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Development of a PSO-optimized deep learning model for effective wheat disease management: A precision agriculture approach

[1]Saurav Mali, [2]Subrata Sinha, [3]Gunjan Mukherjee, [4]Utpala Borgohain, [5]Ujjal Saikia, [6]Gunadeep Chetia, [7]Smriti Priya Medhi, [8]Debashree Borthakur

[1-3]Department of Computational Sciences, Brainware University, Kolkata-700125, West Bengal
[4,5]Centre for Computer Science and Applications, Dibrugarh University, Dibrugarh-786004, Assam
[6]Administrative Branch, Dibrugarh University, Dibrugarh-786004, Assam, India
[7-8]Assam Don Bosco University, Airport Road, Azara, Guwahati--781017, Assam, India

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Abstract: One of the most significant crops and food sources in world is wheat. However, the Growth of wheat is impacted by many diseases of the wheat leaf and many climatic factors. For various types of disease management, farmers detect disease with naked eye, which take lot of time and leads to unhealthy performance, therefore, there is an urgent need of advanced agricultural technology which can automatically and accurately detect the diseases of wheat crop. For our work, VGG19 is a type of CNN model utilized with transfer learning approach for recognizing diseases in wheat leaf images. The parameters of the proposed model is optimized for the classification task and obtained a good accuracy of 98.12%.

Keywords: Deep Learning, CNN, Wheat Disease, Precision Agriculture

1. INTRODUCTION

Wheat is one of the world's most important staple grains and is leading source of calories and plant- derived protein in human food [1]. Agriculture in 2050 will need to produce about 50% more food because of the increase in the world population which is predicted to increase to 9.8 billion and the change in the diet of the population [2]. According to the United Nations Food and Agriculture Organization (UNFAO), one in every 10 people in the world suffers from severe malnutrition due to the scarcity of food. In many developing countries, the per hector yield of grains is very low as compared to the developed countries [3,4]. Research from the Food and Agriculture Organization of the United Nations showed that pests and diseases leads to the loss of 20-40% of global food production[3]. This represents a threat to food security (Food and Agriculture Organization of the United Nation, International Plant Protection Convention2017) [5]. Wheat is world's most widely cultured occupying 22% cultivated area. China is the world's largest wheat producer having yield more than 2.4 billion tonnes of wheat with around 17% of total share production in whole world [6]. In India wheat is the main cereal crop. The total area under crop is about 29.8 million hectores in the country [7]. However, the demand for wheat is much higher than the production of wheat, specifically in developing countries [8].

Many factors can cause low production of wheat, like climate factors, soil factors and many diseases in wheat plants like leaf rust, barely yellow dwarf, black chaff, crown and root rot, fusarium head blight, wheat soil- borne mosaic, wheat streak mosaic etc., [9] which cause 50% losses of wheat globally per year [10]. The appropriate diagnosis of wheat diseases and timely correct remedies can prevent it from wastage, beside that appropriate diagnosis can ensure the quality of the final wheat yield that gives maximum profits to farmers. However due to lack of knowledge, wheat plant disease detection and identification is always tough for farmers, which causes huge loss to farmers. Hence, with advancements in information and communication technologies, newer technological solutions are reaching farmer [11]. Artificial Intelligence can help farmers for early detection of wheat plant disease easily by accessing images through mobile application. The precision agriculture has been instrumental in achievingthe reduced resource utilization and the increased profit . Moreover the application of AI and IOT applications has been good to the early detection of the wheat disease. The easy access to most newer technologies and their appropriate application can even lead to the save of resources of the farmers in the interior side of villages where lack of facilities prevail. Secondly the growth of IOT, AI application along with the communication engineering has performed well for reaching the technology to the doorstep of farmers helping in the economic benefits of them. The pathogens are main cause of concern for the wheat disease which can affect the visible parts like leaf, stem , spikes etc and invisible parts like the roots and the underground part of stem of the plant as well affecting the growth pattern and resulting in the crop yield rate.

In recent years,the machine learning approach has helped a lot to reach to the conclusion depending on the acquired features related to the wheat diseases. The model like SVM, random forests, ANN have responded effectively to the precision of the result but the outcome result has become more prominent by using the concept of deep learning approach. With development of deep learning and particularly Convolutional Neural Network (CNN), image classification task has rapidly advanced in many fields including agriculture and plant disease detection [12].

2. Related Work

In recent years, researchers around the globe are attempting to develop artificial intelligence-based guidance to help farmers make better decisions and take action accordingly against crop diseases. Many researchers have created various machine learning or deep learning models for diagnosing diseases of wheat crops.

In 2018, Atlaf Hussain *et al*. developed a CNN (Convolutional Neural Network) model for automatic wheat disease detection based on the AlexNet architecture. This model was trained for 10 and 30 epochs, achieving an accuracy of 84.45%. The dataset comprised 8828 images, with 7062 used for training and 1766 for testing, following an 80/20 split. All images were resized to 227 x 227 pixels. The model included three disease classes—Yellow Rust, Powdery Mildew, and Stem Rust—and one healthy class. The obtained accuracy was not up to the mark and could have been enhanced to a greater level (Hussain *et al*., 2018).

Nafees Akhter Farooqui and Ritika (2019) developed a novel model for the detection and identification of wheat leaf diseases using K-means clustering, multi-class SVM, and an advanced neural network (ANN). The dataset used for training and testing contained 14,308 images from four different classes of wheat leaf disease: Brown Rust affected leaf, Black Chaff affected leaf, Powdery Mildew affected leaf, Yellow Rust affected leaf, and a Healthy class of wheat leaf. They collected the dataset from Plant Village. Their framework achieved an accuracy of 95.83% (Farooqui & Ritika, 2019). The research was based on extensive feature extraction, which can increase the overall cost of the detection process. Moreover, in-depth knowledge of plant disease characteristics was significantly needed to train the model, making the process time-consuming.

Elias Ennadifi *et al*. (2020) developed a CNN model for detecting wheat diseases from wheat leaves, based on the Feature Pyramid Network (FPN) and ResNet101. They collected 1163 images, classifying them into two groups: sick and healthy, and split the dataset into 80% for training and 20% for evaluation. Hyperparameter optimization was performed using eight different classification models: Inceptionv3 (achieving 90.62% accuracy), VGG19 (65.57% accuracy), ResNet50 (87.3% accuracy), ResNet50V2 (88.11% accuracy), Xception (91.16% accuracy), MobileNet (88.11% accuracy), DenseNet121 (93.47% accuracy), and DenseNet169 (90.75% accuracy). The overall accuracy achieved by this model was 93.47% (Ennadifi *et al*., 2020).

In the same year, Wu Wei *et al*. (2020) used an R-CNN model for the detection and enumeration of wheat grains, employing VGGNet, ResNet, and Inception Net. Their dataset included 1748 images with 29,175 grain objects, collected from three different wheat varieties: Ningmai 13, Yangfumai 4, and Yanmai 23. The dataset was divided into 70% for training, 20% for validation, and 10% for testing. The model exhibited high accuracy when the number of grains in the sample was less than 160, with an error rate below 1%. When the sample size reached 200, the error rate increased but remained relatively low, not exceeding 3.5% (Wei *et al*., 2020). Despite the low error rate, the complexity of this approach was higher compared to other methodologies.

Sindhu and Indirani (2020) developed a new classification model for detecting wheat leaf diseases using an Optimal Deep Neural Network (ODNN) model based on Internet of Things (IoT) and cloud-based technology. To develop this model, the researchers manually collected a dataset of 200 images from several parts of 70 wheat plants affected by various stages of diseases such as Bacterial Leaf Blight, Brown Spot, and Leaf Smut. This dataset served as the training data for the ODNN model, enabling it to learn how to recognize and classify different types of wheat diseases. The model achieved an accuracy of 97.89% (Sindhu & Indirani, 2020). However, the small sample size limits the real-life applicability of this method, potentially resulting in a lack of precision and incorrect decisions regarding wheat plant disease detection on a larger scale.

Zhiwen Mi *et al*. (2020) developed a deep learning model for detecting wheat stripe rust disease using a C-DenseNet architecture. The model was trained on a dataset of 5242 images, collected in natural field conditions using various mobile devices. The dataset contained six levels of stripe rust infection, allowing the model to learn how to detect and classify different degrees of disease severity. This model achieved an accuracy of 97.99% (Mi *et al*., 2020). However, the method proved inefficient in cases where the disease is detectable only through subtle spots.

Jahan *et al*. (2020) developed a machine learning model for detecting and distinguishing wheat diseases using SVM (Stochastic Block Model), NN (Neural Network), GoogleNet, and VGG16 algorithms. This model was trained on a manually collected dataset, which included 500 images of Tan Spot diseased wheat, 200 images of Tan Spot control, 500 images of Leaf Rust diseased wheat, and 200 images of Leaf Rust control. The resolution of the dataset images was 1280 x 7200 pixels. The VGG16 algorithm achieved the highest accuracy at 98%, followed by GoogleNet at 93%, SVM at 86%, and NN at 83% (Jahan *et al*., 2020). The reported study focused on robust feature engineering, as no deep learning model was utilized.

Lakshay Goyal *et al*. (2021) developed a novel CNN model based on the VGG16 and ResNet50 architectures for wheat spike and leaf disease detection. They collected a dataset of 12,000 images encompassing nine different classes of wheat diseases: Karna Bunt, Black Chaff, Crown and Root Rot, Fusarium Head Blight, Leaf Rust, Powdery Mildew, Tan Spot, Wheat Loose Smut, Wheat Streak Mosaic, and one healthy class. The images were resized to 224 x 224 pixels. The model consisted of 13 convolutional layers, 7 max-pooling layers, and 3 fully connected layers, totaling 21 layers. This model achieved an accuracy of 98.62% (Goyal *et al*., 2021). The model was based on a specifically developed deep learning architecture involving a multilayer approach.

Mikhail A. Genaev *et al*. (2021) developed a CNN model for recognizing five fungal wheat diseases, including leaf rust, stem rust, yellow rust, powdery mildew, and Septoria, as well as one healthy plant class. The researchers collected a dataset of 2414 images from various sources, including Google Image Service, Plant Disease Detection Platform (PDDP), Zindi.africa, Saint Petersburg, and Novosibirsk, and used these images to train and test their model. They split the dataset into three subsets: a training set of 1454 images (60%), a validation set of 480 images (20%), and a test set of 480 images (20%). The images were resized to 1500 x 1200 pixels. This model achieved an accuracy of 84.3% (Genaev *et al*., 2021). The accuracy could likely be improved with more advanced deep learning techniques.

Tagel Aboneh *et al*. (2021) developed a CNN model for wheat disease identification and classification using different architectures, such as InceptionV3, ResNet50, and VGG16/19. Their dataset consisted of 1500 images, and the model achieved an accuracy of 99.38% (Aboneh *et al*., 2021). The reported work successfully achieved a high accuracy.

Waleej Haider *et al*. (2021) developed a CNN algorithm for the classification and verification of wheat diseases, including Common Bunt, Fusarium Head Blight, and Sooty Head Molds. The model was trained on a dataset of 9340 images of wheat crops collected from farmers from various sources. They used 6854 images (70%) for training and 2769 images (30%) for testing and validation. This model achieved an accuracy of 97.2%. For this model, they used three conventional (Conv2D) layers and three max-pooling (MaxPooling2D) layers (Haider *et al*., 2021). The accuracy of this model could have been improved by incorporating more layers and optimizing the model further.

Shen *et al*. (2021) proposed a method for detecting impurities in wheat using a Convolutional Neural Network based on ResNet-V2 50, ResNet-V2 101, and a novel model named Wheat V2 architecture. They used a dataset of 21,410 images, which included wheat grain (3550 images), wheat leaf (3750 images), weed (3210 images), wheat straw (3200 images), ladybug (3800 images), and wheat husk (3900 images). The dataset was divided into 60% for training and 40% for validation, and the images were resized to 224 x 224 pixels. Additionally, they selected 270 images from each impurity type as the testing set. This wheat impurities detection model achieved an overall accuracy of 97.83% (Shen *et al*., 2021). The results demonstrate a high level of precision.

Mukhtar *et al*. (2021) developed a deep learning algorithm based on one-shot learning for wheat disease recognition. They collected a dataset of 440 images from the CGIAR crop disease dataset and Google images, which included 11 wheat diseases: Powdery Mildew, Tan Spot, Sharp Eyespot, Leaf Blotch, Leaf Rust, Stem Rust, Black Chaff, Bacterial Streak, Wheat Blast, Phoma Spot, and Stagonosporanodorum. They trained this model on 40 images and tested it on 50 images for each of the 11 diseases. The model achieved an accuracy of around 92% (Mukhtar *et al*., 2021). The study only focused on a selected number of diseases, and future research should extend to cover other disease varieties for broader applicability.

Md Helal Hossen *et al*. (2022) developed a deep learning model for wheat disease detection and classification. They collected a dataset of 4800 images from Kaggle and Github, which included 11 diseased wheat crops: Barley Yellow Dwarf, Black Chaff, Common Root Rot, Fusarium Head Blight, Leaf Rust, Powdery Mildew, Tan Spot, Wheat Loose Smut, Wheat Soil-borne Mosaic, Karnal Bunt, and one healthy wheat crop class. The dataset was divided into three parts: 3840 images for training, 480 images for testing, and 480 images for validation. The model was trained for a total of 30 epochs, achieving an accuracy of 98.84% (Hossen *et al*., 2022). However, the study's limited number of images might not produce realistic results for a properly trained model in real-world scenarios.

In the same year, Jiale Jiang *et al*. (2022) worked on wheat leaf disease identification using a CNN model based on VGG16, InceptionV3, ResNet50, DenseNet121, EfficientNet-B6, ShuffleNet-v2, and MobileNetV3 architectures. The dataset consisted of 2643 field images, including healthy wheat leaves and three common diseases of wheat leaves: Powdery Mildew (561 images), Leaf Rust (808 images), and Stripe Rust (1015 images). These images provide a valuable resource for developing and testing machine learning models. They resized the images to 224 x 224 pixels to reduce the computational complexity of the model. This wheat disease detection model achieved an overall accuracy of 92.05% (Jiang *et al*., 2022). However, the work was somewhat limited by the small size of the target symptoms and the similarity effects among the diseases, which hindered the accuracy.

Habib Khan *et al*. (2022) developed a machine learning technique for the identification of brown and yellow rust diseases in wheat crops. The model classified wheat crop images into three classes: healthy crop, brown-rusted, and yellow-rusted wheat. It was trained and validated on a manually collected dataset of 3000 images, resized from 1026 x 768 pixels to 250 x 250 pixels. This proposed framework achieved an accuracy of 99.8% (Khan *et al*., 2022). However, the study only considered three disease classes, and the accuracy for additional classes was not reported.

Usha Ruby A. *et al*. (2022) developed a deep learning CNN model based on ResNet50, InceptionV3, and DenseNet architectures to classify different wheat leaf diseases. This model was trained with a dataset of 4500 images, which included four classes: three groups of wheat diseases (Leaf Rust, Crown Root Rot, and Wheat Loose Smut) and one healthy class. The dataset was divided into 20% for testing and 80% for training the model. This model achieved an accuracy of 98.44% (Ruby *et al*., 2022). The overall method involved a significant amount of time to achieve the implied accuracy.

Shivani Sood *et al*. (2022) developed a CNN (VGG16) model for classifying wheat rust diseases. They used a dataset of 1486 images, with 876 images for training and 610 images for testing, including two classes of infected wheat (leaf rust and stem rust) and one class of healthy wheat. The model comprised 13 convolutional layers and 3 fully connected layers. This model achieved an overall accuracy of 99.54% after being trained for 80 epochs (Sood *et al*., 2022). However, the model reported in this paper only worked with two types of disease classes.

Laixiang Xu *et al*. (2023) developed a CNN model using VGG19, ZF Net, GoogleNet, and InceptionV4 for detecting wheat leaf diseases. They used a dataset of 7239 images of wheat leaves, consisting of one healthy class (1693 images) and four diseased classes: Powdery Mildew (1471 images), Septoria (1326 images), Blight (1457 images), and Leaf Rust (1292 images). The dataset was randomly divided into training, testing, and validation sets with a ratio of 3:1:1, respectively. This model achieved an accuracy of 99.95% after being trained for 900 epochs (Xu *et al*., 2023). However, the random division of the dataset can lead to the infusion of spurious data, resulting in a potential decrease in accuracy.

Krishna *et al*. (2023) designed an M3FCM (Mask Based Membership Filtering) algorithm based on a CNN, combining SSP (Star Shape Search Pattern), LoG (Laplacian-of-Gaussian), and histogram equalization. They used a dataset of 407 images, including two classes of diseased plants: Stripe Rust (208 images), Septoria (97 images), and 102 images of healthy wheat leaves. The designed model achieved an accuracy of 94.91% (Krishna *et al*., 2023). However, the model could suffer from a deficiency of information due to the masking operation.

Deepak Kumar and Vinay Kukreja (2023) developed a model using GAN (Generative Adversarial Network) and CNN (Convolutional Neural Network) for the classification of different wheat diseases. They manually collected 440 images and sourced 360 images from different online platforms, creating a dataset of 800 images of wheat diseases: Yellow Rust (210 images), Leaf Rust (150 images), Powdery Mildew (150 images), Stem Rust (110 images), and healthy crops (180 images). The images were resized to 436 x 436 pixels and then divided into grids of 29 x 29 and 58 x 58 pixels. Their framework achieved an accuracy of 95.6%, which is quite high for wheat disease detection (Kumar & Kukreja, 2023). However, the model is prone to potential losses, which poses a significant drawback.

Cheng *et al*. (2023) developed a novel model for wheat disease detection based on position information. They trained this model with a dataset of 4115 images, including three diseased samples (Microphthalmia, Rust, and Blastomycosis) totaling 2626 images, and one class of healthy wheat crop with 1486 images, all collected manually. The model achieved an accuracy of 91.7% (Cheng *et al*., 2023). However, the proposed model in this study suffered from limitations in training, resulting in a relatively low accuracy value.

In all the reported works, deep learning algorithms with CNN models have been used with good accuracy results. However, model dependency has become a major issue. Moreover, the time-critical approach for generating results can be costly for operational models, especially when dealing with large datasets. An imminent solution to this situation could be the incorporation of hyperparameter optimization for the model. Hyperparameters can be optimized in several ways. In this paper, PSO (Particle Swarm Optimization) was used to optimize the hyperparameters to improve the model's accuracy.

3. Dataset and CNN Architecture

The proposed wheat disease prediction model has been developed using a convolutional neural network with two types of wheat diseases namely early blight and late blight diseases from the Kaggle.

3.1 Dataset: The image set obtained from Kaggle Plant Village Dataset thus have under gone enhancements to 8000 images through image argumentation process. The different wheat leaves with diseases types brown rust and yellow rust are shown below in the Figure 1.

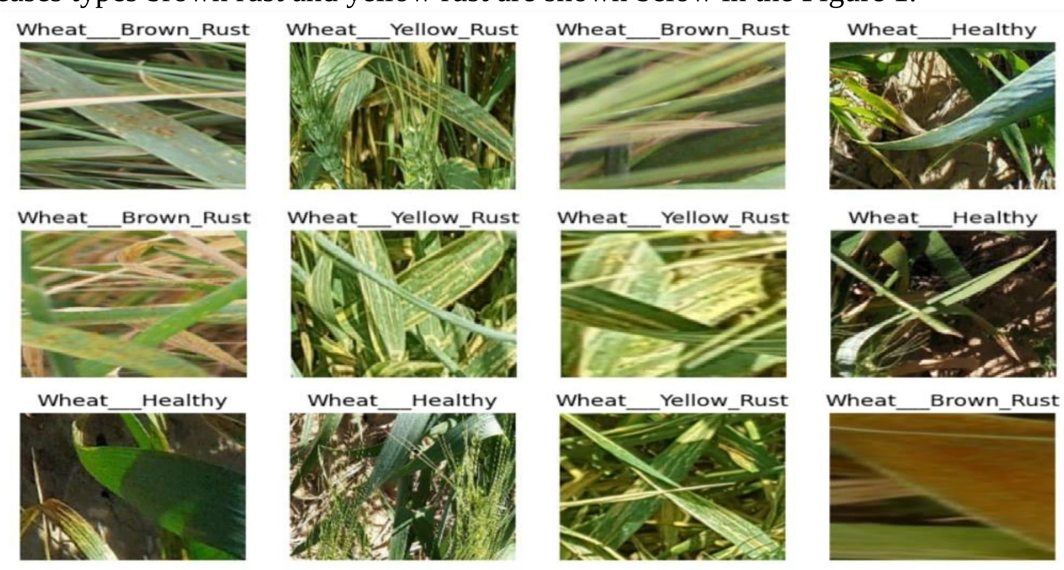

Fig 1. Samples of different wheat disease classes

3.2 Model structure: A CNN model developed with 7 convolutional layer , 3 maxpool layer, 2 fully connected layer {2 conv x 1Max pool}*2 +{3conv x 1Max pool}*1+1 Flatten+2 FC layer + 1 output layer.The training was performed with 30 epochs with 80% of the image in training set, 10% for testing and 10% for validation set. The model summary nof the optimized CNN architecture has been represented in the Table 1.

Table 1. The summary for the CNN model

Layer(type)	Output Shape	Param#
Sequential (Sequential)	(None, 256, 256,)	0
Conv2d_10 (Conv2D)	(32, 254, 254, 32)	896
Conv2d_11 (Conv2D)	(32, 252, 252, 32)	9248
Max_Pooling2d_6 (Maxpooling2d)	(32, 126, 126, 32)	0
Conv2d_12 (Conv2D)	(32, 124, 124, 64)	18496
Conv2d_13 (Conv2D)	(32, 122, 122, 64)	36928
Max_Pooling2d_7 (Maxpooling2d)	(32, 61, 61, 64)	0
Conv2d_14 (Conv2D)	(32, 59, 59, 128)	73856
Conv2d_15 (Conv2D)	(32, 57, 57, 128)	147584
Conv2d_16 (Conv2D)	(32, 55, 55, 128)	147584
Max_Pooling2d_8 (Maxpooling2d)	(32, 27, 27, 128)	0
Flatten_1 (Flatten)	(32, 93312)	0
Dense_4 (Dense)	(32, 256)	23888128
Dense_5 (Dense)	(32, 128)	32896
Dense_6 (Dense)	(32, 3)	387

The kernel size chosen was 3x3. The kernel iterates over the input image performing element-by-element matrix multiplication to conduct convolution. The feature map records the outcome for each receptive field or the region where convolution occurs. To accommodate computational memory, Pooling Layers, which are added after the convolutional layers, reduce the size of the convolved feature map. Two Fully Connected layer has been added to the design after numerous convolutional and pooling layers. This layer connects the neurons between two different layers by using weights and biases in addition to the neurons.

The FC layer receives a flattened version of the input image from the preceding levels. The flattened vector is then put through a few additional FC layers, where the standard operations on mathematical functions happen. The classification procedure starts to take place at this point. These CNN layers lessen the amount of human supervision. Finally, the SoftMax activation function, which determines which model inputs should fire in the forward direction and which ones should not at the end of the network, was applied in the output layer.

3.3 Hyperparameter optimization: The CNN consists of many numbers of convolutional layers which are responsible for extraction of the feature maps of the object through the kernels. Each of the convoluting layers possesses the number of kernels. The individual kernels produces feature maps in scale invariant manner. The immediate poling layer after the conventional layer reduces the dimensions with the help of down sampling operations with the proper replacement of some parts with statistical summaries. The key hyperparameters attached to the model are (i) Number of convolution layers (ii) Number of kernels in each convolution layer (iii) Kernel size (iv) activation functions in each convolution layer (v) Pooling size(vi) Number of dense layers (vii) drop out values (viii)learning rate (ix) learning rules and (x) batch size. Particle swarm optimization (PSO) optimization has been used for optimizing the above hyperparameters with respect to the model.

3.4 Experimental Setup: A desktop PC equipped with an Intel Core-I7 processor and 16 GB of RAM was used for the following experiments. A batch size of 32 was taken and ADAM optimizer was used as the optimizing method. The images dataset was divided into three subsets: training, testing, and validation in the ratio 60:20:20. The image sets are utilized to train up the hyper parameterized CNN model.

4. Result

The optimized values of the hyper parameters after performing PSO optimization are shown in the table:

Table 2: The hyper parameters involved in the model and the corresponding optimum values

Hyper parameter	Initial values	Optimized values
(i) Number of convolution layers	2 or 3 or 4 or 6	6
(ii) Number of kernels in each convolution layer	[16, 32, 64]	64
(iii) Kernel size	(3, 3), (5, 5), (3, 3)	(3,3)
(iv) Activation functions in each convolution layer	ReLU, Tanh, Leaky ReLU	ReLU
(v) Pooling size	(2, 2), (3, 3), (2, 2)	(3,3)
(vi) Number of dense layers	1, 2, 3	3
(vii) Drop out values	0.2, 0.3, 0.5	0.5
viii)Learning rate rules	0.001, 0.01, 0.0001	0.01
(ix) Optimization Algorithm	Adam, RMSprop, SGD	Adam
(x) Batch size	32, 64, 128	32

The convergence of the training curve for optimized CNN model has been shown in the Fig. 2. The accuracy value of the training curve has been plotted against the epoch. The curve initially has grown to a certain value and finally has got converged after the epoch value 6.0. The considerable convergence has been observed after the inflexion point which continued till some point with the appreciable convergence. The onset of the convergence of curve has confirmed the good responses of optimization task brought about by the PSO techniques.

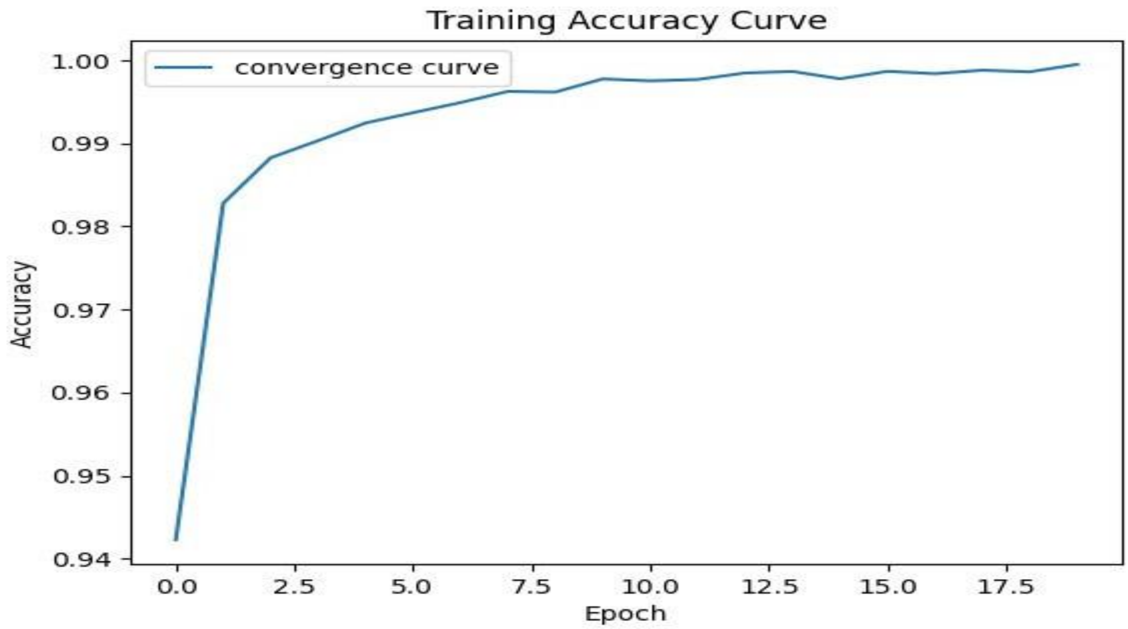

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Fig 2. The convergence curve for the model

The convergence of the objective function for the optimized model has been in accordance with the accuracy value of training and validation. The close compliance of the values has become obviously observed between the curves.

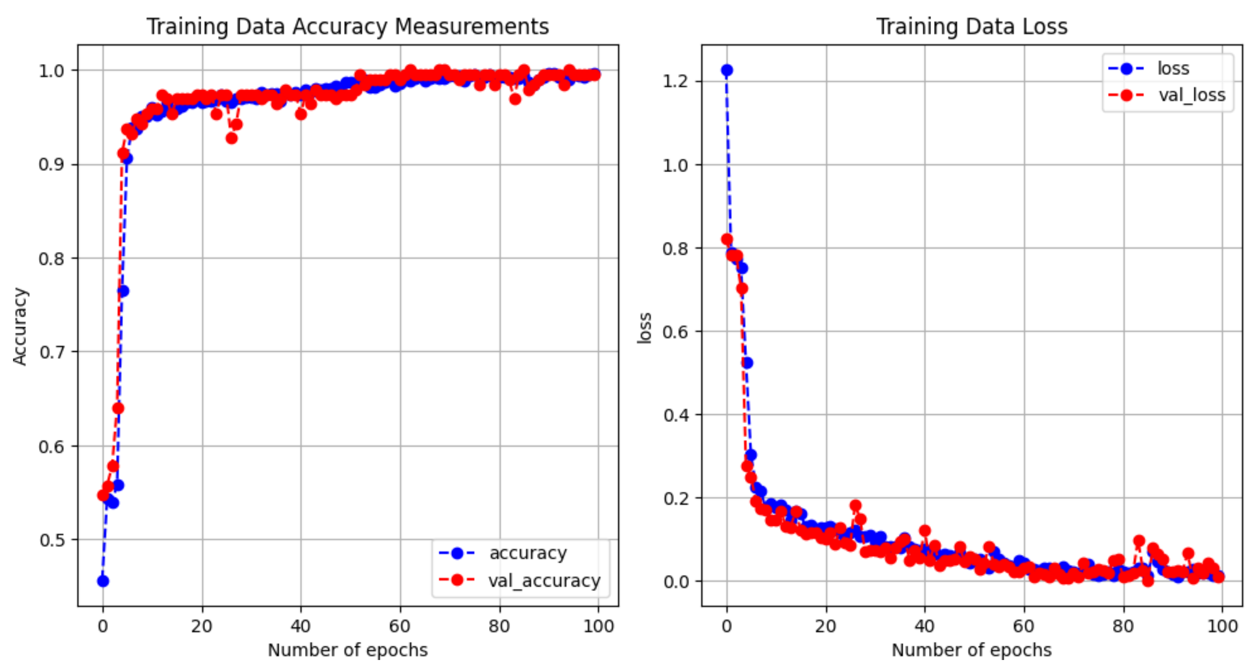

Fig. 3. The accuracy and loss curves for the CNN model

The training data accuracy measurements in Fig. 3 show that accuracy starts around 0.5 and rapidly increases, reaching near 1.0 within the first 20 epochs. Both training and validation accuracy closely mirror each other and plateau around 1.0. Similarly, the training data loss decreases sharply within the first 10 epochs. Both training and validation loss closely follow each other and stabilize at a low value close to 0 after around 20 epochs. This rapid improvement in both accuracy and loss within the initial epochs indicates effective learning by the model. The close mirroring of training and validation metrics suggests that the model is generalizing well and not overfitting. The plateau in accuracy and stabilization of loss values around 20 epochs indicate that the model has reached optimal performance with the given data and training configuration. Further training beyond this point is unlikely to yield significant improvements in performance.

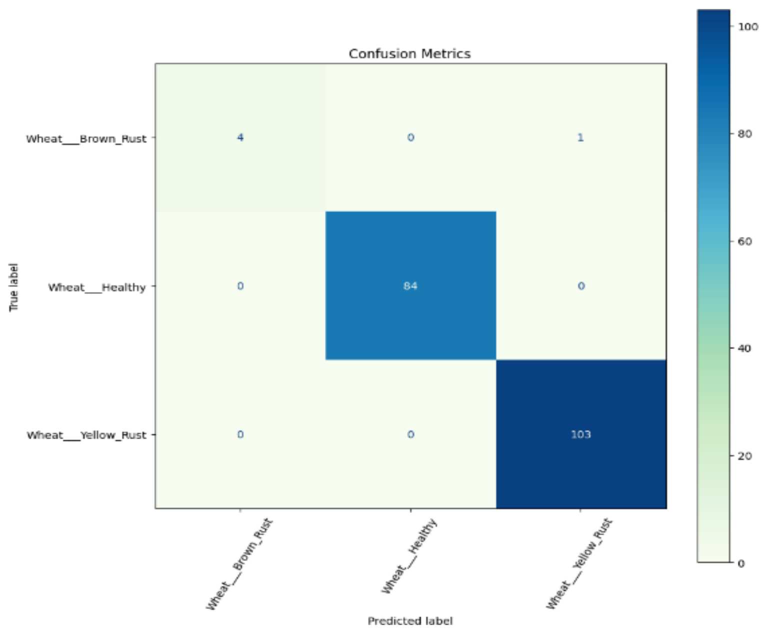

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Fig 4. Confusion matrix

Fig.4 suggests, the model has high accuracy for Healthy and Yellow Rust, with no misclassifications for these classes. There is a single misclassification where Brown Rust is incorrectly predicted as Yellow Rust. The overall performance indicates that the model is highly accurate in distinguishing between the different classes, with very few errors.

The confidence report as shown in Fig. 5, demonstrates the model's high accuracy in classifying wheat conditions. Each sub-image is labeled with the actual and predicted conditions, along with the confidence level of the prediction. The model correctly identifies Wheat_Yellow_Rust and Wheat_Healthy in all instances, with confidence levels ranging from 99.23% to 100.0%. This consistent high confidence across multiple examples highlights the model's reliability and precision. The model's ability to accurately and confidently distinguish between healthy wheat and wheat affected by yellow rust underscores its effectiveness in classification tasks.

Fig 5. Confidence Report of the proposed model

Table 3. Performance metrics of the proposed model

Disease class	ACC	PRE	SEN	SPE	F1-SCORE	NPV	MCC
Brown _rust	1.00	1.00	0.80	1.00	0.89	1.00	0.89
Healthy	0.93	1.00	0.86	1.00	0.92	0.89	0.87
Yellow_rust	0.93	0.87	1.00	0.85	0.93	1.00	0.86

Table 3 reveals that the proposed deep learning model exhibits impressive performance across all disease classes and metrics, with particularly high accuracy (ACC) of 1.00 for both Brown Rust and Yellow Rust, and a strong 0.93 for Healthy wheat, indicating the model's effectiveness in identifying both diseased and healthy instances. The model achieves perfect precision (1.00) for Brown Rust and Healthy, though it has slightly lower sensitivity (0.80 for Brown Rust and 0.86 for Healthy), suggesting some missed cases for these classes. For Yellow Rust, while precision is lower at 0.87, indicating more false positives, the model demonstrates perfect sensitivity (1.00), effectively detecting all Yellow Rust instances. Both Brown Rust and Healthy classes show perfect specificity (1.00), while Yellow Rust has a slightly lower specificity of 0.85. The F1-Scores for all classes are high, with 0.89 for Brown Rust, 0.92 for Healthy, and 0.93 for Yellow Rust, reflecting a good balance between precision and sensitivity. The Matthews Correlation Coefficient (MCC) values are strong across the board, with 0.89 for Brown Rust, 0.87 for Healthy, and 0.86 for Yellow Rust, indicating a strong overall correlation between predicted and actual classifications. While the model performs well, there is room for improvement in increasing sensitivity for Brown Rust and precision for Yellow Rust. Future work could explore data augmentation, hyperparameter tuning, or advanced architectures to address these limitations and enhance model performance.

5. Discussion

The development of a PSO-optimized deep learning model for wheat disease management has demonstrated significant advancements in precision agriculture. The model's architecture, based on VGG19 and optimized through particle swarm optimization (PSO), achieved an impressive accuracy of 98.12%. The inclusion of transfer learning enabled the model to classify wheat diseases effectively, with high precision and reliability.

The training data accuracy and loss curves indicate rapid learning, with accuracy starting around 0.5 and reaching near 1.0 within the first 20 epochs. Both training and validation accuracy closely mirror each other and plateau around 1.0. Similarly, the training data loss starts high at 1.2 and decreases sharply within the first 10 epochs, stabilizing at a low value close to 0 after around 20 epochs. This rapid convergence suggests that the model's hyperparameters are well-tuned, and the PSO optimization effectively enhances the model's performance.

The confusion matrix shows the model's high accuracy for Healthy and Yellow Rust, with no misclassifications for these classes. There is a single misclassification where Brown Rust is incorrectly predicted as Yellow Rust. The confidence report further validates the model's robustness, showing consistent high confidence across multiple examples, with confidence levels ranging from 99.23% to 100.0%.

These results underscore the model's reliability and precision in practical applications, indicating its potential for real-world deployment in agricultural settings. However, the slight decrease in sensitivity for Brown Rust, which is 0.80, suggests that some instances might be missed, highlighting the need for further refinement. Additionally, while the model performs well with the current dataset, its generalizability to other datasets and environmental conditions should be tested. Future work could focus on expanding the dataset to include more diverse images and incorporating additional disease classes. Enhancing the model's architecture and exploring advanced machine learning techniques, such as ensemble learning or hybrid models, could further improve performance.

6. Conclusions

The PSO-optimized deep learning model for wheat disease management presents a significant step forward in precision agriculture. By leveraging the capabilities of CNNs and optimizing hyperparameters through PSO, the model achieves high accuracy and reliability in classifying wheat diseases. The results demonstrate the model's effectiveness in early disease detection, which is crucial for preventing crop losses and ensuring optimal yield. The study highlights the potential of integrating advanced AI techniques in agricultural practices to enhance disease management and support sustainable farming. Future research should focus on addressing the model's limitations and exploring new methodologies to further improve its accuracy and applicability across diverse agricultural scenarios.

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