ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

Optimized Deep Convolution Networks for Wheat Leaf Disease Detection & Classification

[1] Juttiga Naga Durga Bhavani , [2] Pati Apurva, [3] Gandikota Mahima Kumar, [4] Chandaka Vishnu Vardhan, [5] Dr. B. V. Ram Kumar

[1,2,3,4] Student, Dept. of CSE, DNR College of Engineering & Technology, Balusumudi, Bhimavaram, India.

[5] Professor, Dept. of CSE, DNR College of Engineering & Technology, Balusumudi, Bhimavaram, India.

A B S T R A C T

When it comes to grain consumption and harvesting, wheat is third in the world. However, many wheat harvests are destroyed by diseases. More than twenty distinct diseases may infect wheat crops. Because of this, manual diagnosis of many illnesses becomes very challenging. Automated disease categorization systems have the potential to improve wheat harvest yields in terms of both quantity and quality. Furthermore, it might be a useful tool for determining crop quality and pricing. Image analysis using deep learning could help in disease classification and diagnosis. The wheat plant's spike and leaves are the areas that suffer the most damage. It is possible to diagnose the majority of diseases based on the features of these components. The paper presents a novel method for classifying wheat diseases. In order to accurately classify ten distinct wheat diseases, we develop a new deep learning model. The proposed method is very accurate, having achieved a testing accuracy of 97.88%. Its accuracy is 7.01% higher than that of VGG16 and 15.92% higher than that of RESNET50, two other popular deep learning models. Memory, f-score, and accuracy are only a few of the experimental measures that show how the proposed approach surpasses the state-of-the-art.

Introduction and related work

Worldwide, wheat ranks third in grain consumption, behind only rice and maize. One out of ten people on Earth are severely malnourished because of food shortages, says the United Nations Food and Agriculture Organization (UNFAO). Developed nations often have much higher grain yields per acre than many emerging nations [1]. The utilization of cutting-edge technology and methods in several industries also contributes to this discrepancy. Currently, the world is being shaken to its foundations by the fourth industrial revolution. The use of AI, ML, the Internet of Things (IoT), and edge computing is substantially altering the agricultural industry [2]. Reduced resource waste and greater revenues are the results of these technologies' assistance to precision agriculture [3]. Wheat may be saved from waste with the right identification of illnesses and prompt corrective treatment. Furthermore, it may guarantee a high-quality wheat harvest, which in turn maximizes farmers' profits. To a satisfactory degree, deep learning can resolve picture categorization issues. Support vector machines, random forests, and other conventional feature-based supervised learning methods are at odds with these techniques. Because they don't need manually created features as input, supervised deep learning techniques are considered end-to-end approaches. Alternatively, the activities at the foundational level are capable of autonomous feature extraction and learning. Recently, picture categorization has seen extensive application of deep learning models. Many deep learning models are already available, having been trained on large datasets. The quality of grains used for food has an effect on many parts of human existence. Developing nations, especially those in Africa and Asia, are fighting an uphill battle against hunger and malnutrition due to the worldwide scarcity of food. The general welfare of rural households is impacted by low agricultural productivity [27]. Newer technical solutions are making their way to farmers as a result of developments in information and communication technology. In this area, AI-powered mobile apps are finding increasing utility; for example, Uzhinskiy et al. [27] suggested a deep learning-based app for wheat disease categorization. Wheat illnesses that reduce harvest yield are mostly caused by pathogens [28]. Both the visible and unseen aspects of the wheat plant are susceptible to pathogens. sections that are visible include the stems, spikes, and leaves, whereas sections that are concealed include the roots. One study that looked at the link between

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

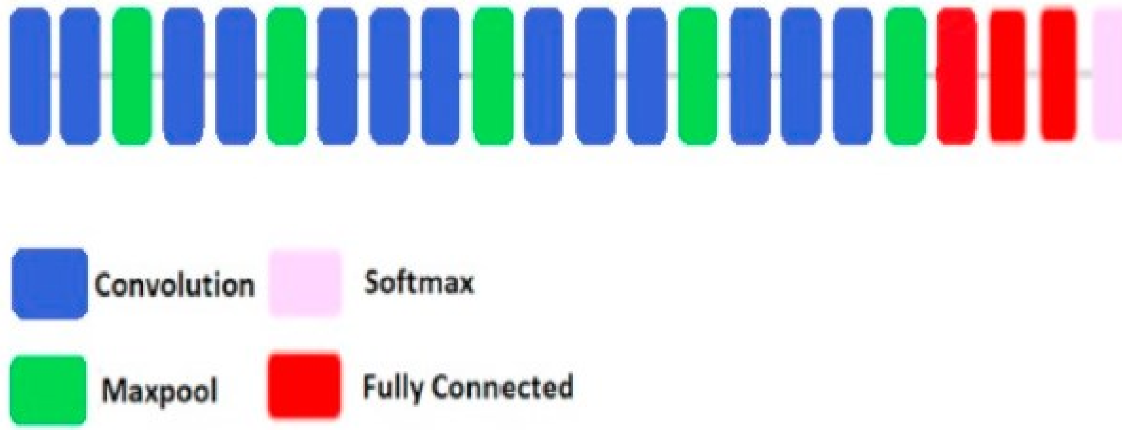


Fig. 1. VGG16 architecture.

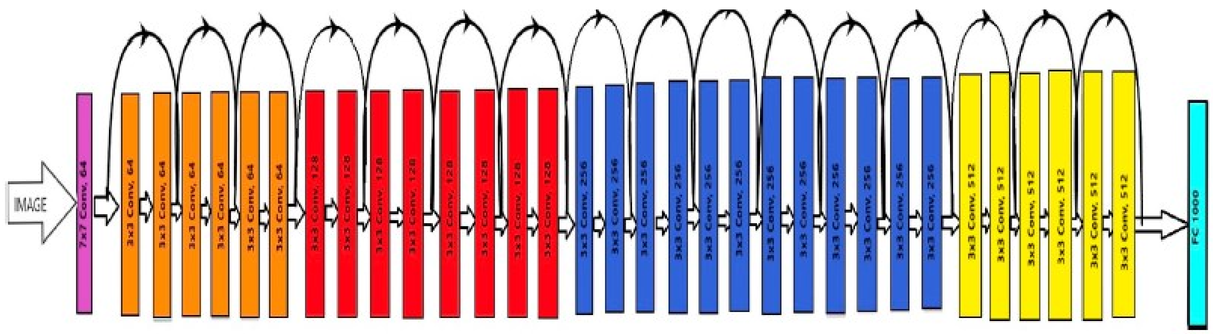


Fig. 2. ResNet50 architecture.

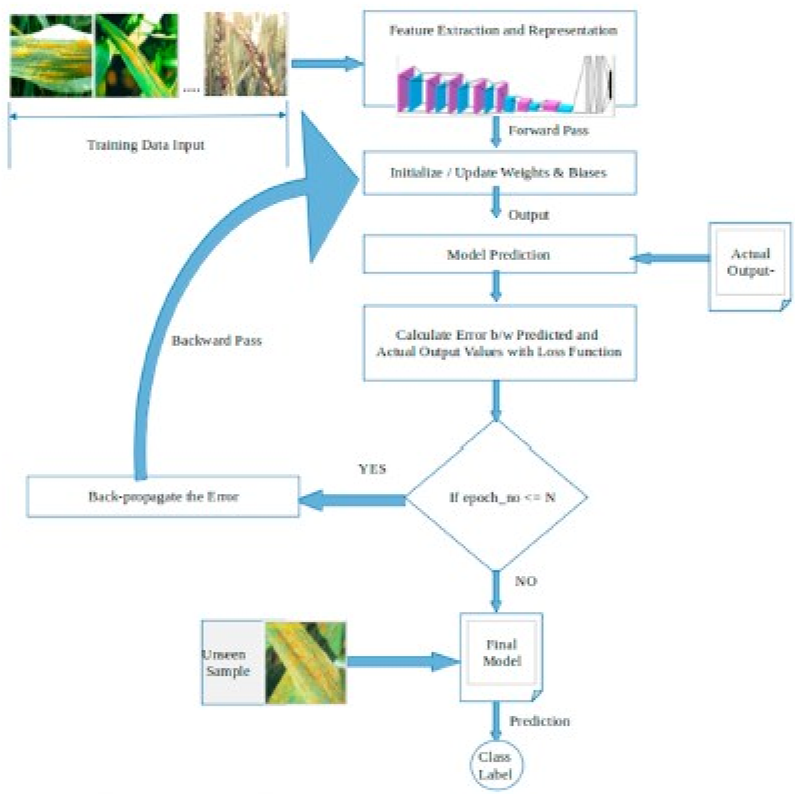
wheat lines for fusarium head blight (FHB) and morphological and biochemical traits by using a data-driven and AI-powered strategy. The topic of wheat disease detection in the field is now the subject of some study [4]. created a dataset on wheat diseases and a system to diagnose them using a poorly supervised method. Alterations to genes have the potential to make people more resistant to certain illnesses. It is a whole separate field of study. Still, AI may facilitate the discovery of novel approaches. Wheat rust resistance crop genome selection was covered in Gonz'alez-Camacho et al. [5] as an application of machine learning. Additionally, machine learning was used by Azadbakht et al. [6] to classify wheat diseases. Support vector machines (SVMs), k-Neighbors classifiers (KNNs), decision forests, linear discriminant analysis (LDAs), naive Bayes classifiers, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and others have all been employed for disease classification in wheat [15-19]. The other approaches that rely on feature selection have not been as successful as decision forests and support vector machines. Feature extraction may be done automatically during the learning process for deep learning models. Using these qualities, these methods can learn and extract data independently. Applications involving the categorization of agricultural diseases benefit greatly from deep learning techniques, which are known as end-to-end machine learning methods [20-25]. When it comes to picture categorization, deep neural networks that use convolutional neural networks as their foundation function effectively. These techniques have recently outperformed the more conventional supervised learning methods when it comes to classification. Researchers have made significant advancements in the models of deep learning networks. To get around CNNs' shortcomings, one may use recurrent neural networks (RNN). In addition, RNNs are improved by long-short term memory (LSTM). However, there are a few restrictions on the use of deep learning classifiers as well. In order to train, these algorithms are very resource-intensive and need massive volumes of data. Another typical problem is overfitting, which happens when there is a large discrepancy between the model's accuracy in training and test. This occurs when the model fails to learn from the instances and instead memorizes them. Having a large amount of data, regularization, and dropout may all assist reduce the risk of overfitting. If there is a shortage of both data and computing resources, transfer learning may help with classification performance [26]. The term "transfer learning" describes the process of using the parameters of an existing model that was trained using a different dataset. Many pre-trained deep learning

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

architectures are available, including VGG16, VGG19, RESNET 50, MobileNet V2, and others, for common picture categorization tasks. Size, diversity, and class imbalance are three factors that influence a deep learning model's classification accuracy [7]. looks at how different dataset sizes and types affect how well a model performs [8]. use illness categorization algorithms powered by deep learning [9]. completed an overview of deep learning methods for various crop plantings.

Deep learning for image classification

Have provided an in-depth analysis of plant disease identification, and there are a plethora of deep learning architectures accessible for picture categorization and understanding [10]. Their research has included a wide range of pandemics, illnesses, and detection techniques. In their study, the authors of [11] compiled a list of all the deep learning algorithms and the problems they solve. Presented an additional overview of deep learning for medical image analysis in [12]. The use of machine learning for picture recognition has been covered in the literature [13,14]. Here we will take a quick look at two of these well-known designs, ResNet 50 and VGG16. Historically, these designs have mostly



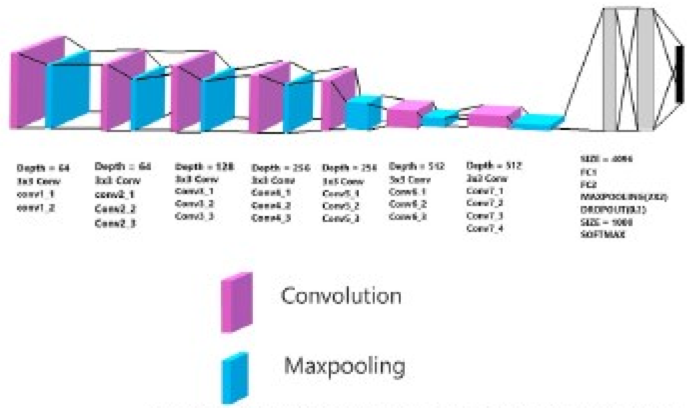
(a). Schematic Flow Diagram of the Proposed System for What Disease Classification

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025



(b). The Proposed Deep Learning Model for Supervised Learning

Fig. 3. (a). Schematic flow diagram of the proposed system for what disease classification

Fig. 3(b). The proposed deep learning model for supervised learning.

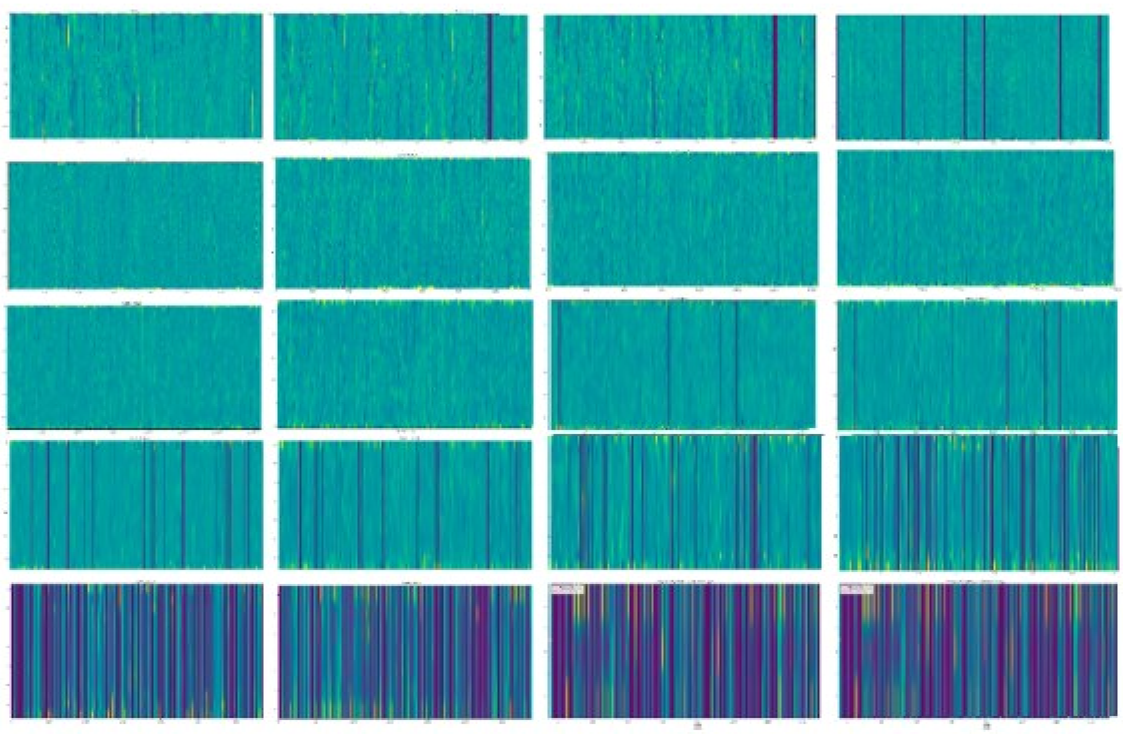


Fig. 4. Snapshot of deep learning from the data.

used for picture object identification jobs. On the other hand, when it comes to tasks like semantic segmentation, video classification, picture indexing and retrieval, etc., they may be fine-tuned and used with transfer learning to perform adequately. We used VGG16 and ResNet 50 for wheat disease classification later on in the experimental findings. Let me give you a quick rundown of what they are.

VGG16 deep learning architecture

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

A deep learning architecture based on Convolutional Neural Networks (CNNs), the VGG16 has 16 weighted layers. Convolutional, Max Pooling, Activation, and other types of layers are all part of this framework. An exact count of 21 layers yields 13 Convolutional, 5 Max Pooling, and 3 thick layers. Nevertheless, the design only makes use of sixteen weighted layers. Two 4096-node layers form the basis of a softmax classifier. Starting with a modest 64, the network width increases by a factor of 2 after each pooling layer. In contrast, VGG16 makes use of 140 million parameters. For comparable image recognition issues, you may use the pre-trained VGG16 model as a transfer earning model; it was developed on the massive ImageNet dataset (see Fig. 1).

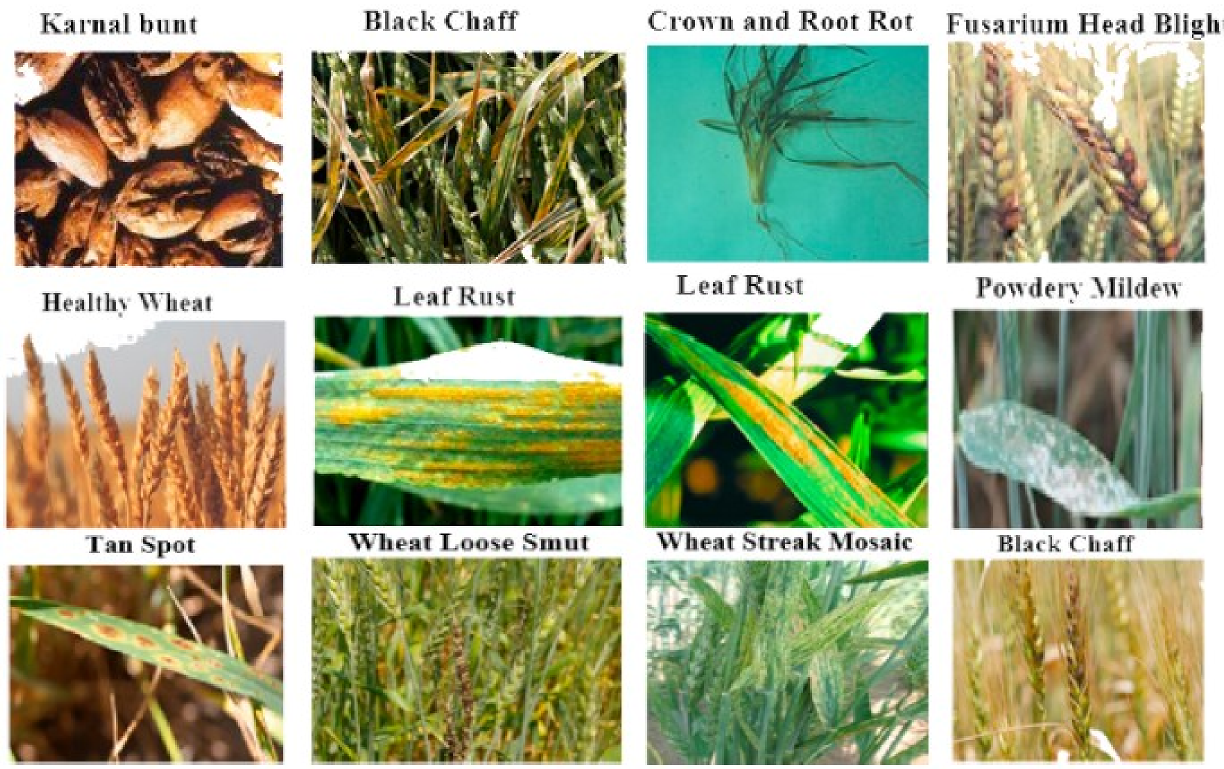


Fig. 5. Samples selected from the collected dataset LWDCD2020.

Table 1
The composition of Large Wheat Disease Classification Dataset (LWDCD2020).

Wheat Disease Class	#Images
Karnal bunt	1150
Black Chaff	1100
Crown and Root Rot	1040
Fusarium Head Blight	1270
Healthy Wheat	1280
Leaf Rust	1620
Powdery Mildew	1230
Tan Spot	1220
Wheat Loose Smut	1100
Wheat Streak Mosaic	1150

ResNet50 deep learning architecture

Another kind of neural network design, ResNet 50 (Residual Networks) has 50 layers. A "characteristic alternate way of association" that does not include any layers is believed to be the core notion behind ResNet. Figure 2 depicts the architecture of ResNet 50. There are 23,587,712 parameters in the typical ResNet50 model. Which leaves 53,120 parameters that cannot be trained and 23,534,592 that can.

Proposed methodology for wheat disease classification

Figure 3 (a) depicts the system architecture for wheat disease classification that has been suggested. Figure 3 (b) shows the training dataset being fed into the deep learning model. The model then learns the distinguishing characteristics of the ten data classes, as illustrated in Figure 5 (see to Figure 4). During the backward pass, the model's weights (parameters) are adjusted in order to transmit the estimated error with the anticipated and expected values backwards. There is a limited amount of iterations, or epochs, in the training process. After the training process ends, the accuracy of the model is recorded and saved to disk. A further step involves categorizing the unseen data using this model. In order to classify wheat diseases, the suggested deep convolutional model is shown in Fig. 3(b). When implemented at various points in the signal processing pipeline, convolution, pooling, and regularization operations enable convolutional neural networks to efficiently solve picture categorization issues. Over twelve thousand photos of wheat illnesses were used to train the suggested model. When the trained model is ready, it may take in a picture and assign it a disease class (or, if applicable, "healthy wheat"). A 224 × 224 pixel RGB picture is fed into it for the purpose of training. The 3 x 3 kernel size is used by the model's convolutional layers. Applying max pooling helps to decrease the size of the training vector space. There are a total of 21 layers in the proposed model: 3 fully linked, 7 max-pooling, and 21 convolutional. Rectified Linear Unit (ReLU) and Leaky ReLU are the activation functions used in the convolutional layer. Dense layers use the ReLU activation function. Dropout (0.5) and a SoftMax classifier follow two fully linked layers. Adam is the optimizer that is utilized. A pixel-based convolution stride is used. The network's breadth starts at an approximation of 64 and doubles after each pooling layer. Approximately 25, 305, 356 parameters are learned by the suggested design. Only the convolution and fully linked layers have weights that can be trained. The input picture is reduced in size using the max pooling layer, and the final choice is made using softmax. Prior to the thick layers that are used for learning and prediction, convolution and pooling layers aid in feature identification. The activation function is used to normalize a distribution dynamics from K amount of composite functional concatenations at the finish of the Dense layer SoftMax. The results generated by one layer of nodes are used as a basis for training by subsequent layers. As a result, nodes in successive layers are able to identify more complicated and detailed aspects. Computer program. DS: Matrix including one healthy wheat class and nine distinct wheat disease classes. Each class's training set includes around 1200 photos. Point iij: Displaying the i-th picture inside a specified category using three channels

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

Fig. 6. The outcomes for the following wheat diseases and pests: Healthy Wheat, Fusarium Head Blight, Black Chaff, Karnal Bunt, Tan Spot, Powdery Mildew, Leaf Rust, and Fusarium Head Blight.

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

Table 2
Accuracy measures of proposed method.

CLASSES	PRECISION	RECALL	F1-SCORE
Karnal Bunt	0.97	0.98	0.97
Black Chaff	0.98	0.98	0.98
Crown & Root Rot	0.98	0.98	0.98
Fusarium Head Blight	0.98	0.98	0.98
Healthy Wheat	0.98	0.98	0.98
Leaf Rust	0.99	0.98	0.98
Powdery Mildew	0.98	0.98	0.98
Tan Spot	0.97	0.98	0.97
Wheat Loose Smut	0.97	0.97	0.97
Wheat Streak Mosaic	0.96	0.97	0.96

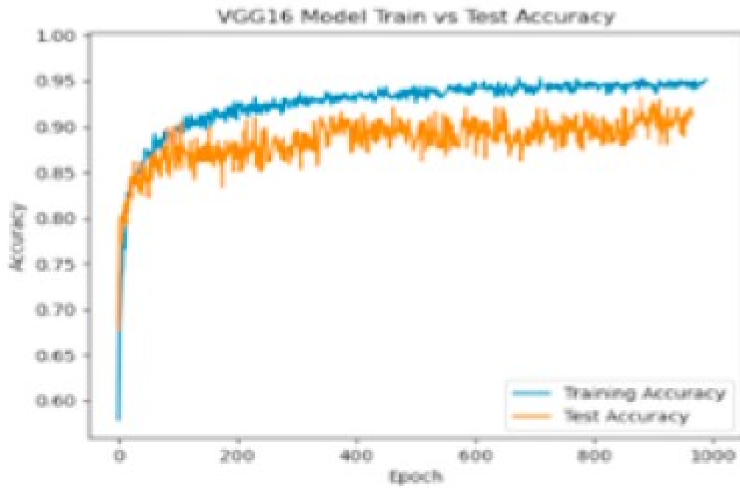
Karnal bunt, Black Chaff, Fusarium Head Blight, Healthy Wheat, Leaf Rust, Powdery Mildew, Tan Spot, Wheat Loose Smut, and Wheat Streak Mosaic are the labels assigned to DS. The first step is to load and prepare the data. • Take the photographs and make sure they are 224 × 224 before loading them. After standardization, do the following: • Perform a train-test split of the data • Convert it into numerical vectors Phase 2: Model Definition

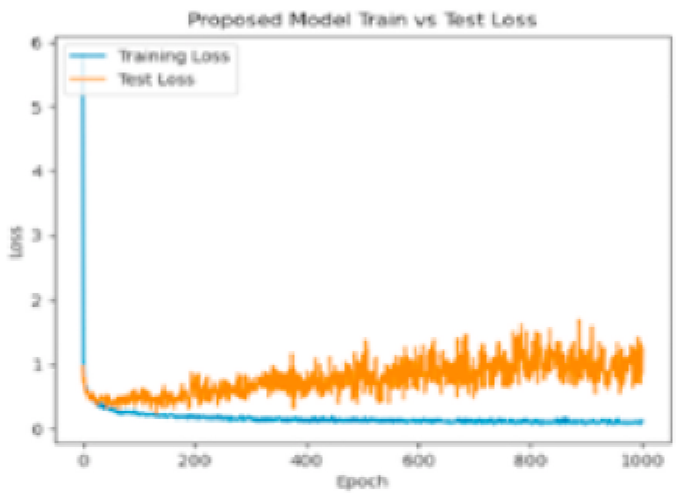
Table 3
Architectural comparison of different models.

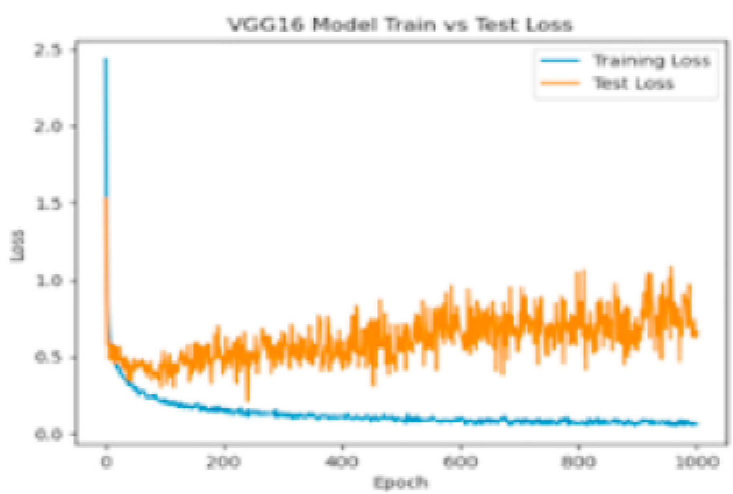
MODEL	SIZE (M)	LAYERS	MODEL DESCRIPTION	TRAINING ACCURACY	TESTING ACCURACY
PROPOSED MODEL	650	24	21 conv + 3 fc layers	98.62%	97.88%
VGG16	528	16	13 conv + 3 fc layers	94.66%	90.87%
RESNET-50	100	50	49 conv + 1 fc layer	93.66%	81.96%

• Use non-linearity with ReLU and LeakyRelu and pooling to reduce dimensionality • Specify the sequential order and other hyper-parameters for each model layer • In order to reduce the risk of overfitting utilize Failure to complete Step 3: Building and Training the Model • Develop the model using Stochastic Gradient Descent for the loss and Adam for the optimizer.

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025







ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

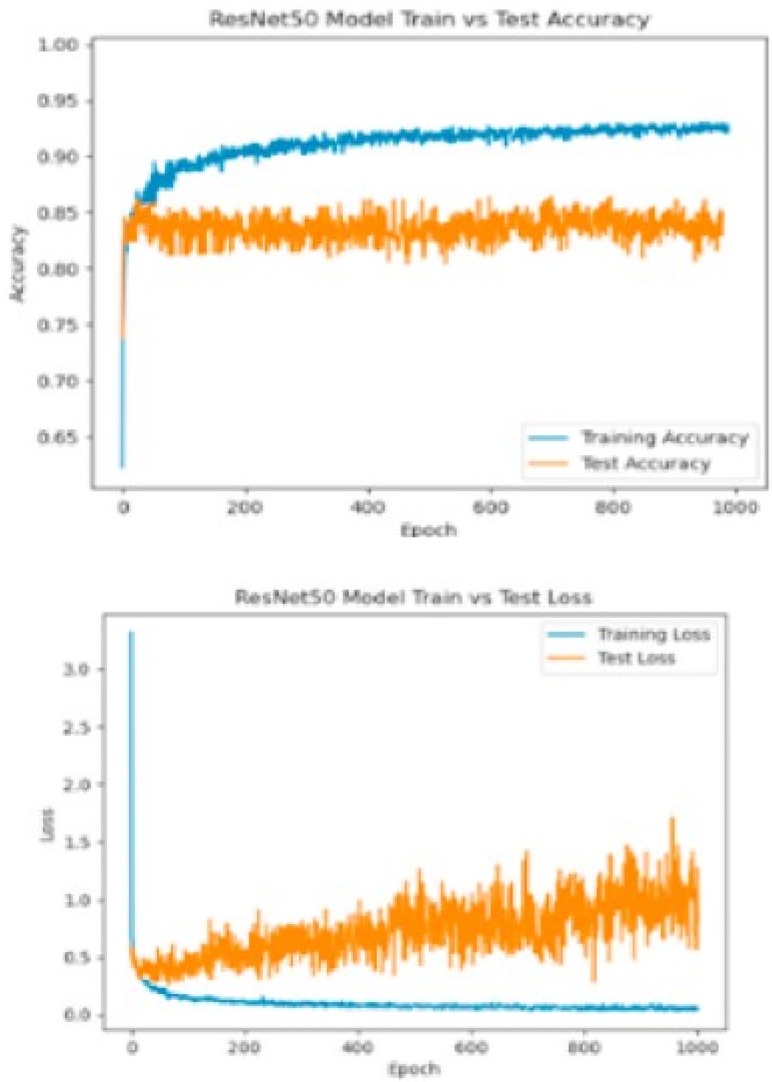


Fig. 7. Accuracy and loss of proposed model with VGG16 and RESNET50.

SGD is used to update the model's weights as it learns from the data. • Accuracy and era-to-epoch record loss The fourth step is prediction labeling, which entails loading the trained model and label binarizer, preprocessing the picture, making a label prediction, and finally, deciding on the label using majority polling.

Dataset: large wheat disease classification dataset (LWDCD2020)

We employ a massive picture library for the system's training. Roughly 40% of these photographs were from fieldwork, while the rest are repurposed from publicly accessible sources. About 12,000 photos representing nine categories of wheat illnesses and one category representing normal wheat are part of the newly curated dataset (LWDCD2020). Dimensional homogeneity has been pre-processed into the photos. In Table 1, we can see a more comprehensive description of the dataset. An additional class was added to the dataset to distinguish between healthy and sick wheat. This class includes one kind of ailment that was mentioned in relation to this photo. LWDCD2020 photos contain a variety of wheat diseases with comparable characteristics, as well as complicated backdrops, diverse capture settings, and characterisation for each stage of disease progression. Improving the dataset with enhanced photos was the next step. The primary goal of every particular test is to train the network to recognize the characteristics that distinguish one category from another. Consequently, the network has more chances to get proficient with the right characteristics while using more enhanced photos.

ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

Experimental results & discussion

Section 4.1: Tools and Experimental Environment The proposed method relies on Keras and Tensorflow for its backend. This trial PC ran Windows 10, had 16 GB of random-access memory, a 6 GB NVIDIA GeForce GTX 1660 Ti Max-Q graphics card, and a Ryzen 7 quad-core CPU. The networks were trained using the Adam optimizer for as many as 1,000 iterations. At around six hours, the training was over. The results on the LWDCD2020 dataset are shown in Figure 6. Prediction results for LWDCD2020 (4.2) Figures 6(a), 6(b), 6(c), 6(d), 6(e), 6(f), 6(g), 6(h), 6(i), and 6(j) show the outcomes of the predictions for the following diseases: Wheat Streak Mosaic, Fusarium Head Blight, Black Chaff, Karnal Bunt, Leaf Rust, Healthy Wheat, Fusarium Head Blight, Crown & Root Rot, and Black Chaff. For each prediction, four images were captured. The results show that the proposed approach can accurately identify these frames using the majority polling strategy. Table 2 displays a number of accuracy measures for the proposed method. It incorporates F1 score, memory, and accuracy. A harmonic weighted average of memory and accuracy yields the F1 score. As part of this score, we also add the total number of false positives and false negatives. It keeps the balance between accuracy and recall constant. F1 Score = 2*(Recall × Precision) / (Recall + Precision) 4.3.1. In comparison to other state-of-the-art methods Table 3 shows the architectural comparisons between the three deep learning models. We compare models based on their size, number of layers, complexity, and training/testing accuracy, among other measures. Figure 7 shows the accuracy and loss charts of several models during training and testing. Figure 7 displays the accuracy and loss plots of the proposed model, with the middle plots representing VGG16 and the bottom plots representing ResNet50.

Conclusion

A novel deep convolutional architecture is described in this study as a means of wheat disease classification. A key aspect of the proposed model is its resource efficiency in learning from large training datasets. As an example of a test on the proposed method, disease categorization was performed on the LWDCD2020 dataset. Ten classes of wheat diseases are classified using the proposed method, which achieves an outstanding test accuracy of 97.88% and an average training accuracy of 98.62%: Wheat Loose Smut, Tan Spot, Powdery Mildew, Leaf Rust, Healthy Wheat, Fusarium Head Blight, Crown & Root Rot, Black Chaff, Karnal Bunt, and Wheat Streak Mosaic. A significant improvement in performance is shown when compared to other deep learning approaches. When compared to VGG16 and RESNET50, the accuracy is 7.01% and 15.92% higher, respectively. This means that the proposed approaches have good potential for application in wheat disease classification.

References

[1] Pawlak K. Food security situation of selected highly developed countries against developing countries. J Agribusiness Rural Dev 2016;40(2):385–98.

[2] Trivelli L, Apicella A, Chiarello F, Rana R, Fantoni G, Tarabella A. From precision agriculture to Industry 4.0. Br Food J 2019;121(8):1730–43.

[3] Shadrin D, Menshchikov A, Somov A, Bornemann G, Hauslage J, Fedorov M. Enabling precision agriculture through embedded sensing with artificial intelligence. IEEE Trans Instrum Meas 2019;69(7):4103–13.

[4] Lu J, Hu J, Zhao G, Mei F, Zhang C. An in-field automatic wheat disease diagnosis system. Comput Electron Agric 2017;142:369–79.

[5] Gonz´alez-Camacho JM, Ornella L, P´erez-Rodríguez P, Gianola D, Dreisigacker S, Crossa J. Applications of machine learning methods to genomic selection in breeding wheat for rust resistance. Plant Genome 2018;11(2):170104.

[6] Azadbakht M, Ashourloo D, Aghighi H, Radiom S, Alimohammadi A. Wheat leaf rust detection at canopy scale under different LAI levels using machine learning techniques. Comput Electron Agric 2019;156:119–28.

[7] Barbedo JGA. Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. Comput Electron Agric 2018;153:46–53.

[8] Saleem MH, Potgieter J, Arif KM. Plant disease detection and classification by deep learning. Plants 2019;8(11):468.

[9] Yang X, Sun M. A survey on deep learning in crop planting. In: IOP conference series: materials science and engineering, 490. IOP Publishing; 2019, April. p. 6. 062053.

[10] Fang Y, Ramasamy RP. Current and prospective methods for plant disease detection. Biosensors 2015;5(3):537–61.

[11] Pouyanfar S, Sadiq S, Yan Y, Tian H, Tao Y, Reyes MP, Iyengar SS. A survey on deep learning: algorithms, techniques, and applications. ACM Comput Surv 2018;51(5): 1–36.

[12] Litjens G, Kooi T, Bejnordi BE, Setio AAA, Ciompi F, Ghafoorian M, S´anchez CI. A survey on deep learning in medical image analysis. Med Image Anal 2017;42: 60–88.

[13] Sharma CM, Kushwaha AKS, Roshan R, Porwal R, Khare A. Intelligent video object classification scheme using offline feature extraction and machine learning based approach. Int J Computer Sci Issues 2012;9(1):247.

[14] Dogra J, Jain S, Sharma A, Kumar R, Sood M. Brain tumor detection from MR images employing fuzzy graph cut technique. Recent Adv in Computer Sci Communications (Formerly: Recent Pat Comput Sci 2020;13(3):362–9.

[15] Nema S, Dixit A. Wheat leaf detection and prevention using support vector machine. In: 2018 international conference on circuits and systems in digital enterprise technology (ICCSDET). IEEE; 2018, December. p. 1–5.

[16] Picon A, Alvarez-Gila A, Seitz M, Ortiz-Barredo A, Echazarra J, Johannes A. Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. Comput Electron Agric 2019;161:280–90.

[17] Mi Z, Zhang X, Su J, Han D, Su B. Wheat stripe rust grading by deep learning with attention mechanism and images from mobile devices. Front Plant Sci 2020;11.

[18] Lin Z, Mu S, Huang F, Mateen KA, Wang M, Gao W, Jia J. A unified matrix-based convolutional neural network for fine-grained image classification of wheat leaf diseases. IEEE Access 2019;7:11570–90.

[19] Jin X, Jie L, Wang S, Qi HJ, Li SW. Classifying wheat hyperspectral pixels of healthy heads and Fusarium head blight disease using a deep neural network in the wild field. Rem Sens 2018;10(3):395.

[20] Argüeso D, Picon A, Irusta U, Medela A, San-Emeterio MG, Bereciartua A, Alvarez- Gila A. Few-Shot Learning approach for plant disease classification using images taken in the field. Comput Electron Agric 2020;175:105542.

[21] Loey M, ElSawy A, Afify M. Deep learning in plant diseases detection for agricultural crops: a survey. Int J Serv Sci Manag Eng Technol 2020;11(2):41–58.

[22] Su J, Yi D, Su B, Mi Z, Liu C, Hu X, Chen WH. Aerial visual perception in smart farming: field study of wheat yellow rust monitoring. IEEE Trans Indust Informatics 2020;17(3):2242–9.

[23] Nagaraju M, Chawla P. Systematic review of deep learning techniques in plant disease detection. Intl J System Assurance Eng Manag 2020;11:547–60.

[24] Stewart EL, Wiesner-Hanks T, Kaczmar N, DeChant C, Wu H, Lipson H, Gore MA. Quantitative phenotyping of Northern Leaf Blight in UAV images using deep learning. Rem Sens 2019;11(19):2209.

[25] Hasan MM, Chopin JP, Laga H, Miklavcic SJ. Detection and analysis of wheat spikes using convolutional neural networks. Plant Methods 2018;14(1):1–13.

[26] Garg K, Bhugra S, Lall B. Automatic quantification of plant disease from field image data using deep learning. In: Proceedings of the IEEE/CVF winter conference on applications of computer vision; 2021. p. 1965–72.

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

[27] Uzhinskiy A, Ososkov G, Goncharov P, Nechaevskiy A. Multifunctional platform and mobile application for plant disease detection. In: In *Proc. 27th Symp. Nucl. Electr. Comp. CEUR Workshop Proc*. NEC; 2019. p. 110–4.

[28] Azimi N, et al. Statistical and Machine Learning-Based FHB Detection in Durum Wheat. Plant Breed Biotech. 2020;8:265–80. https://doi.org/10.9787/ PBB.2020.8.3.265.