images. The implemented OFAC-Net models integrate Principal Component Analysis (PCA) used for feature extraction and reduce the dimensionality, alongside hybrid feature selection techniques utilizing the Whale Optimization Algorithm (WOA) and Firefly Algorithm (FFA) to refine the extracted features and boost accuracy. This combination addresses existing challenges and improves classification performance, with the results being classified through a Convolutional Neural Network (CNN). The implemented model attained a classification Accuracy of 98%, Precision of 98.76%, Recall of 99%, and Mean Square Error (MSE) of 1.98%. The dataset, curated from the several severity levels of yellow rust disease, in wheat, consists of a total of 15,000 wheat leaf images. It was designed to support the classification tasks, with leaf images evenly divided across severity levels of yellow rust disease in wheat. These results highlight the techniques` superiority over traditional machine learning (ML) techniques and other advanced models. The proposed OFAC-Net model is a promising solution for real-time agricultural applications, offering both high performance and computational efficiency suitable for mobile and edge devices.

Keywords: Yellow Rust Disease in Wheat, Deep Learning (DL), Optimized Feature-Augmented Convolutional Neural Network (OFAC-Net) Model, Convolutional Neural Networks (CNN).

INTRODUCTION

Wheat, a keystone of global agriculture, is a primary source of food and industrial raw materials, playing a pivotal role in food security and economic stability. Wheat rust diseases are among the primary biotic factors contributing to the instability in crop production (welling & C.R., 2011). However, wheat plants show great sensitivity to various diseases that threaten yield and quality, with the rust, triggered by the Puccinia striiformis fungus, being among the most destructive. This disease is characterized by its rapid spread under favorable conditions and significant impact on wheat production (Sabenca& Ribeiro, 2021). Infected plants experience stunted growth, lower grain quality, and substantial yield losses if left untreated. Traditional methods for assessing yellow rust severity, such as visual inspection, are not only subjective and error-prone but also time-consuming, leading to ineffective disease management and potential economic losses (Chai & Senay, 2022). It is essential to create accurate, effective, and automated systems for the early identification and categorization of wheat yellow rust disease.

In the last few decades, creative solutions to agricultural problems have been made possible by developments in AI and computer vision. The identification and categorization of plant diseases can now be automated with great success thanks to ML and DL techniques (Biel &Jaroszewska, 2021). Techniques leveraging hyper spectral and multispectral imaging, combined with regression and classification algorithms, have shown promise in assessing wheat disease severity (Yao & Li, 2021). However, these techniques may face limitations like high costs, computational complexity, and resource-intensive data processing, making them less practical for real-time applications, particularly on mobile or edge devices. To stop the spread of the disease and increase wheat yield and quality, a thorough evaluation of the disease severity is critical (Igam, 2021). Traditional manual diagnostic methods are time-intensive, labour-intensive, subjective, and prone to error, while advanced biochemical techniques like polymerase chain reaction (PCR) offer precision but are costly and time-consuming (Arosova & Ripl, 2018). A promising approach for quick, accurate, and automated disease assessment is the combination of ML and incorporating remote sensing tools. Tools like hyper spectral, multispectral, and RGB imaging exploit the spectral and color characteristics of plant leaves to detect diseases. These approaches, combined with regression models have shown great promise (Dixit & Nema, 2018). However, high costs, complex data processing requirements, and the limitations of traditional DL networks such as large computational demands and extended training times remain significant barriers to their widespread adoption, particularly for mobile and real-time applications.

Recently one research has focused on overcoming the challenges of traditional DL models by developing an optimized GhostNetV2 model designed for mobile and edge applications. This model integrated channel rearrangement operations, replaced initial layers with Fused-MBConv for improved training efficiency, and utilized the Efficient Channel Attention (ECA) mechanism to enhance its ability to identify diseases. The approach proved to be an efficient and lightweight solution for real-time disease detection (Li & Fang, 2023).

Another study has made significant advancements in computational approaches for detecting wheat yellow rust. The study proposed an ML framework that classified infection types using texture features combined with classifiers like CatBoost and XGBoost. The study demonstrated the effectiveness of these techniques and highlighted the potential for enhanced accuracy by leveraging larger datasets and DL models (Shafi & Mumtaz, 2021).

The Optimized Feature-Augmented Convolutional Neural Network (OFAC-Net) model defines various benefits over existing techniques. It improves the efficiency, robustness, and accuracy rate of the implemented model. The objectives include analyzing existing approaches to wheat yellow rust detection, enhancing image pre-processing techniques, integrating advanced DL methods like PCA, WAO+FFA, and CNN for superior detection and classification, and validating the proposed model using standard metrics. By using lightweight CNN architectures to detect and manage wheat yellow rust, the study seeks to enhance precision agriculture by providing an accurate, scalable, and affordable solution. By integrating advanced image pre-processing techniques and optimizing feature augmentation within the CNN framework, OFAC-Net seeks to improve disease detection accuracy, support timely intervention, and ultimately enhance wheat yield and quality.

This research article is structured as trails: Section 2, relevant research on the detection of wheat yellow rust disease is reviewed. Section 3 describes the suggested approach for creating the OFAC-Net model. The outcomes of the experiment and the dataset analysis are shown in Section 4. Section 5 wraps up with key findings and suggestions for future research.

RELATED WORKS

A few literature reviews for the yellow rust disease in wheat utilizing other techniques are discussed below:

In yellow rust disease in wheat image identification, recent research employing machine and DL techniques has demonstrated encouraging outcomes in precisely detecting and forecasting the disease, assisting farmers in taking prompt preventive action. Since the effectiveness of these models depends on the dataset, future studies may result in more economical and efficient techniques for agricultural disease identification. To improve the precision and dependability of detection models, researchers must keep gathering and improving data, and cooperation between agricultural and technological specialists might result in creative solutions. (Li & Fang, 2023) described the safety of wheat crops as being threatened by the worldwide disease known as wheat yellow rust. Symptoms appear in the middle and late phases, but they are hard to spot in the early stages. Due to their complexity and resource requirements, traditional DL network models are challenging to implement on edge and mobile terminals. To overcome these problems, this paper suggests an enhanced GhostNetV2 strategy. The Fused-MBConv approach outperforms GhostNetV2 in terms of accuracy rate (95.44%), improves group communication, and drastically cuts training time (37.49%). This leads to faster and more accurate detection than previous lightweight model approaches. Shafi & Mumtaz et.al., (2021) described Wheat as a staple crop in Pakistan and is significantly affected by rust disease, a harmful fungal disease that can reduce yield by 20-30%. Food security is seriously threatened by wheat rust's quick spread, which makes accurate infection-type identification essential for efficient control. Using a dataset from mobile cameras and a variety of methods, an ML framework was created to categorize the different types of rust infection. CatBoost's 92.30% accuracy over GLCM texture characteristics should help agricultural communities detect yellow rust early and manage crop productivity.

Hayıt, Tolga; Erbay, Hasan; Varçın, Fatih, st. al., (2023) described a terrible disease that has a major effect on wheat quality and productivity is yellow rust. Fungicides, suitable farming methods, and resistant cultivars can all help control it. The texture of wheat leaves is deformed, so early identification is essential. In recent advances in image analysis, deep features are extracted using CNN, yet the GLCM is still a classic texture feature descriptor. The study examined the application of pre-trained DenseNet by integrating textural and deep characteristics. Using a variety of color spaces and classification techniques, different models were developed for the Yellow-Rust-19 dataset. The CNN-CGLCM HSV model, which combined HSV and the SVM reached an accuracy of 92.4%. (Shafi , Mumtaz, and Mahmood, 2023) described four forms of wheat rust disease that have been identified and categorized using a proposed system: susceptible, resistant, moderate, and healthy. The goal was to reduce the 5.5 million tonnes of wheat that were lost each year. They utilized DL classifiers and achieved 96% accuracy. The study evaluates these classifiers based on accuracy, memory usage, and prediction time to help the farming community implement preventative actions and enhance wheat yield and quality.

Mandava & Vinta et al. (2024) described a major problem for the world's wheat sector as yellow rust disease, which is brought on by Puccinia striiformis. This study explores the possibilities of several methods for identifying and categorizing wheat yellow rust illness. Three cutting-edge CNN models were employed to evaluate wheat leaf photos and extract pertinent characteristics. Both healthy and afflicted plants are included in the extensive dataset of annotated wheat pictures used to enhance the algorithms. The findings demonstrate that CNN models based on DL perform better than conventional ML methods in identifying and categorizing wheat yellow rust illness.

Kumar & Kukreja et al., (2023) described a severe fungal problem, wheat rust illnesses result in 15%–20% annual crop quality losses. Early detection can improve the quality of wheat production, but identifying these illnesses is time-consuming and expensive. A model called the cross-entropy SVM (CE-SVM) is suggested as a solution to this problem. This method put on region extraction CNN for wheat plant patch extraction using 2300 secondary source photos that have been enhanced using flipping, cropping, and rotation procedures. The CE-SVM Gaussian kernel function outperforms histogram equalization in wheat stripe rust illness classification with an accuracy of 93.60%.

Genaev & Skolotnevaet al. (2021) established a method for detecting five fungal diseases, including powdery mildew, yellow rust, and septoria. In the Wheat Fungus Diseases (WFD2020) dataset, 2,414 input photos were successfully labeled with the disease type. As per the picture hashing method, a technique was implemented to regulate the dissoluteness of the data training. The authors used the Efficient Net model to create a CNN-based disease detection technique. The suggested model performed better, achieving 0.942.

Mumtaz & Maqsood,et al. (2023) outlined how to use DL and image processing (IP) techniques to address wheat crop problems. To differentiate wheat stripe rust, the authors created several IP and DL techniques. Several IP techniques were needed, including segmentation, cropping, Visual Atmospheric Resistance Index (VARI) computation, and single and dual-band processing. These techniques were combined with several DL techniques, including TL and additional CNN techniques. The suggested model's results were acquired using the dataset and confirmed to achieve the images. The dataset was used to obtain the findings of the suggested model, which showed that it could produce the images. At 84.10%, the suggested model performed better.

Schirrmann & Landwehr, et al. (2021) described an image classifier for symptom detection based on a deep RNN model. For this motive, massive databases were used for implementation. Image classification was conducted with 224x224 pixel patches, and the testing phase was completed using the classifier. The presentation of the advanced model was attained with 90% accuracy. So, the proposed development for the training and testing image recognition processes was deployed based on DL for disease detection.

Bukhari & Mumtaz, et al.(2021) developed a realistic analysis model for analyzing and assessing several segmentation methods using Grab-cut, Watershed, and U2-Net. These methods were utilized to detect rust statistics to create numerous datasets. Consequently, the ResNet-18 was used to evaluate the control of segmentation scheduled classification performance. The classification of the proposed model reached 96.19% using a dataset segmented through U2-Net. The investigation primarily influences segmentation on accurately interpreting wheat stripe rust and disease.

Deng & Zhou., et al. (2022) highlighted Wheat strip rust as a serious foliar disease because of its detrimental effects on wheat yield. To track the prevalence of wheat rust illnesses, a perfect assessment of the disease's severity was cultivated during the seasonal stage. The authors suggested a paradigm for rust analysis to address these problems. The segmentation of wheat rust states was utilized in the study to identify illnesses, and the former approach proved to be the most effective. On an actual dataset, the former approach obtained 72.60% of the F1-score. The study discovered that minority class detection was impacted by unbalanced data, necessitating revaluation and loss function remedies.

Pan & Gao.,et al. (2021) highlighted the main problems caused by yellow rust infection in wheat cultivation. Yellow rust detection methods that were done by hand were ineffective and time-consuming. To detect diseases, the scientists created a DL model that they applied to unmanned aerial vehicle (UAV) imagery. The "pyramid scene parsing network (PSPNet)" is the name given to the suggested semantic segmentation method. They provided superior classification, and the SVM technique was used to address labeling problems in sizable image datasets. Accordingly, the suggested PSPNet model uses the SVM approach to achieve 94% accuracy.

After the analysis, the above survey defined that DL-based and SVM methods suffered from misclassification, labeling problems, over fitting, and time complexity problems. Thus, a few categories of wheat leaf images are still restricted due to an insufficient quality of training data. On the other hand, the performance metrics are accuracy was calculated as relatively minimal, and the MSE rate was calculated as maximum. To overcome these issues and gaps, this proposed work is an OFAC-Net model with hybrid optimization Whale+FFA method to identify multi-class classification issues of the yellow rust disease in the wheat image dataset.

METHODOLOGY

This section outlines the step-by-step approach for developing the proposed OFAC-Net model, ensuring a systematic flow from data preparation to model evaluation for accurate and efficient classification, as shown in Figure 1.

In this research paper, initially, the YELLOW-RUST-19 dataset, containing categorized images of wheat leaves with varying severity levels, is uploaded and prepared for analysis. The dataset is pre-processed with steps such as image resizing, converting RGB to grayscale, and applying filtration techniques to ensure high-quality input data. To extract essential features, PCA is applied, minimizing the dimensionality of the data. These extracted features are further optimized using a hybrid approach combining the WAO and FFA. The optimized features are labeled and organized into feature vectors, which are subsequently fed into an enhanced CNN model designed to classify wheat yellow rust effectively. The trained CNN model is then loaded, and the optimized feature vectors are tested to validate the system’s performance. Finally, the model classifies the input samples into predefined categories, such as healthy or various severity levels of yellow rust, providing accurate and reliable predictions. This methodology ensures a robust framework for efficient detection and classification of wheat yellow rust, addressing critical challenges in traditional detection techniques.

Data Collection

For this research, the Yellow-Rust-19 dataset (Kaggle.com,2025) sourced from Kaggle, was employed to support the detection and classification of wheat yellow rust. Developed by a collaborative team of researchers from Turkey and domain experts, this dataset is specifically curated to advance studies on wheat diseases. The pre-processed section comprises 15,000 images, distributed equally among six categories as shown in Table 1, with each category containing 2,500 images. It includes both raw and pre-processed images of wheat leaves, classified into healthy and yellow rust-infected categories based on different severity levels, as shown in Figure 2.

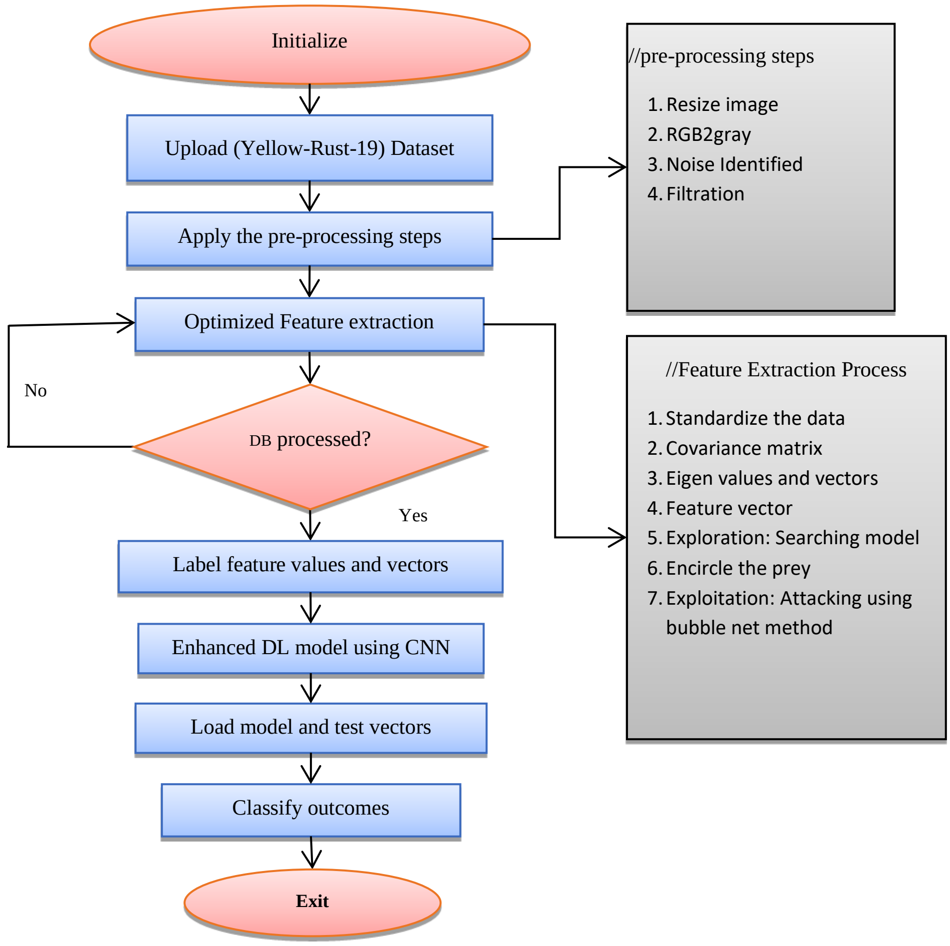

Figure 1 Flowchart for the Proposed Method

Table 1 Image details of the dataset used

Category	Full Form	Pre-Processed Images	Raw Images
0	Healthy	2500	205
R	Resistant	2500	361
MR	Moderately Resistant	2500	564
MRMS	Moderately Resistant to Susceptible	2500	1135
MS	Moderately Susceptible	2500	1795
S	Susceptible	2500	1361
Total		15,000	5421

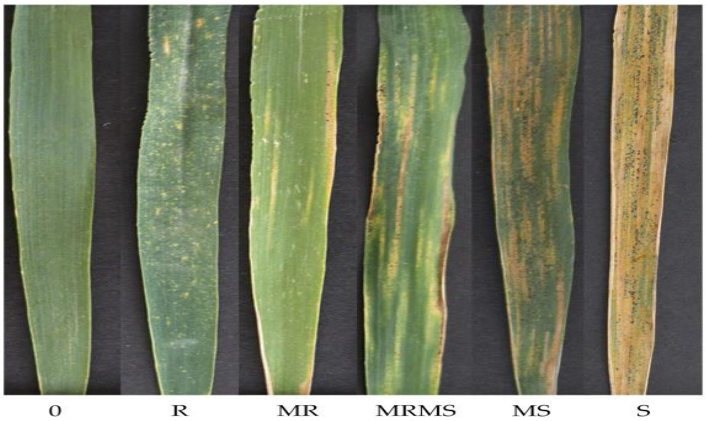

Figure 2 Wheat Leaf image of each category

Pre-processing

After the data collection, pre-processing is applied in this section. To ensure the efficiency of the implemented model, pre-processing steps were applied to the images from the YELLOW-RUST-19 dataset. Initially, all dataset images are resized with a uniform resolution of 256*256 pixels, standardizing their dimensions for consistent input into the model. Following this, the RGB to Gray image conversion simplifies the data and reduces computational complexity while retaining essential texture information. Noise within the images, such as salt-and-pepper noise potentially caused by environmental factors or data acquisition processes, was identified and addressed using a median filter. This filtration technique effectively removed irrelevant artefacts while preserving the quality of the image features critical for accurate yellow rust detection. These pre-processing procedures enhanced the dataset's suitability for training and evaluation, forming a solid foundation for the subsequent DL-based analysis. Figure 3 defines the representation of the pre-process outcome. Figure 3(i) shows the uploaded input image, Figure 3(ii) represents the resized image in 256*256 dimensions, Figure 3(iii) grayscale converted image to reduce the colour dimensions, Figure 3(iv) represents the distorted image with artificial noises, and Figure 3(v) defines the noise-free image or filtered image.

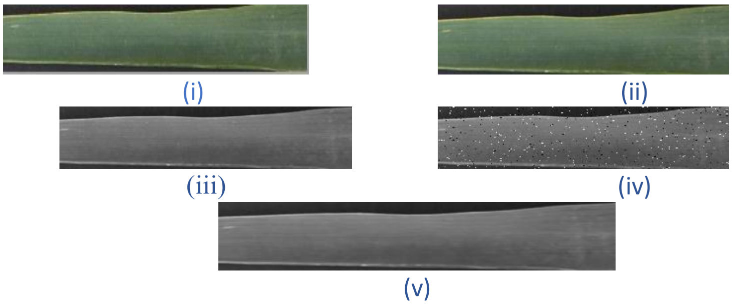

Figure 3 (i) Input Image (ii) Resize Image (iii) Grayscale Image (iv) Noise Image, and (v) Filter Image

Feature Extraction

After pre-processing, processed data is served into the feature extraction procedure to extract the reliable features. The main objective of feature extraction is important for extracting reliable features required for classification. The proposed PCA algorithm helps enhance the efficiency of yellow rust disease in wheat leaf image detection systems by optimizing the computational complexity and potentially improving the accuracy rate. It is a popular method for simplifying large datasets while maintaining important patterns and features by reducing their dimensionality. In this study, PCA was employed as a key feature extraction method to identify the most significant components in the wheat yellow rust images, thereby reducing the number of variables without sacrificing critical information. The grayscale images from the pre-processed dataset were standardized. Every feature is given a mean of zero and a standard deviation (SD) of one through standardization, which keeps any one feature from controlling the principal components because of different scales (Sarkar. S., 2022).

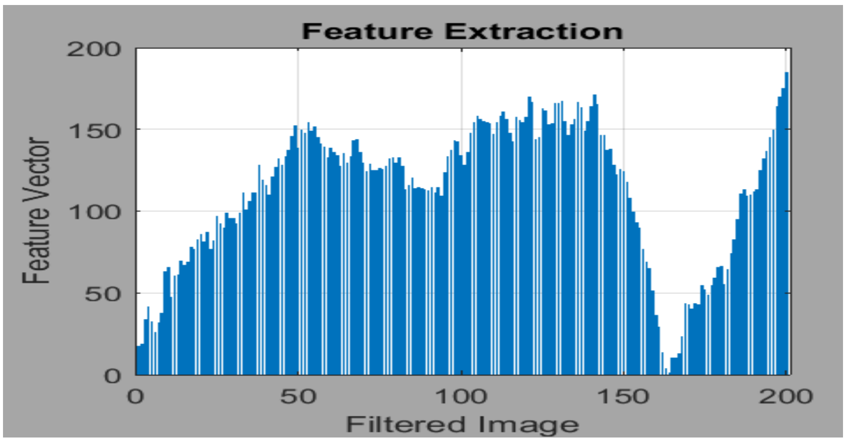

Figure 4 Extracted Feature Values

After standardization, PCA was applied to compute the covariance matrix, which encapsulates the relationships between various features in the dataset. The principal components are linear combinations of the original features capturing the highest variance and were then selected. A subset of these components was chosen based on the explained variance ratio, ensuring that the reduced feature set retained a significant portion of the total variance. Figure 4 illustrates the outcome of the extracted features.

The PCA algorithm 1 (Karamizadeh & Abdullah., et al. ,2013) involves the following steps:

Algorithm 1: PCA algorithm

1: Vector Representation of leaf images
Signify the set of M images (B_1, B_2, B_3,....., B_M) of size N×N as column or row vectors of size N^2.

2: Compute the Average leaf image
Calculate the average image (μ) of the training set using the formula:

$$\mu = \frac{1}{M}\sum_{n=1}^{M} B_n \qquad (1)$$

3: Difference Vector Calculation
For each image in the training set, compute the difference vector (W_i) by subtracting the average image (μ):

$$W_i = B_i - \mu \qquad (2)$$

4: Compute the covariance matrix
From the covariance matrix (C) using the difference vectors (W_1, W_2, W_3,.............., W_M):

$$C = AA^T = \sum_{n=1}^{M} w_n w_n^T \qquad (3)$$

Here, A=[W_1, W_2, W_3........., W_n] represents a matrix formed by concatenating the difference vectors.

5: Determine eigenvectors and eigenvalues
Compute eigenvectors (U_L) and eigenvalues (λ_L) of the covariance matrix (C).

6: Generate Feature Space and Weights
Construct the feature space for image classification by measuring the weights (Ω_T):

$$\Omega_T = [w_1, w_2, w_3 \dots \dots \dots, w_{M`}]$$

Where H_k is given by:

$$H_k = U_k^T\,(B - \mu), \qquad k=1, 2,\ldots\ldots,M`$$

Projecting the original data onto the principal components enabled PCA to reduce the high-dimensional image data into a concise set of features. These extracted features were subsequently used as input for further analysis and classification tasks, helping the model to focus on the most informative aspects of the images while reducing computational complexity for the subsequent DL models.

Feature Selection

The feature-extracted data is fed into the feature selection procedure to choose the reliable features. The main objective of feature selection is an important for address a minimum no. of reliable and important features compulsory for classification. The implemented Whale+Firefly algorithms help enhance the efficacy of detection systems by optimizing the computational complexity and improving the accuracy rate. These are classified into different models: Filter, Wrapper, and embedded. Feature selection and optimization are crucial steps in improving the performance of ML models, especially in complex datasets like wheat yellow rust detection. In this study, the WAO combined with the FFA was used to enhance feature selection and optimization. The hybrid WAO+FFA approach helps in identifying the most relevant features and optimizing the model's parameters, which can lead to better classification accuracy and model efficiency.

Whale Optimization Algorithm (WOA)

The procedure starts with the identification of a subset of features extracted through PCA. WAO is an optimization technique inspired by the chasing nature of whales, where each whale searches for a target by exploring the search space and updating their position toward the best solution (Mohammed & Umar., 2019). In the WAO algorithm, whales are initialized randomly within the search space, representing potential solutions for the feature selection problem. They update their locations depending on the distance to the best solution found, using a combination of exploration and exploitation strategies (Rana & Latiff., 2020). Algorithm 2 defines the Whale optimizer steps.

Arithmetical method and optimization algorithm

This sub-section outlines the arithmetical method of encircling prey, the spiral bubble-net feeding maneuver, and the initial exploration process for prey. The optimization method (Mirjalli, S., 2016) is then implemented.

Encircling Prey

Humpback whales can be reliable in identifying the position of their prey and encircle them. Similarly, the Whale algorithm, since the optimized solution in the search space is unidentified earlier, supposes that the recent best candidate solution either corresponds to the target prey or is near to the optimal target. After verification, the enduring agents update their locations by affecting the fitness search agent. This procedure is defined by the below-defined equations.

$$d' = |c'.x'^{*}(T) - x' * (T)| \qquad (1)$$

$$x' * (T+1) = x'^{*}(T) - a'.d' \qquad (2)$$

Here, in Equations (1) and (2) T define the recent epoch, a' and d' are coefficient vectors, x* is the position_vector of the reliable solution attained so far, x' is the position_vector, | | represents the absolute value, and . is the multiplication of the element by element. The vector a' and c' are evaluated as follows:

$$a' = 2A'.R' - A' \qquad (3)$$

$$c' = 2.R' \qquad (4)$$

In Equations (3) and (4) A' is linearly reduced from 2-0 over the source of epochs, and R' is a kind of random vector in 0,1.

Exploitation Phase

This arithmetical model simulates the bubble net behavior of humpback whales, and two methods are described below:

Shrinking Encircling Mechanism: This nature is attained by reducing the value of A' in the Equation (3). Variation range of a' is also reduced by A'.

Spiral updation locations: This method initially evaluates the distance between the whale and prey locations.

Algorithm 2: Whale optimization algorithm (WOA)

Initial_data: no.of whales in the pack "n", control_coefficient "au", and max_iterations (m_itr).
Outcome: Gbest whale location, y_{best}, and fit (y_{best}) best fitness value.

Start
Generate init_pop of n whale. y_i (i= 1,2,3,....n)
Set itr_counter Cn_t = 0
Evaluate the fitness of each whale
Verify the best_whale depends on the fitness that is y_{best}
While (Cn_t < m_itr)
  For each whale do
    Evaluate "au" a and c by eqs (1) and (2)
If (randval <0.5)
If (|a| <1)
 Update the position of the recent whale
Else if (|a| >=1)
Choose a random whale, Y_{ran}
Update the location of the recent whale
End if
Else if (randval >= 0.5)
Update the location of the recent whale
End if
End for
Evaluate the best of all whales

Update the value of y_{best} depends on the fitness
++ The recent itr Cn_t by 1
End while
Return the best_location, y_{best}
End

Firefly Algorithm (FFA)

However, to further improve the optimization process, the FFA is integrated into WAO. FFA has the flashing behavior of fireflies, where brighter fireflies attract others, leading to a convergence towards the most optimal solutions. In the context of feature selection, the WAO+FFA algorithm works in two phases. During the exploration phase, the algorithm searches the feature space for promising areas by randomly selecting solutions. In the exploitation phase, it intensifies the search for the best solutions, fine-tuning the feature selection process. The result is a set of optimized features that are highly relevant to the detection and classification of wheat yellow rust.

An adaption of the real nature of the firefly (FF) in a method is too difficult; the following verified principles are measured by applying the FFA:

- All FFs are males and females.
- Their attraction is relative to their brightness, and
- The brightness of a FF is influenced by the landscape of the objective function (OF).

Algorithm 3 is defined below in the detailed description and working of the whole algorithm.

Algorithm 3: Firefly Algorithm (FFA)

Input data: firefly population X = (X_1, X_2, ... X_n) and objective function F (X_i).
Outcome: best solution X_b and its value F_{Min} = min (F(X_b)).
Create init_pop $X^o = X_1^o$ .... X_N^o
F($X^o{}_i$) = calculate novel sol and update light_intensity.
Set T = 0 (iteration counter)
While T <max_gen, repeat:
    For each firefly i=1 to n do
        For each firefly j =1 to n do
            If the light intensity $II_j > II_j$ then
                Move Firefly i towards Firefly j using a uniform distribution.
        End if
        Calculate new sol F($X^T{}_i$) and update light intensity
    End for
    Rank FF and explore the best
    Increment iteration: T = T+1
End while.

Once the optimal features have been identified, the selected feature set is passed on to the classification model. This ensures that the model is trained with a more efficient, smaller set of features, which not only improves computational efficiency but also enhances the accuracy of the classification process. The WAO+FFA method efficiently manages the balance between exploration and exploitation, ensuring a thorough search of the feature space while honing in on the best features for the task at hand.

In the optimized feature extraction process, labeling feature values (eigenvalues) and vectors (eigenvectors) are essential for organizing and interpreting extracted features. Eigenvalues indicate the variance explained by each principal component, ranked to prioritize components with higher variance. Corresponding eigenvectors define the directions of maximum variance in the feature space. Each eigenvalue and eigenvector is labelled systematically (e.g., Eigenvalue 1, Feature Vector 1) to guide dimensionality reduction. The transformed data, represented by labeled principal components (e.g., Principal Component 1), retains the most significant features for analysis and classification, ensuring model interpretability and effectiveness.

Enhanced DL model using CNN

In the enhanced DL model, CNNs are employed to significantly improve the classification and categorization of wheat yellow rust disease. In image recognition tasks, CNNs are very effective because they can automatically extract spatial hierarchies of features from input images. In this context, CNNs are used to learn the underlying patterns and textures associated with healthy and diseased wheat leaves, specifically targeting yellow rust infection. The CNN model employs convolutional (CL), pooling (PL), and fully connected layers (FCL) to use filters to identify fundamental features in input images, such as edges, corners, and textures. PLs are employed to reduce computational costs and maintain essential spatial information in the images. The full CLs of the network combine learned features to predict the type of infection or the severity of the disease (Hemalatha &Karthik., 2022). Training is done by utilizing a dataset of wheat leaf images, and the CNN automatically adjusts its filters during training through back propagation to minimize the classification error. By using deep architectures with more layers and filters, the CNN is capable of learning more complex patterns, making it robust in distinguishing between different severity levels of yellow rust infection.

By removing the need for manual feature engineering and carrying out feature extraction and classification straight from raw images, the improved CNN model simplifies detection. This model is optimized for real-time applications in agricultural disease management because it can achieve higher accuracy by utilizing data augmentation and transfer learning techniques.

Proposed OFAC-Net Model

The OFAC-Net model is designed to improve the efficiency and accuracy of wheat yellow rust disease identification and classification. This advanced model integrates PCA, WOA+FFA, and CNN to leverage the strengths of each technique. The process begins with PCA for dimensionality reduction, extracting the most significant features from the pre-processed dataset. PCA minimizes redundant information while retaining critical patterns, reducing computational complexity for subsequent stages.

The optimization phase utilizes a hybrid WOA and FFA approach to refine the feature selection process. WOA simulates the intelligent foraging behavior of whales, effectively encircling and converging on optimal solutions. FFA further enhances the process by simulating the natural attraction of fireflies, ensuring robust exploration and exploitation of the feature space. This dual optimization strategy guarantees the selection of only the most relevant and distinguishing features for the CNN model. The CNN component, serving as the core of OFAC-Net, is responsible for feature extraction and classification. It is enhanced by the optimized feature set derived from PCA, WOA, and FFA. The CNN architecture, comprising various layers, is fine-tuned to recognize intricate patterns and textures indicative of healthy and diseased wheat leaves. The inclusion of deep architectures and advanced techniques ensures high performance, even with moderate dataset sizes.

OFAC-Net's integration of PCA, WOA, FFA, and CNN creates a powerful synergy, enabling precise identification and classification of wheat yellow rust. This technique is tailored for real-time agricultural applications, addressing the challenges of large-scale field deployment with its efficient and accurate design. Figure 5 shows the classification output based on the OFAC-Net model.

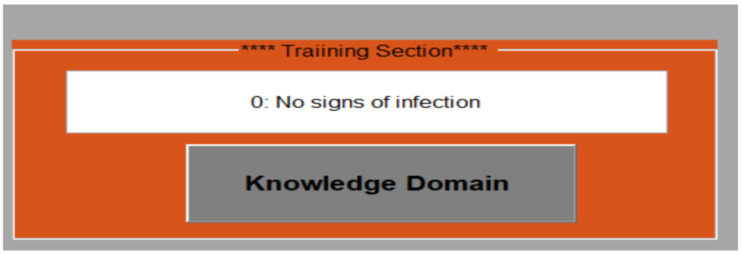

Figure 5 Classify the Yellow Rust Disease in Wheat leaf images

Performance Metrics

The efficacy and dependability of the OFAC-Net model were thoroughly assessed using a range of metrics to gauge its overall performance. The metrics provide a thorough evaluation of the model's performance, concentrating on error minimization, prediction reliability, and classification accuracy.

EXPERIMENTAL RESULTS

In this section, experiment result analysis is confirmed using a dataset namely, the Yellow-Rust-19 dataset to carry out a calculation of the planned OFAC-Net model. The implementation of the research method is carried out utilizing MATLAB 2021a on a Windows 10 (64-bit) operating system (OS) with 8GB RAM, and an Intel Core i7 processor. The GUI was designed as a desktop application to enhance user interactivity and simplify operational workflows. The model's presentation evaluation relies on a database stored in a *.mat file format. The presentation of the implemented model is assessed using standard performance metrics that are defined by Equations (5) to (8).

$$Accuracy = \frac{T_P+T_N}{T_P+T_N+F_P+F_N} \quad (5)$$

$$Precision = \frac{T_P}{T_P+F_P} \quad (6)$$

$$Recall = \frac{T_P}{T_P+F_N} \quad (7)$$

Here: Tp is True Positive, Fp is False Positive, Fn is False Negative, and Tn is True Negative.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y`_i - y_i)^2 \quad (8)$$

Here: $y`_i$ represents the predicted value, y_i is the actual value, and n is the no. of samples.

Qualitative and Quantitative Analysis

In this sub-section, a summary of the performance of the models including the implemented OFAC-Net model, using a variety of evaluation metrics is provided as illustrated in Tables 2, 3, and 4.

Table 2 Performance of proposed OFAC-Net model

Metrics	Values (%)
Accuracy	98.00
Precision	98.76
Recall	99.00
MSE	1.98

Table 2 illustrates the OFAC-Net model's performance, including a high accuracy rate of 98.00% in correctly classifying samples shows how well it works to reduce FPs. The recall value of 99.00% validates the model's resilience in detecting true positive cases. Additionally, the model demonstrated a low mean squared error (MSE) of 1.98, emphasizing its reliability and minimal prediction errors. Figure 6 illustrates the visual representation of the proposed OFAC-Net model.

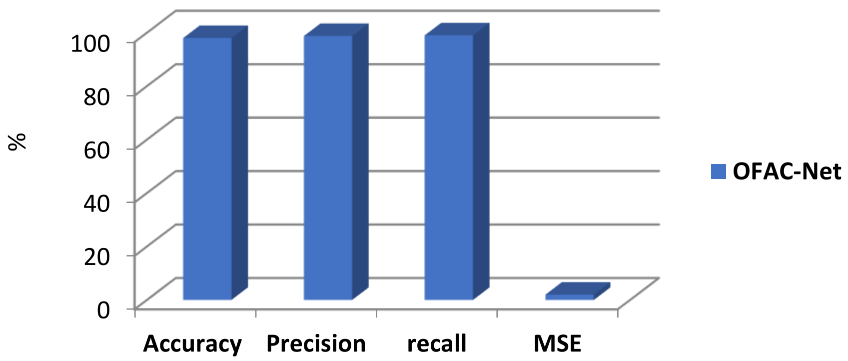

Figure 6 The graphical representation based on the proposed OFAC-Net model w.r.t different metrics

Table 3 and Figure 7 illustrate the existing GhostNet [9] model's performance metrics, with 92.56% accuracy, indicating its accurate classification of samples. The precision, recorded at 92.42%, indicates its effectiveness in reducing false positives. The model's accuracy in identifying true positive cases is emphasized by its recall value of 92.50% and its F1 score of 92.46%.

Table 3 Performance of GhostNet model

Metrics	Values (%)
Accuracy	92.56
Precision	92.42
Recall	92.50
F1-score	92.46

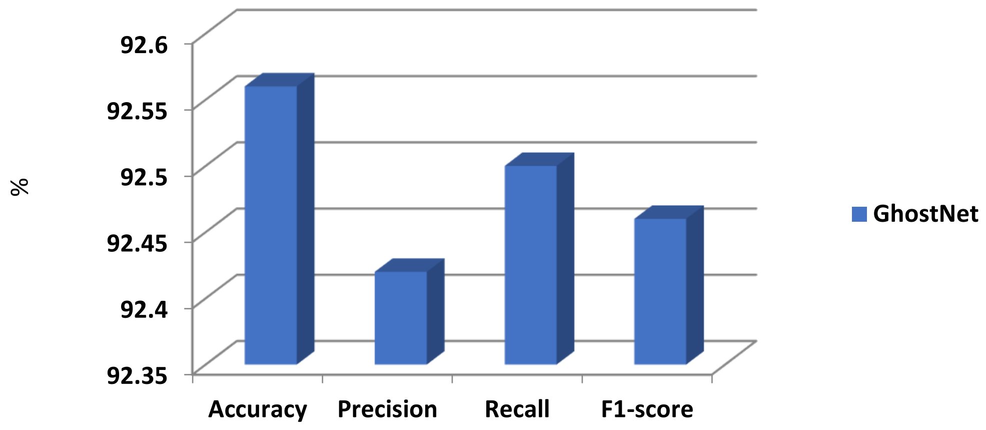

Figure 7 Visual representation of GhostNet model

Table 4 compares the performance of various ML models based on three feature extraction methods: GLCM, LBP, and GLCM-LBP. The evaluation includes each model under the different methods. The DT model shows an accuracy of 81.2% with GLCM, 74.2% with LBP, and 82.6% with GLCM-LBP, indicating a noticeable improvement with the combined method. Precision, recall, and F1-score follow a similar trend, with GLCM-LBP consistently outperforming individual methods. The RF model achieves higher accuracy across all methods, with 90.9% for GLCM, 88.62% for LBP, and 90.30% for GLCM-LBP. Performance is also higher, reinforcing the model's reliability. XGBoost performs competitively, with an accuracy of 89.2% for GLCM, 87.9% for LBP, and 89.63% for GLCM-LBP. It exhibits balanced precision, recall, and F1-score values across the methods.

LightGBM demonstrates the highest performance, with an accuracy of 90.96% for GLCM-LBP, surpassing other methods and models. It also maintains consistent improvements, underscoring the effectiveness of the combined feature extraction approach. This table highlights that the GLCM-LBP method generally enhances the performance of all models compared to using GLCM or LBP alone, while Figure 8 illustrates a graphical representation of the presentation.

Table 4 Performance of various models based on three different methods

Algorithm	Accuracy			Precision			Recall			F1-score		
	GLCM	LBP	GLCM-LBP	GLCM	LBP	GLCM-LBP	GLCM	LBP	GLCM-LBP	GLCM	LBP	GLCM-LBP
Decision tree (DT)	81.2	74.2	82.6	80	74	82	80	73	82	80	73	82
Random forest (RF)	90.9	88.62	90.30	91	88	90	90	87	89	90	88	89

XGBoost	89.2	87.9	89.63	89	88	89	89	86	89	89	87	89
LightGBM	9.63	89.29	90.96	91	90	92	91	88	90	91	88	90
Proposed OFAC-Net		**98.00**			**98.76**			**99.00**			---	

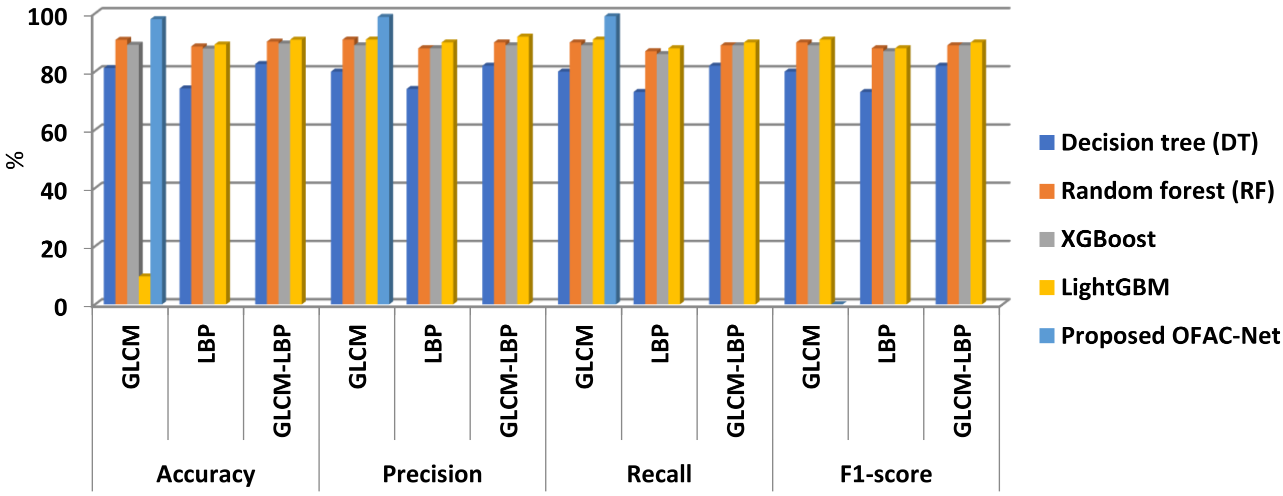

Figure 8 Visual representation of various models based on different extraction methods

Table 5 Comparison Analysis Based on Implemented Models

Metrics	OFAC-Net Model	Ghost Model
Accuracy	98.00	92.56
Precision	98.76	92.42
Recall	99.00	92.50

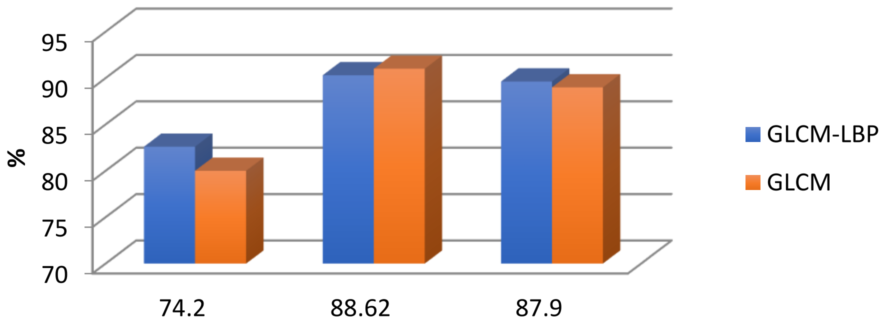

Figure 9 Comparison Analysis based Proposed Model and Existing Implemented Model

Table 5 discusses the comparison between the implemented OFAC-Net model and the existing Ghost Model. The proposed model has achieved a high accuracy rate as compared with the Ghost method. The proposed model's highly extracted features reduce the existing challenges and improve the performance analysis which is shown in Figure 9.

Discussion

In this section, the challenges and benefits are defined in comparison to the existing techniques like Ghost (Li & Fang, 2023), LBP-LightGBM (Shafi & Mumtaz et.al., 2021), GLCM-LightGBM (Shafi & Mumtaz et.al., 2021), etc. The overall evaluation of the models demonstrates the effectiveness of combining feature extraction techniques and advanced algorithms in achieving high performance. Among the methods tested, the OFAC-Net model consistently outperformed traditional ML techniques, including DT and RF, in accurately detecting and classifying wheat yellow rust disease. The results highlight the importance of selecting optimal feature extraction methods and robust ML models for applications requiring detailed pattern analysis in agriculture. Existing methods such as DT and RF, struggle with handling complex, high-dimensional data, leading to suboptimal performance due to issues like overfitting, lower accuracy in multi-class problems, and increased computational overhead. Models like XGBoost and LightGBM, while effective, still face challenges with time complexity and parameter tuning.

The proposed OFAC-Net model overcomes these limitations by leveraging an optimized feature-augmented convolutional network, which effectively captures fine-grained details of wheat yellow rust disease. By incorporating both spatial and feature-level information, the model ensures precise classification. Additionally, its low MSE ensures reliable predictions with minimal computational overhead. The model demonstrated exceptional performance metrics, achieving 98% accuracy, 98.76% precision, 99% recall, and a 1.98% MSE rate, making it a promising solution for real-time wheat disease detection. Compared to traditional ML techniques like DT and RF, as well as advanced models like XGBoost and LightGBM, the OFAC-Net model significantly outperforms them in terms of classification accuracy, efficiency, and applicability to real-world scenarios.

CONCLUSION AND FUTURE SCOPE SSION

This research aims at the development of the OFAC-Net model, which significantly improves the identification and classification of wheat yellow rust. The proposed methodology integrates advanced techniques such as PCA for dimensionality reduction, and the hybrid optimization approach combining WOA with FFA to optimize feature extraction. This approach confirms, that only the most relevant and discriminative features are used, improving the efficiency and accuracy of the disease identification process. The OFAC-Net model utilizes a CNN to learn complex patterns from the image data, achieving superior performance in disease classification.

Testing on the YELLOW-RUST-19 dataset demonstrates the effectiveness of the proposed method. The OFAC-Net model outperforms traditional ML techniques, such as DT and RF, as well as other advanced models like XGBoost and LightGBM. It achieves 98% accuracy, 98.76% precision, 99% recall, and an MSE of just 1.98%, highlighting its robustness and reliability in detecting wheat yellow rust with high precision.

The outcomes of this study suggest that the OFAC-Net model is a promising solution for real-time agricultural applications and scalability for mobile and edge devices. We envision that the model could be further improved by integrating additional optimization algorithms or exploring its application to other crop diseases, thus broadening its potential impact on precision agriculture and disease management.

REFRENCES

[1] Arošová, J., Ripl, J., Fousek, J., & Kundu, J. K. (2018). TaqMan Multiplex Real-Time qPCR assays for the detection and quantification of Barley yellow dwarf virus, Wheat dwarf virus and Wheat streak mosaic virus and the study of their interactions. Crop Pasture Sci, 69, 755–764.

[2] Biel, W., Jaroszewska, A., Stankowski, S., Sobolewska, M., & Kępińska-Pacelik, J. (2021). Comparison of yield, chemical composition and farinograph properties of common and ancient wheat grains. European Food Research and Technology, 247(6), 1525–1538. https://doi.org/10.1007/s00217-021-03729-7.

[3] Bukhari, H. R., Mumtaz, R., Inayat, S., Shafi, U., Haq, I. U., Zaidi, S. M. H., & Hafeez, M. (2021). Assessing the impact of segmentation on wheat stripe rust disease classification using computer vision and deep learning. IEEE Access: Practical Innovations, Open Solutions, 9, 164986–165004. https://doi.org/10.1109/access.2021.3134196.

[4] Chai, Y., Senay, S., Horvath, D., & Pardey, P. (2022). Multi-peril pathogen risks to global wheat production: A probabilistic loss and investment assessment. Frontiers in Plant Science, 13, 1034600. https://doi.org/10.3389/fpls.2022.1034600.

[5] Deng, J., Zhou, H., Lv, X., Yang, L., Shang, J., Sun, Q., Zheng, X., Zhou, C., Zhao, B., Wu, J., & Ma, Z. (2022). Applying convolutional neural networks for detecting wheat stripe rust transmission centers under complex field conditions using RGB-based high spatial resolution images from UAVs. Computers and Electronics in Agriculture, 200(107211), 107211. https://doi.org/10.1016/j.compag.2022.107211.

[6] Dixit, A., & Nema, S. (2018). Wheat Leaf Disease Detection Using Machine Learning Method-A Review. Int. J. Comput. Sci. Mob. Comput, 7, 124–129.

[7] Genaev, M. A., Skolotneva, E. S., Gultyaeva, E. I., Orlova, E. A., Bechtold, N. P., & Afonnikov, D. A. (2021). Image-based wheat fungi diseases identification by deep learning. Plants, 10(8), 1500. https://doi.org/10.3390/plants10081500.

[8] Hayıt, T., Erbay, H., Varçın, F., Hayıt, F., & Akci, N. (2023). The classification of wheat yellow rust disease based on a combination of textural and deep features, " Multimed. Multimed. Tools Appl, 1–19.

[9] Hemalatha, B., Karthik, B., Krishna Reddy, C. V., & Latha, A. (2022). Deep learning approach for segmentation and classification of blood cells using enhanced CNN. Measurement. Sensors, 24(100582), 100582. https://doi.org/10.1016/j.measen.2022.100582

[10] Igam, S. (2021). Wheat Disease Severity Estimation: A Deep Learning Approach. In Conference Proceedings on 6th International Conference on Internet of Things and Connected Technologies (ICIoTCT) (pp. 185–193).

[11] Kaggle.com. (n.d.). Kaggle.com. Retrieved January 13, 2025, from https://www.kaggle.com/datasets/tolgahayit/yellowrust19-yellow-rust-disease-in-wheat/data".

[12] Karamizadeh, S., Abdullah, S. M., Manaf, A. A., Zamani, M., & Hooman, A. (2013). An overview of principal component analysis. Journal of Signal and Information Processing, 04(03), 173–175. https://doi.org/10.4236/jsip.2013.43b031.

[13] Kumar, D., Kukreja, V., Dogra, A., Goyal, B., & Ali, T. T. (2023). Fusion of region extraction and cross-entropy SVM models for wheat rust diseases classification. Computers, Materials & Continua, 77(2), 2097–2121. https://doi.org/10.32604/cmc.2023.044287.

[14] Li, Z., Fang, X., Zhen, T., & Zhu, Y. (n.d.). Detection of Wheat Yellow Rust Disease Severity Based on Improved GhostNetV2. Appl. Sci, 2023.

[15] Mandava, M., Vinta, S. R., Ghosh, H., & Rahat, I. S. (2024). Identification and Categorization of Yellow Rust Infection in Wheat through Deep Learning Techniques. EAI Endorsed Transactions on Internet of Things.

[16] Mirjalili, S. (2016). A "The whale optimization algorithm. Advances in Engineering Software, 95, 51–67.

[17] Mohammed, H. M., Umar, S. U., & Rashid, T. A. (2019). A systematic and meta-analysis survey of whale optimization algorithm. Computational Intelligence and Neuroscience, 2019, 8718571. https://doi.org/10.1155/2019/8718571

[18] Mumtaz, R., Maqsood, M. H., Haq, I. ul, Shafi, U., Mahmood, Z., & Mumtaz, M. (2023). Integrated digital image processing techniques and deep learning approaches for wheat stripe rust disease detection and grading. Decision Analytics Journal, 8(100305), 100305. https://doi.org/10.1016/j.dajour.2023.100305

[19] Pan, Q., Gao, M., Wu, P., Yan, J., & Li, S. (2021). A deep-learning-based approach for wheat yellow rust disease recognition from unmanned aerial vehicle images. Sensors (Basel, Switzerland), 21(19), 6540. https://doi.org/10.3390/s21196540

[20] Rana, N., Latiff, M. S. A., Abdulhamid, S. M., & Chiroma, H. (2020). Whale optimization algorithm: a systematic review of contemporary applications, modifications and developments. Neural Computing & Applications, 32(20), 16245–16277. https://doi.org/10.1007/s00521-020-04849-z

[21] Sabença, C., Ribeiro, M., Sousa, T. de, Poeta, P., Bagulho, A. S., & Igrejas, G. (2021). Wheat/gluten-related disorders and gluten-free diet misconceptions: A review. Foods (Basel, Switzerland), 10(8), 1765. https://doi.org/10.3390/foods10081765

[22] Sarkar, S. (2022). Understanding multi-dimensions of food and nutrition security in odisha: A methodological approach using principal component analysis (PCA). Journal Of Rural Development, 40(3), 332. https://doi.org/10.25175/jrd/2021/v40/i3/134093

[23] Schirrmann, M., Landwehr, N., Giebel, A., Garz, A., & Dammer, K.-H. (2021). Early detection of stripe rust in winter wheat using deep residual neural networks," Front. Plant Sci, 12.

[24] Shafi, U., Mumtaz, R., Haq, I. U., Hafeez, M., Iqbal, N., Shaukat, A., Zaidi, S. M. H., & Mahmood, Z. (2021). Wheat yellow rust disease infection type classification using texture features. Sensors (Basel, Switzerland), 22(1), 146. https://doi.org/10.3390/s22010146

[25] Shafi, U., Mumtaz, R., Qureshi, M. D. M., Mahmood, Z., Tanveer, S. K., Haq, I. U., & Zaidi, S. M. H. (2023). Embedded AI for wheat yellow rust infection type classification. IEEE Access: Practical Innovations, Open Solutions, 11, 23726–23738. https://doi.org/10.1109/access.2023.3254430

[26] Wellings, C. R. (2011). Global status of stripe rust: a review of historical and current threats. Euphytica; Netherlands Journal of Plant Breeding, 179(1), 129–141. https://doi.org/10.1007/s10681-011-0360-y

[27] Yao, F.-M., Li, Q.-Y., Zeng, R.-Y., & Shi, S.-Q. (2021). Effects of different agricultural treatments on narrowing winter wheat yield gap and nitrogen use efficiency in China. Journal of Integrative Agriculture, 20(2), 383–394. https://doi.org/10.1016/s2095-3119(20)63317-2.