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Leveraging Deep Learning for Early Detection and Diagnosis of Wheat Diseases: Challenges and Innovations

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Abstract

This research introduces a deep learning system for the early identification and categorization of wheat illnesses, with the objective of optimizing crop health and promoting agricultural sustainability. Results in up to high classification accuracy for brown rust, yellow rust, leaf rust, and septoria. The combination of artificial intelligence (AI) with image processing methodologies such as rescaling and augmentation allows the system to accurately classify wheat crops that are well or unhealthy. The presented system is of great interest for precision agriculture, providing an affordable means to reduce the application of pesticides and encourage sustainable agricultural practices. Ongoing research involves linking this diagnostic platform with drone technology to facilitate on-demand, point-by-point disease surveillance and monitoring across large areas, further extending the platform's applicability in field applications for food securit.

Keywords

Wheat disease detection, deep learning, convolutional neural networks (CNNs).

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Introduction

Wheat production is a strategic priority for food security in many agricultural locations worldwide, where it plays a vi tal role as a staple food. Disease conditions related to wheat, mainly rusts and septoria, are a major pestilence for farmers resulting in yield losses and deterioration in quality. Disease control procedures are often late in emphasizing such condi tions, resulting in a significant hit on the quantity and quality of yield. Reducing pesticide usage has become a major priority in modern agriculture due to its environmental and health impacts. Early and accurate disease detection systems can significantly minimize unnecessary chemical applications, contributing to more sustainable agricultural practices. In addition, the growing pressure of climate change increases the spread and severity of plant diseases, making efficient detection tools essential. The lag time creates tremendous losses, particularly in locations that are highly dependent on wheat as a primary food and a source of livelihood. The rapid advancements in artificial intelligence technologies have produced CNN based approaches as exciting and promising techniques in the detection and diagnosis of wheat diseases. However promising, such pieces of equipment are still far from being adopted in practical farming. This is probably one of the most crit ical questions: how to correctly introduce these tools into farming practices so that each was able to properly fit into the specific features of unsustainable disease management in heterogeneously practicing agricultural systems with varying resources and constraints?

"Reducing the pesticide applications in agriculture are of paramount importance and it is suggested an inexpensive op tical device to be implemented in the remote disease detec tion in crop fields by analyzing the canopy reflectance. Yellow rust detection in wheat was accomplished using in-field spectral images by recording in-field spectral images with a spectrograph attached on the spray boom height. To take into account reflectance and light intensity differences, a normalization technique was used, and a dataset referred "leaf spectra" was constituted. Disease detection algorithms were trained using neural network, in particular, multilayer per ceptron (MLP). Classification accuracy went up dramatically, from 95% to more than 99%. This demonstrates the promise of suchanoptical device in the early diagnosis of disease with the result of decreased pesticide applications and adoption of sustainable agricultural methods" (Moshou et al., 2004).

"Modern computer vision methods are proposed are pre sented for the detection of various wheat leaf diseases, specif ically yellow spots, yellow rust, and brown rust. Neural network architectures were applied to reach a high accuracy from 0.95 to 0.99 on specific disease categories, thereby equalling the performance of skilled phytopathologists. A new way of doing multilabel classification was proposed to enable the recognition of more than one disease from the same image. An image dataset for diseased wheat leaves manifesting different diseases was developed and utilized in the model training to encourage the creation of high precision disease detection systems. Preprocessing was applied to enhance the performance of the model: rotation, flipping, and image normalization. GoogleNet was chosen for multilabel classification because it has a very lightweight neural network architecture with great performance and effi ciency. The accuracy, precision, recall, and F1-score metrics were used in the assessment of the performance ofthis model; hence, this showed high accurate rates over individual dis ease classes. Its light weight makes the model deployable on mobile devices to quickly and automatically diagnose wheat crop diseases. The proposed method is scalable and possible in practical agricultural scenarios and holds great potential for application on mobile devices. The results show that the proposed models have achieved high accuracies in the diag nosis of diseases in wheat leaves, which further demonstrates the effectiveness of the models in automated agricultural dis ease diagnosis" (Arinichev et al., 2022).

"The objective is to develop a deep transfer learning model for disease identification in wheat crops using artificial in telligence (AI). The study utilized the WheatRust21 dataset, which was collected on the spot and included stripe, leaf, and stem rust occurrences in wheat farming. The work mainly fo cused on the use of Convolutional Neural Networks (CNN) and EfficientNet architectures for recognizing wheat rust dis eases. Further, the study tried to make the model deployable on mobile devices to facilitate real-time, image-based iden tification of wheat diseases on the farm. Thus, proving that AI-based approaches were really effective in this task, a deep transfer learning model with a 99.35% accuracy level was obtained in disease identification. Disease detection perfor mance wasimproved further by using the CNN and Efficient Net architectures. Further, due to its compatibility with the use of mobile devices in real-time on-site identification, this model provides a great opportunity for easy disease manage ment in wheat crops. This research has shown the strength of the artificial intelligence-driven schemes in dealing with agri cultural diseases, especially in the step of disease identifica tion, and pointed out the possibility of applying these models on a mobile platform for real applications in the field" (Nigam et al., 2023).

"Wheat disease problem is discussed, mainly focusing on the great importance of wheat leaf diseases' impact on agricul tural yield and food safety. A new deep learning model, called RFE-CNN, has been developed based on Residual Channel Attention Blocks (RCABs), Feature Boosters (FBs) and Embedding-based Metric Learning (EML) with the LWDCD 2020 dataset and Convolutional Neural Networks (CNN) to get accurate disease detection in wheat crops. The study uses parallel CNNs, RCABs, and FBs to extract relevant features and enhance classification accuracy. The to tal classification accuracy achieved was 98.83%, whereas the highest testing accuracy achieved was 99.95%. The average accuracy score was 99.50%. RFE-CNN is superior to tradi tional CNN models in accuracy, efficiency, and adaptability and proves to be better for the task of disease identification; further research should focus on strengthening disease recog nition over the ecological regions and varieties by using hyperspectral imaging technology" (Xu et al., 2023).

"The ongoing threat to the cultivation of wheat around the world by wheat rust pathogens is discussed, underlining the economic losses running into billions of dollars annually. VG16 and Capsule Networks have been tried out with an ac curacy score of 93%. Rust fungi rely on living host cells for their growth and reproduction activities, which explains chal lenges related to controlling their spread. Continuous emer gence of new rust races is a significant hindrance to achiev ing genetic resistance in wheat varieties. Scientific studies show that race-specific genes in wheat code for NBS-LRR proteins, hence providing useful insight into the genetic ways through which resistance to rust pathogens is achieved. Man agement strategies for diseases of wheat include fungicide application, cultural practices, and optimization of planting dates to reduce the impact ofrust pathogens and other diseases on wheat yield." (Rathore and Prasad, 2022).

"Identification and control of wheat diseases, specifically yel low rust, Septoria tritici blotch, brown rust, and mildew, are critical since they cause severe damage in crop yield and quality. The challenge arises because, at some stages in their development cycles, the aforementioned diseases tend to exhibit identical appearances. To handle this challenge, deep learning approaches—particularly convolutional neu ral networks (CNNs)—are investigated in automatically detecting and classifying wheat diseases using image analysis. The images used in this research were taken in 2019 from several sites across the UK and Ireland under natural and glasshouse conditions, showing wheat leaves with variously visible symptoms of diseases and healthy leaves. The dataset used in the research had more than 19,000 images represent ing five different classes: septoria, yellow rust, brown rust, mildew, and healthy. In the present study, a CNN called CerealConv is developed and trained to automatically detect and classify wheat diseases. This CNN had 13 convolutional layers with batch normalization, max pooling, and dropout. CerealConv achieved a classification accuracy of over 97% on a test set of five well-known disease classes. Compared against manual classifications by five specialist pathologists, CerealConv outperformed the pathologists with its accuracy 2% higher than the best-performing pathologist. The convo lutional neural network also classified an abridged data set of 999 images both faster and more accurately than the pathologists. To ensure that CerealConv relies on relevant informa tion to perform its classification task, masked images were used. The large drop in classification accuracy upon blocking key image components indicates that it really depends on valid information to perform its task effectively. Overall, this study shows that deep learning methods, specially the developed CNN model—CerealConv—handle real field condition images ofwheatdiseases effectively and at least as well as expert pathologists in disease identification and classification" (Long et al., 2023).

"It emphasizes the importance of wheat in ethiopia being the second most consumed grain crop, contributing to 14% calo rie consumption. Ethiopia´s wheat production is almost ex clusively for subsistence, produced by small holder farmers. For this reason, deep learning-based classification systems to improve early identification of wheat diseases can provide an important contribution in the disease management. Wheat farmers in Ethiopian experience market constraints due to lack of access for timely information and insufficient mar ket linkage which lowers productivity and profitability. The genetic variation in wheat species is important to combat dis eases; hence there are breeding programs and scope for genetics. The VGG19 model seems to be able to classify wheat diseases well, and we have seen it performing relatively well for the disease detection task. An automated system for this identification process will help in reducing the large amounts of yield losses and further back Ethiopia’s agricultural sector to increase productivity and food security" (Aboneh et al., 2021).

"This includes the million-dollar losses from diseases in wheat, a major worldwide grain of 4.5 and reasons for crop spoilage Optimizing crop yield by identifying diseases and classes of the wheat disease with high accuracy—automatic classification for wheat disease detection in deep learning ar chitecture Even though the deep learning classifiers are pow erful, they might suffer from overfitting and can require large datasets computational resources. Finding: Transfer learning as a means of boosting classification performance, especially when having constraints on data and resources making use of pre-trained models. The model proposed is based on the VGG16 architecture, performs well in classifying wheat diseases, showing promise to enhance crop management practice. The newly devised deep learning model exhibited high performance, acquiring a test accuracy of 97.88% on discrim inating ten different wheat diseases which were tested Such a high accuracy is indicative of how well it can determine and classify wheat diseases, which in turn will allow for prompt management practices to be utilized enough to prevent crop yield reductions. Moreover, while the VGG16 architecture is applied to illustrate that our model can achieve high accuracy in disease classification tasks; this exhausts its application capabilities—from a practical perspective—and practically it could augment field-based strategies and processes on crop management ensuring food security" (Jadhav et al., 2021).

"Thefocus is onusing convolutional neural networks (CNNs) to identify soybean leaf diseases with the help of AlexNet and GoogleNet models. The used dataset includes soybean leaf images which were gathered from farms of Kolhapur block in Maharashtra state, India. It contains

649 images for training the AlexNet model, and 550 images for training the GoogleNet model, which were divided into four cat egories: bacterial blight, brown spot, frogeye leaf spot, and healthy leaves. Both models achieved accuracy of over 95% and above the designed targets." "Outdated recognition systems are the main limitation of farmers in understanding plants which makes them suscep tible to diseases that seriously affect agricultural productiv ity. even though farmers are knowledgeable locally, there are restrictions in terms of sharing such capabilities due to absence of platforms. Further, the constant decrease in agricultural yields was never disconnected with diseases, farming habits or weak location understanding. To address this, the information provided to the farmers is sourced through other farmers, experts and agricultural stakeholders, which informs the farmers about prevalent diseases so they can take action according to the situation. Machine Learning (ML) as a tool is always greatly appreciated which however, suffers from interfacing with static data and maltreating nuances of lo cal knowledge from experts, leading to poor generalizations across regions. In order to address this problem, an effort was made in crowdsourcing images and symptom based data for training purpose. For wheat disease recognition and clas sification, a new framework integrating Decision Trees (DT) with deep learning models is presented. The Decision Tree, following an expert validation, City University achieved a 28.5% increase in accuracy, from 51.6% to 80.1%, and an increase of 4.3% in CNN, resulting in a final accuracy of 97.2%, with most of the decision rules integrated into a decision support system for managing wheat diseases" (Niedbała et al., 2019).

"The impacte of climate change-on-wheat production scenar ios for Iran were assessed with the CERES-Wheat model, and the new wheat disease dataset (WDD2017) was built to provide a more precise diagnosis of plant diseases by the DMIL-WDDS model, achieving mean accuracies of 97.95% ...... and 95.12% via 5-fold cross-validation. The CERES-Wheat model predicts wheat yield with a clear correlation between the predicted and measured values, thereby confirming its usefulness in simulating the climate change problem in the f ield of wheat production. In addition, the DMIL-WDDS could distinguish diseases better than the traditional CNN approaches since climate change showed a negative impact on wheat yield and biomass, specifically due to temperature rise, stressing the critical importance of predicting climate change impact for sustainable agriculture in Iran" (Haider et al., 2021).

"The objective is to classify Fusarium Head Blight disease in wheat by employing deep neural networks on hyperspec tral imaging data collected in the field. The experiment took place from April 29 to May 15, 2017, under varying wind conditions and relative humidity and temperature. Ninety samples of wheat ears were segregated into 10 segments in turn, and a Deep Convolutional Neural Network (CNN) was employed for analysis. Metrics such as precision, recall, and F1 score, among others, were used to evaluate the performance of the model. The experiments maintain that deep neural networks can positively identify Fusarium Head Blight in wheat. This work proposes hybrid neural networks as a suitable approach to disease diagnosis and upgrades in agri cultural disease management" (Lu et al., 2017).

Materials and methods

System architecture

The proposed model for wheat disease detection is based on a master-slave sequential architecture proposed in (Bencheriet and Bencheriet, 2023), composed of three distinct modules (Figure 1):

Module 1: Data preprocessing

Module 2: The Master (Disease detection network)

Module 3: The Slave (Disease diagnosis network)

Remarque: All models were implemented, trained, and evaluated by the authors using Python in 2025.

Data preprocessing

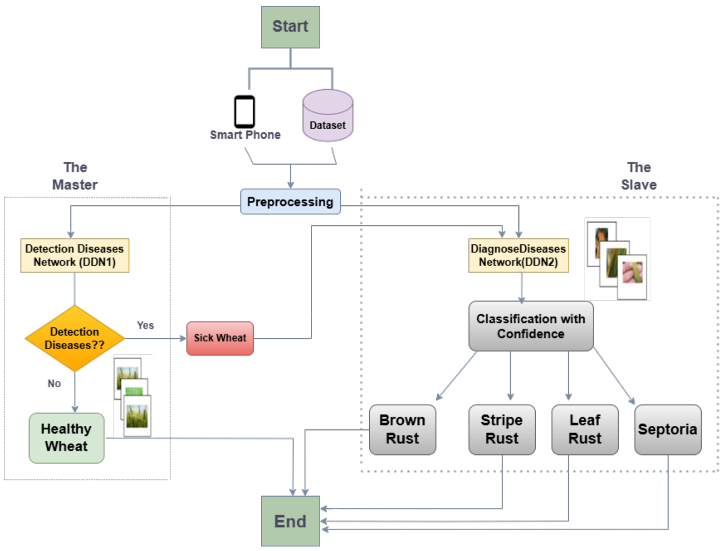
Image preprocessing starts by captur ing images of wheat ears, and then these images are resized to a uniform size of 255x255 pixels. This resizing enables the images to be standardized so that they will fit into the neural network. After the images are resized, the images are fed to the corresponding network for disease detection and diagnosis.

Image resizing

Resizing includes changes of the image sizes (255x255 pixels) to guarantee the uniformity of the input for mat. In this step, the image quality and resolution are kept in law, and the performance of the model is optimized.

Split data

The data is divided as follows: 80% for training, which is used to train the model; 10% for validation, which is used for hyper-parameter tuning and model evaluation during training; and 10% for testing, which is used to evaluate the f inal performance of the trained model (Figure 2, 3).



Source: Authors' own design (2025)

Figure 1: Architecture of our system.

Class	Train 80%	Validation 10%	Test 10%
Healthy	588	74	73
Sick	2215	277	276

Source: Authors' dataset partitioning (2025)

Figure 2: Split dataset for DDN1 model.

Class	Train	Validation	Test
Septoria	166	21	21
Leaf rust	20	8	8
Brown rust	902	113	113
Stripe rust	1116	140	140

Source: Authors' dataset partitioning (2025)

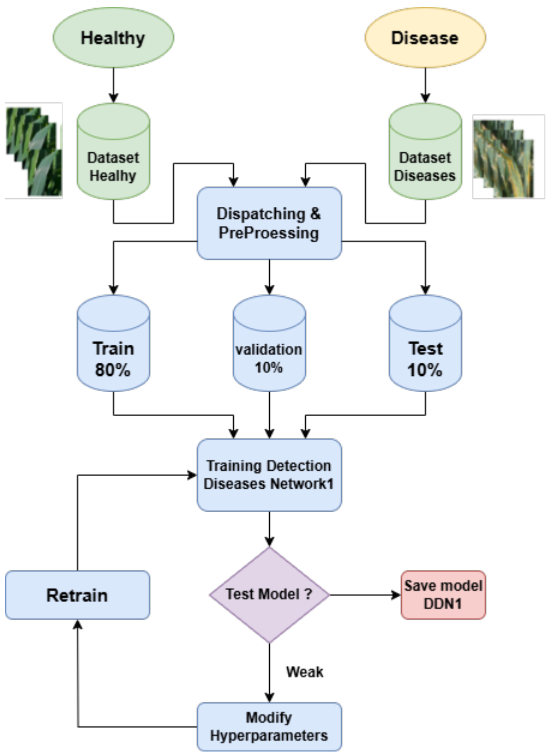
Figure 3: Split dataset for DDN2 model.

The Master Network (DDN1)

Initial classification of wheat ear by Master Network (DDN1) is carried out to diagnose wheat ear as it is healthy or not healthy. The model is based on a deep convolutional network, in which the images are processed with a succession of convolution and pooling lay ers in order to extract relevant features. After the image is preprocessed, the image is then redirected to the disease detection network for subsequent analysis (Figure 4).

Data training

Data are divided into three sets: 80/10/10% for training, validation and testing, respectively. Parameters of the training procedure are optimized and results are classified on the basis of their accuracy (high or low).

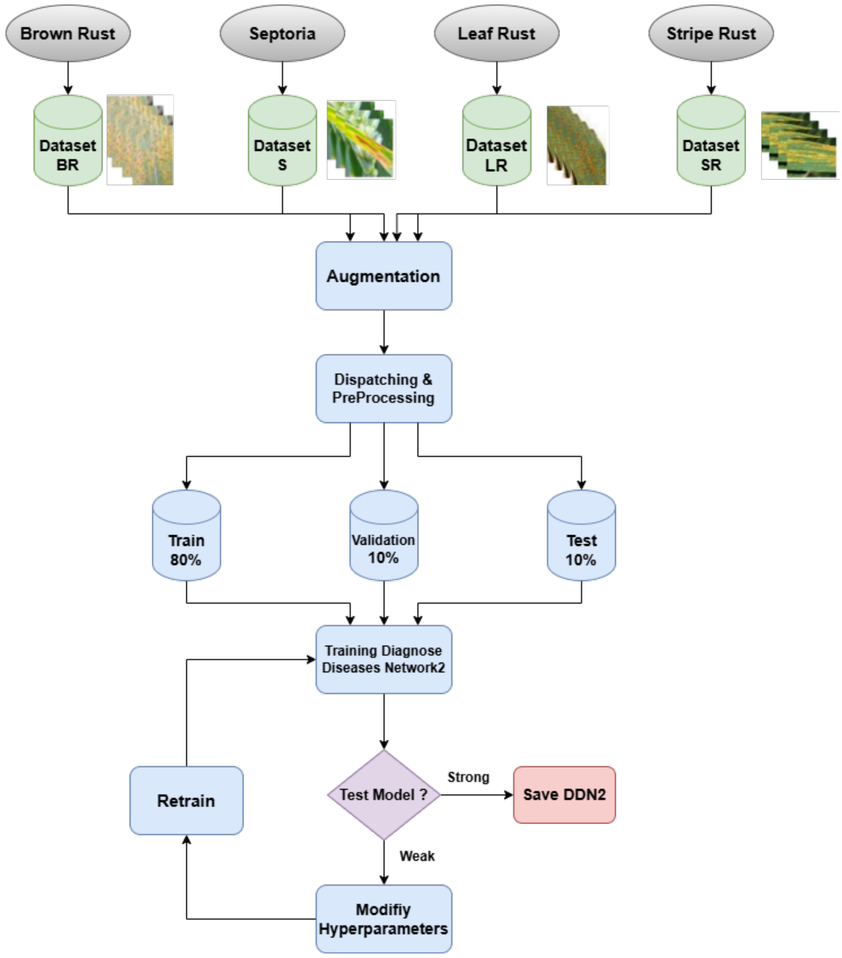


Source: Authors' own model training results (2025)

Figure 4: Train Detection Disease Network (DDN1).

The Slave Network (DDN2)

Once the disease has been de tected by the Master Network, the Slave Network takes over to classify the specific disease into four classes: yellow rust, brown rust, spot rust and healthy. This network uses addi tional layers to refine the classification and provide an accurate diagnosis (Figure 5).



Source: Authors' own model training results (2025)

Figure 5: Train Diagnose Disease Network (DDN2).

Image augmentation

Image augmentation is applied to enhance the diversity of the dataset and generalize the model. These modifications include rotation, flipping, and scaling to generate new, varied images from the same samples.

Data training

The training of this network is very similar to that of Master Network, where the data is split and trained using optimal hyper-parameters. The model is tested for its ability of classifying images into the four classes of diseases and the results are classified according to accuracy.

Model architecture

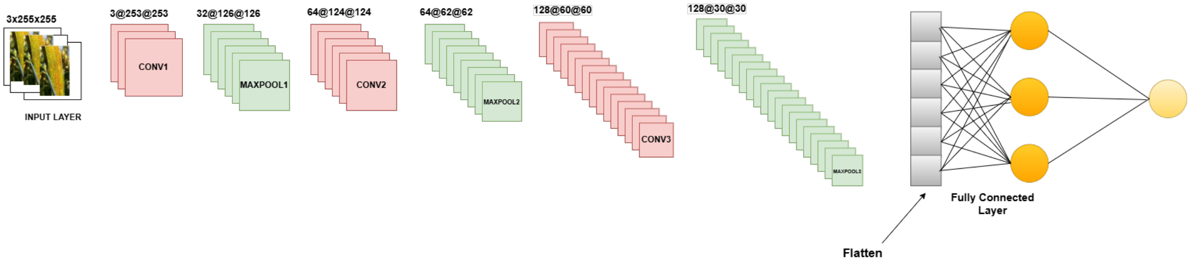
The general structure of the system is as follows:

Diseases Detection Network: General model architecture

The main network (DDN1) is responsible for checking the health of the wheat ears. It processes all the images sent by the user, resizing them to 255x255 pixels and applying filters. Next, the images pass through three layers Conv2D and Max Pooling2D, where the difference between these layers lies in the size of the kernel and the shape of the output. In addition, the images are divided into three parts to deepen the analysis, increasing the depth to 32, then 64, and finally 128. After these successive operations, the activation function used is the sigmoid function. The output classification label is either 0, indicating a healthy wheat ear, or 1, indicating a diseased wheat ear. If the final prediction is healthy, the process stops. On the other hand, if the wheat ear is classified as diseased, the secondary (slave) model is called to classify the specific disease (Figure 6).

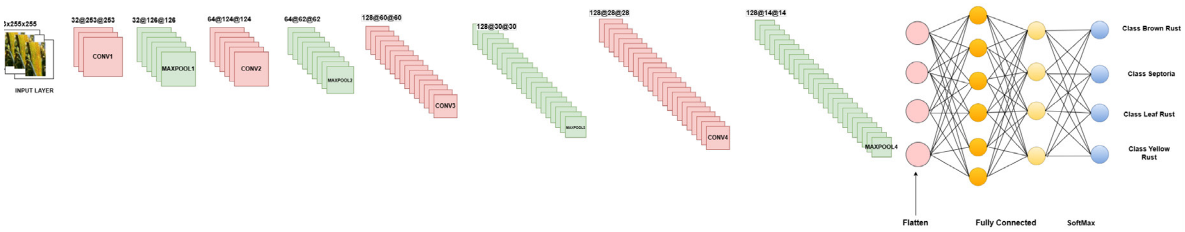
Diseases Diagnose Network: General model architecture

The DDN2 model is responsible for detecting wheat diseases and classifying them into four categories (Figure 7). It processes all images



Source: Authors' own architecture (2025)

Figure 6: Architecture of Master Network (DDN1).



Source: Authors' own architecture (2025)

Figure 7: General Architecture of the Slave Network (DNN2).

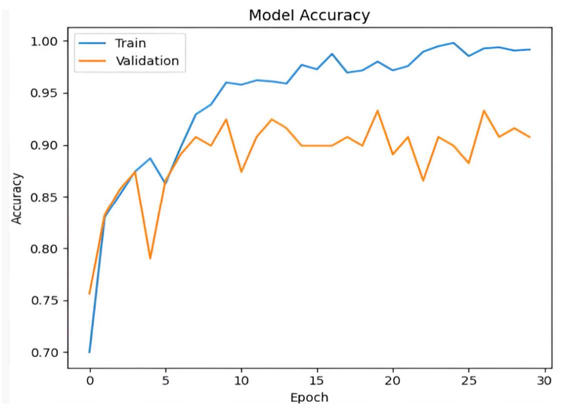
sent by the user, resizing them to 255x255 pixels and applying filters. NMS2 uses the Softmax activation function and performs operations similar to those of the first model, but with a difference in the number of classes. The same input dataset is used, and the initial structure remains un changed from the first model. The diagram below shows our second architecture, with four layers of Conv2D and Max Pooling2D. The fourth Conv2D layer is 128x28x28, followed by the MaxPooling2D layer at 128x14x14. At the end of the architecture, the feature maps are flattened to a size of 25088. Unlike the first model, where the activation function was sig moidal, the Dense layer here uses Softmax for the final clas sification of the four classes.

Results and discussion

Training of the DDN1 (Master Network)

The Detection Diseases Network (DDN1) was conducted using the following configurations (Figure 8):

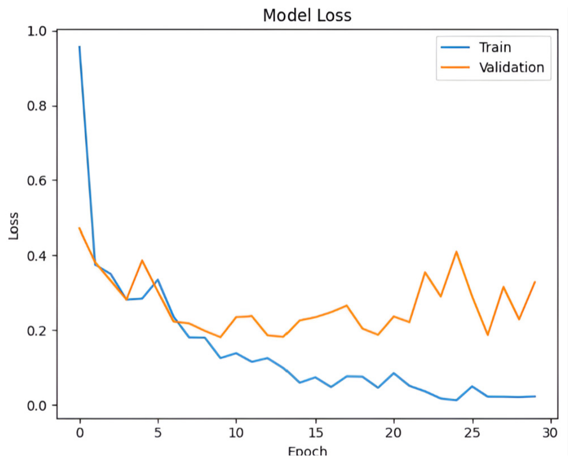
- Optimizer: Adam
- Batch size: 32
- Activation function: ReLU for all convolutional layers except the output layer (Softmax)
- Epochs: 30



Source: Authors' training results (2025)

Figure 8: Graph of the accuracy train and validation for DDN1.

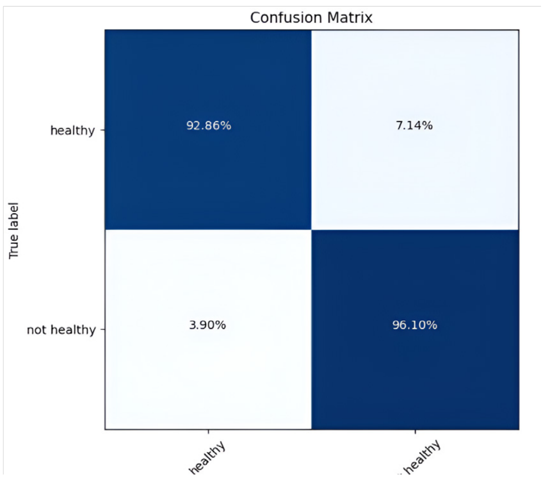
- Training Accuracy: The accuracy improved steadily with each epoch, reaching nearly 98% by the end. This indicates that the model was learning the training data very well, with minimal overfitting.
- Validation Accuracy: Initially, the validation accuracy improved, but after around 5 epochs, it started fluctuating and declined temporarily. Despite these fluctuations, the validation accuracy ultimately reached 90% (Figure 9).



Source: Authors' training results (2025)

Figure 9: Graph of the train and validation loos for the DDN1.

- Training loss : The training loss decreased steadily, starting from a high value and gradually approaching zero, suggesting that the model was fitting the training data well.
- Validation loss: The validation loss decreased at first but began fluctuating after a few epochs, remaining higher than the training loss and even slightly increasing towards the end (Figure 10).



Source: Authors' evaluation results (2025)

Figure 10: Confusion matrix for the Master Network (DDN1).

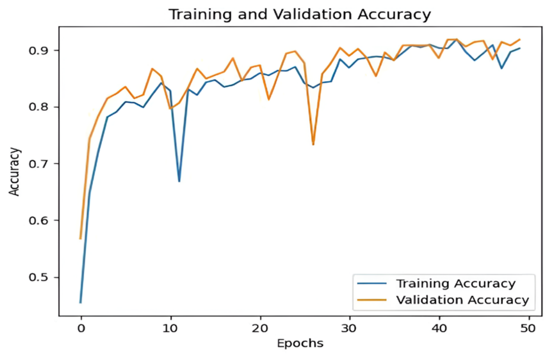
The confusion matrix for the Master Network (DDN1) reveals the following insights:

- High precision and recall: The model demonstrated excellent performance in distinguishing between healthy and unhealthy wheat, with high correct classification rates for both classes.
- False positives and false negatives: The model had relatively low rates of false positives and false negatives, indicating good precision and recall for both healthy and diseased wheat classes.
- These results suggest that the Master Network (DDN1) is highly effective in distinguishing between healthy and diseased wheat, with a very good ability to classify the wheat as either healthy or diseased.

Training of the DDN2 (Slave Network)

The Diagnose Diseases Network (DDN2) was trained using the following configurations (Figure 11)**:**

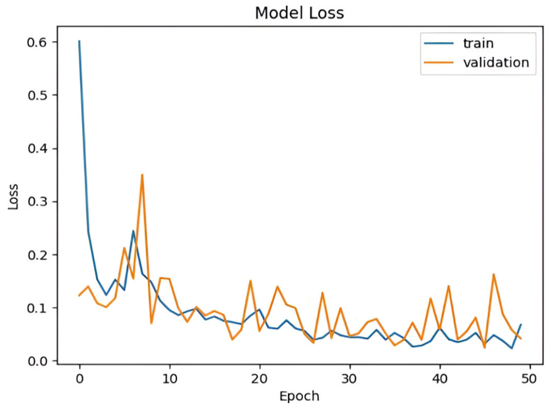
- Optimizer: Adam
- Batch size: 32
- Activation function: ReLU for all convolutional layers, with Softmax used for the output layer.
- Epochs: 50



Source: Authors' training results (2025)

Figure 11. Graph of train and validation accuracy for the Slave Network (DDN2).

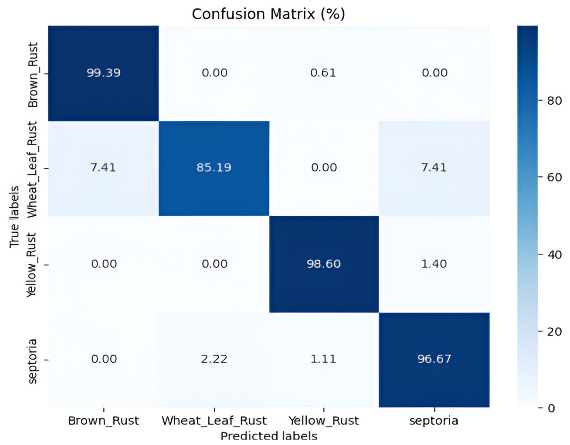
- Accuracy for training and validation starts at around 50% in the initial epoch. Gradually, these two metrics improve with each subsequent epoch, eventually reaching nearly 91% accuracy (Figure 12).



Source: Authors' training results (2025)

Figure 12: Train and validation loss for DNN2.

- The model loss for both training and validation datasets decreases significantly during the first 60% of the epochs and then stabilizes at low values. This trend indicates effective learning, strong model performance, and minimal overfitting, with a final overfitting value of approximately 0.08 (Figure 13).



Source: Authors' evaluation results (2025)

Figure 13: Confusion matrix for the slave model.

- The model shows a high accuracy for all diseases classes and, in addition, a very low misclassification rate. Brown rust, is diagnosed at the best accuracy of 99.39%, while wheat leaf rust, is diagnosed at the lowest accuracy of 85.19%. Results of misclassifications are 7.41% Wheat leaf rust samples classified as brown rust and 7.41% as septoria, probably because of the high visual similarity of wheat leaf rust, brown rust, and septoria.

To provide a more detailed analysis of the model's performance, we report additional metrics including precision, recall, and F1-score for each wheat disease class (Table 1). These metrics offer a deeper understanding of the behavior of the model beyond global accuracy, especially in terms of class-wise reliability. The F1-score, in particular, reflects the balance between false positives and false negatives, confirming the robustness of the proposed dual-CNN system across all disease categories.

Class	Precision	Recall	F1-score
Brown Rust	0.93	0.99	0.96
Wheat Leaf Rust	0.97	0.85	0.91
Yellow Rust	0.98	0.99	0.98
Septoria	0.93	0.97	0.95

Source: Authors' own calculations (2025)

Table 1: Evaluation metrics by disease class.

Conclusion

In conclusion, this study highlights the transformative potential of deep learning techniques, particularly convolutional neural networks (CNNs), in enhancing wheat disease detection and classification. Using a dual CNN system, designed to be in a master-slave fashion, the model is able, in an effective manner, to learn the diagnosis of the wheat health and to predict the diseases (yellow rust, brown rust, leaf rust and septoria). The achieved high classification accuracy shows the effectiveness of the system, and therefore the system can be considered practical in precision agriculture.

Beyond improving detection accuracy, the proposed system contributes to sustainable agriculture by optimizing pesticide usage and reducing chemical dispersion into soil and ecosystems. This environmentally friendly approach is particularly relevant considering the increasing ecological challenges posed by climate change.

This system is a significant contribution towards agricultural problem solving, sustainable food provisioning, and pesticide minimization. Through combining AI-based disease diagnosis with drone technology, the system will allow real-time surveillance, delivering quick, precise interventions to curb crop loss and guarantee food security. However, with the changing of the technology, in future investigations the model will be refined for a variety of agricultural environments and the model's robustness to uncertain cases (i.e., different wheat varieties) will be encouraged. Overall, the joint integration of smart detection technologies and drones represents the start of the "SMART Agriculture" age, greatly improving food safety, and its sustainability and crop yields.

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