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A Novel Hybrid Approach Based on CNN for Corn Diseases Detection

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Abstract

Corn is one of the most economically important crops globally, significantly improving food security and agricultural productivity. However, corn plants face various foliar diseases, which can significantly reduce crop productivity. Accurate and early detection of corn diseases is an imperative task for maintaining crop health and ensuring food security. In this study, we propose a novel approach for corn disease detection by integrating DenseNet121, a powerful convolutional neural network (CNN) architecture, with a deep neural network (DNN) classifier. This hybrid model, called DenseNetDNN, combines the feature extraction capabilities of DenseNet121 with the classification capabilities of a DNN, aiming to enhance disease detection accuracy. The proposed model's performance is compared against four widely used pre-trained CNN models: ResNet50, MobileNet, EfficientNetB0, and Xception. All models are evaluated using accuracy, precision, and recall. Additionally, the study employs GradeCam, an advanced grading system, to automate and standardize the performance evaluation of the proposed model. Results demonstrate that the DenseNetDNN model outperformed all other models in terms of identifying corn diseases; it achieves superior performance with an accuracy of 96.1%, precession of 0.952, and Recall of 0.958. which demonstrates the efficiency of DenseNetDNN in advancing agricultural disease detection. This research contributes to the development of automated solutions for agricultural monitoring, with implications for improving crop management practices and ensuring global food security.

Keywords: Machine Learning; Deep Neural Network; DenseNet; Convolutional Neural Network; Corn Disease Detection.

1 | Introduction

The corn crop is one of the most important staple crops worldwide, serving as a cornerstone of global food security and agricultural productivity [1]. However, corn health and yield are constantly threatened by various diseases, which affect the productivity of the yield. Early and accurate detection of these diseases is a very important process for farmers to minimize their negative impact and ensure optimal crop production [2]. Conventional methods, including visual examinations, for diagnosing plant leaf diseases often rely on human

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expertise, are labor-intensive, time-consuming, impractical for large-scale farming operations, and offer certain drawbacks, such as human exhaustion, which may often lead to delays in diagnosis and inaccurate disease classification, resulting in significant crop losses [3].

In recent years, artificial intelligence (AI) techniques, in particular deep learning (DL), have proven to be remarkably effective at reliably and effectively extracting characteristics from complex data. This revolutionary technique has applications in many different fields, including healthcare [4, 5], e-commerce [6], agriculture [7-9], and other domains [10, 11]. DL techniques, including CNN, have the potential to revolutionize how we identify and manage diseases in corn crops. By analyzing large amounts of data and recognizing subtle and hidden patterns [12]. CNN is a powerful DL model commonly used for image recognition tasks. It is effective at automatically learning hierarchical features from the input image, making it well-suited for tasks such as image classification. It is a widely used model for the detection and recognition of plant diseases using leaf images [13-15].

In this study, we propose a novel approach for detecting corn diseases by combining the power of the DenseNet121 model architecture with a deep neural network (DNN) classifier. This hybrid model, referred to as DenseNetDNN, aims to leverage the strengths of both architectures to achieve superior performance in corn disease detection. To evaluate the effectiveness of our proposed model, we compare it against four widely used pre-trained CNN models: ResNet50, MobileNet, EfficientNetB0, and Xception. These models represent a spectrum of architectures with varying complexity and performance characteristics. The evaluation metrics used for comparison include accuracy, precision, recall, and F1-score, which collectively provide insights into the overall performance and effectiveness of each model in distinguishing between healthy and diseased corn plants. Additionally, to enhance the robustness of our evaluation, we employed Gradient-weighted Class Activation Mapping (GradeCam) [16], an advanced grading system, to automate and standardize the process of evaluating the models' performance on a large-scale dataset. GradeCam not only provides accurate and consistent assessments but also reduces human bias and ensures the reproducibility of results. The experimental results showed that the proposed model (DenseNetDNN) outperformed all other pre-trained models and achieved the best performance; it achieved accuracy, precession, recall, and an F1-score of 0.961, 0.952, 0.958, and 0955, respectively, which demonstrates the effectiveness of our proposed approach in accurately detecting corn diseases, thereby offering promising implications for agricultural new techniques.

The remainder of the paper is structured as follows: Section 2 presents the recent related works. Section 3 describes the utilized materials and methods including the proposed model in detail. The experimental results are presented and discussed in Section 4. Section 5 presents the implications of this work. Finally, the conclusions and future works are presented in Section 6.

2 | Related Work

In recent years, studies investigating the applicability of utilizing artificial intelligence techniques such as machine learning and DL in plant disease detection, especially corn diseases, have been conducted more frequently. Haque et al. [17], presented a proposed deep convolution neural network (DCNN) model for identifying the diseases of maize crops. The model was trained on around 3850 leaf images collected from a well-known PlantVillage dataset. The model was trained and tested to identify three corn diseases, and it results from impressive results in recognizing the new diseased images of the maize crop. Furthermore, according to the overall performance analysis, The proposed CNN model outperforms the widely used pre-trained models and is highly successful at identifying images of diseases affecting maize.

Singh et al. [18], proposed a new hybrid DL model that merges CNN and Random Forest classifier for early detection of corn leaf diseases. This hybrid mode took advantage of CNN to extract important features from leaf images, and then the classifier algorithm was utilized with Random Forest to classify healthy and diseased images of maize. The model's performance was evaluated against several disease classes, and the results demonstrated that the proposed model produces significant results for recognizing various corn disease classes and providing accurate and dependable results in corn disease detection and recognition.

Another contribution by [19] presented a deep transfer learning model named AlexNet for the detection of plant leaf diseases. AlexNet is a pre-trained model that utilizes CNN layers for important feature extraction from leaf images. The model's performance is compared against two other pre-trained models, namely, VGG-16 and Lenet-5. The models were trained to detect leaf disease in various plants, including corn, rice, and tomatoes. The obtained results show that the proposed method will successfully identify the crop species with 96.76% accuracy and outperform the other two pre-trained models.

Amin et al. [20], Proposed a novel DL model for identifying diseased corn plant leaves, keeping in mind the model's number of factors. The model utilizes two pre-trained CNN-based models named DenseNet121 and EfficientNetB0 For deep feature extraction from corn leaf images. Then, a concatenation technique is used to merge the deep features that were extracted from each CNN, creating a more complicated feature set that will help the model learn more about the dataset. The proposed model's performance is evaluated and compared against two other pre-trained CNN models, named InceptionV3 and ResNet152, and the experimental results demonstrate the superiority of the proposed model over other models, it achieved the best performance with a classification accuracy of 98.56%.

Small sample sizes of image datasets and noisy or complex field backgrounds still represent a complicated problem that affects the model accuracy. To address this problem, a study by [21], proposed A novel DL technique based on complicated background datasets with small sample sizes for the diagnosis of maize diseases, Convolutional block attention module (CBAM) and multi-dilated module attention mechanisms were combined in this model. The model utilizes transfer learning and attention mechanisms to accurately extract the most significant features from corn leaf images. Furthermore, an auxiliary generative adversarial network is utilized for data augmentation. The proposed model was evaluated and compared against a set of pre-trained models, and tested using three kinds of maize leaf images from the PlantVillage dataset. The experimental results showed that, with an accuracy of 98.84%, the proposed model performed better than all other models for the identification of diseased complex background maize leaf images.

Another study [22] proposed a hybrid 3D-CNN and LSTM model for optimal identification and classification of corn leaf disease, which comprises RNN layers to give the model a time component and capture ongoing changes in leaf appearance as the disease progresses, and six 3D convolutional layers to improve the detection of 3-dimensional images. Moreover, the hybrid 3DCNN-RNN models' hyperparameters are optimized through the use of the Whale Optimization Algorithm with Joint Search Mechanisms (JSWOA).. Two datasets, Maize_in_field, and KaraAgro AI maize, are used to train and test experiments. Furthermore, the model's performance is evaluated using different performance metrics like accuracy, precision, recall, and AUC and compared against DenseNet and AlexNet pre-trained models. According to the results, the proposed hybrid model predicts different classes of maize leaves on both datasets with a performance level above 90%. Thus, it performs better than the state-of-the-art approach.

3 | Methodology and Materials

This section provides an in-depth description of the methods and techniques used in the study to develop and evaluate the proposed hybrid model architecture. We also describe the preparation stages, the models' training processes, and the utilized dataset in this study.

The proposed system consists of several stages, including dataset accusation, then data preprocessing and preparation for feeding to the machine learning models; after that, the stage of building the proposed hybrid model; and finally, evaluating the model's performance through a variety of evaluation metrics and ensuring the system's reliability through explainable AI techniques. The overall stages of the process of detecting diseases in corn are shown in Figure 1. Moreover, each step of the proposal will be described below:

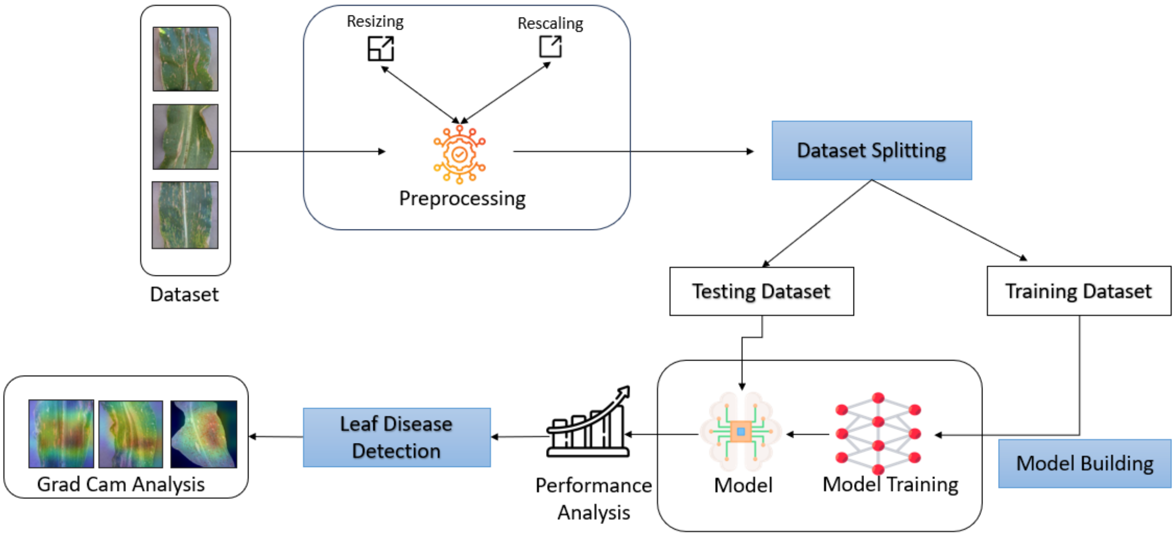

Figure 1. Proposed system stages for corn diseases for this study.

3.1 | Dataset

In this study, the Corn Leaf Disease Dataset was used which contains four classes and 4188 images [23]. The data set consists of color images of different sizes. The dataset was created by combining PlantDr with PlantVillage for corn plant leaves and removing images that were not useful. Table 1 shows a statistics summary of the dataset.

Table 1. Statistics summary of the dataset.

	Classes	Images	Percentage	Total
Diseased	Common Rust	1306	0.311%	2964
	Gray Leaf Spot	512	0.137%	
	Blight	1146	0.273 %	
Healthy	Healthy leaf	1162	0.277 %	1162

3.2 | Dataset Preprocessing

The data set is entered into the system to be pre-processed to enhance the performance of models. In this paper, the Preprocessing step was done by resizing images (224,224) and normalizing data to speed up the convergence speed. This method is based on rounding the pixels of the images from 0 to 1 through Eq. (1).

$$I' = \frac{I}{255} \quad (1)$$

where I' is a normalized image, I input image, and the grayscale image's maximum intensity value per pixel is represented by 255. Then The data was divided into three parts: Train, Test, and Valid 90% of the dataset for Train data, where the Train data is used to train the model, the valid data for testing the model after every epoch, and the test data for testing the model after the training process ends.

3.3 | Building the Studied DL Models

At this stage, DL models were created with the default parameter. All models were compiled to determine the loss function the Adam Optimizer was used to measure the error rate, and the evaluation metrics were used to evaluate its performance. The categorical cross entropy (CCE) loss function is used to optimize the initial weights of certain DL models to increase classification accuracy. The loss function is mathematically defined as follows:

Minimize: $\mathrm{loss(CCE)} = -\sum_{i=1}^{M} y_i \cdot \log \breve{y}_i$ (2)

Where y_i is true value $\breve{y}_i$ is shorthand for a vector that contains all of the outputs that were predicted based on the training samples.

3.4 | Compared Deep Learning Models

In this work, a group of DL pre-trained models was built, namely Xception, ResNet50, and EfficientNet, and a comparison was made between them and the proposed model.

3.4.1 | Xception

Chollet proposed Xception [24], which is a depth-wise separable convolutional neural network architecture. Xception does not require convolution across all channels, similar to conventional convolution. This decreases the number of connections, making the model lighter.

3.4.2 | ResNet50

ResNet50 [25] model is a subset of the ResNet family which consists of 50 layers (48 convolutional layers, one maxpool Layer, and one average Pool Layer). ResNet consists of residual blocks created to address the vanishing/exploding gradient problem.

3.4.3 | EfficientNet

EfficientNet [26] is a type of convolutional neural network based on complex coefficient technology, which works by measuring the depth, width, and accuracy of the network using a set of specified coefficients. Its construction depends on MobileNetV2's inverted bottleneck residual blocks and squeeze-and-excitation blocks.

3.4.4 | MobileNet

MobileNet [27] is a version of the CNN model introduced by Google and is based on the depthwise separable convolution which contains two main stages first Stage depthwise convolution Applies one Convolution Filter for input Channels, Second stage Applies pointwise Convolution to make a linear combination between all output.

3.5 | Proposed Model

Our proposed model is based on DenSeNet121 combined with DNN layers. DenSeNet121 is a subset of the DenseNet family. DenseNet [28] is a type of convolutional neural network presented by Gao Huang. It is based on two layers: DenseBlock, where each layer is connected to the other, and Transition Block, which is used for reducing the number of model parameters. Figure 2 shows the proposed model (DenSeNetDNN). The extraction of deep features has been achieved using the DenSeNet121 model. Using the ImageNet dataset, the model was pre-trained. The following by GlobalAverage pooling is used to downsample the input by averaging the width and height of it. Then these features are fed to the DNN layers (dense layers), which combine the features learned by convolutional and pooling layers to make predictions or classifications. These layers enable the network to learn complex relationships in the data and generate meaningful output based on the learned representations. In the proposed model, there are two dense layers: the first combines the features learned by convolutional and pooling layers, followed by a dropout layer that helps prevent overfitting problems, and then the output layer to output the final results or prediction.

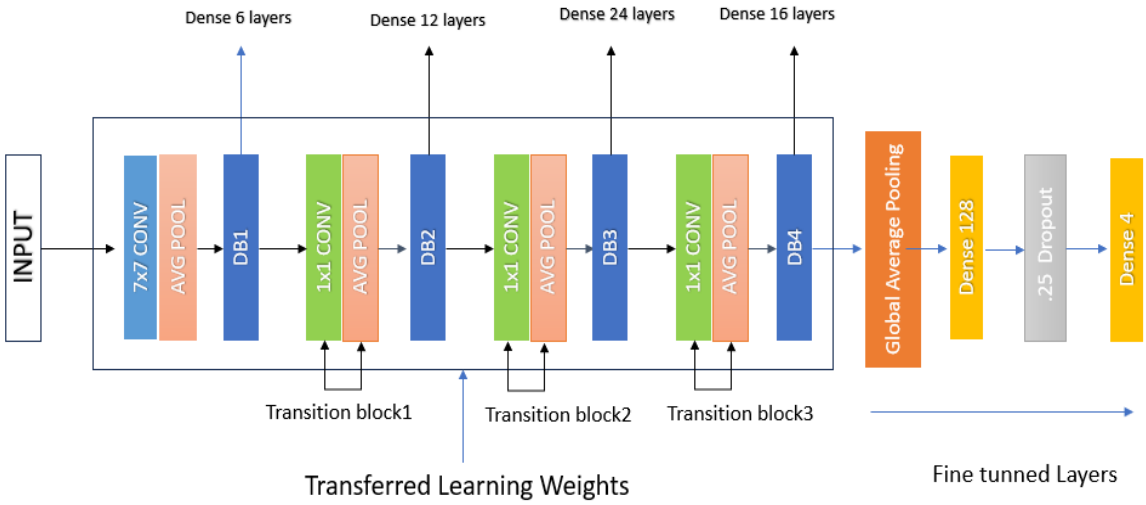

Figure 2. The proposed hybrid model architecture (DenSeNetDNN).

3.6 | Grad Cam Analysis

Grad-Cam is a generalization of CAM that provides an image localization map according to the chosen layer [16]. Grad-Cam $\mathcal{D}^{c}_{GRAD-CAM} \in \mathbb{R}^{m\times n}$Following the training of a convolutional layer in DCNN its feature mappings β are employed to determine the gradient of the layer g^{C}. The importance weights α_k^c are obtained by global average-pooling these gradients flowing back.

$$\alpha_k^c = \frac{1}{Z}\sum_i \sum_j \frac{\partial g^c}{\partial \beta_{ij}^k} \tag{3}$$

Grad-CAM heat maps are weighted combinations of feature maps, similar to CAM, except they are preceded by a ReLU:

$$D^{c}_{\text{Grad-CAM}} = \text{ReLU}(\sum_k \alpha_k^c B^k) \tag{4}$$

4 | Result and Discussion

The section presented extensively compares the performance of several DLs and the proposed hybrid model. Through the training Corn Dataset and set of evaluation metrics.

4.1 | Experimental Environment Setup

All Compared Models implemented on the Kaggle have GPU Nvidia Tesla P100 with RAM 16 GB, Python Version 3.7.6, and Keras Version 2.3.1 [28]. All DL Models were trained using Adam optimizer, with a learning rate of .0001 using batch size 32 of images.

4.2 | Performance Evaluation

To evaluate the proposed model and compare it with the utilized pre-trained models (Xception, ResNet50, and Efficient Net), four evaluation metrics are used namely, accuracy, precision, recall, in addition to F1-score. These evaluation metrics are mathematically represented in Eqs. (5-8) respectively.

- Accuracy – For measuring the overall correctness of predictions.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})} \quad (5)$$

- Precision – To assess the precision of positive predictions among all predicted positives

$$\text{Precision} = \frac{TP}{(TP + FP)} \quad (6)$$

- Recall - For quantifying the model's ability to correctly identify all relevant instances.

$$\text{Recall} = \frac{TP}{(TP + FN)} \quad (7)$$

- F1 Score - For balancing both precision and recall for a holistic performance.

$$F1 \text{ Score} = 2 \times \frac{\text{recall} \times \text{Precision}}{\text{recall} + \text{Precision}} \quad (8)$$

4.3 | Experimental Results and Discussion

The proposed model was trained on 90% of the utilized dataset as other retrained models, and the remaining images were utilized for validating and testing the models. Table 2 shows the performance of models with the utilized evaluation metrics. The results showed that the proposed model achieved the best performance and outperformed all other models. It achieves an accuracy of 0.961, while the MobileNet model achieved the lowest accuracy of 0.922. Figure 3 shows the rank of each model with different matrices. The Proposed model (DenseNetDNN) achieves the highest rank, followed by the MobileNet model. Figure 4 presents the Confusion Matrix to describe the performance of a Proposed model (DenseNetDNN) in each category and summarize it. Figure 5 shows the accuracy and loss curves of the Proposed model (DenseNetDNN) during the training process by evaluating each epoch on the validation dataset.

Table 2. Performance of the proposed model against the other pre-trained model.

	Acc.	Precision	Recall	F1 Score
ResNet50	0.937	0.937	0.910	0.919
MobileNet	0.922	0.908	0.903	0.905
EfficientNetB0	0.943	0.936	0.930	0.933
Xception	0.945	0.956	0.909	0.923
DenseNetDNN	0.961	0.952	0.958	0.955

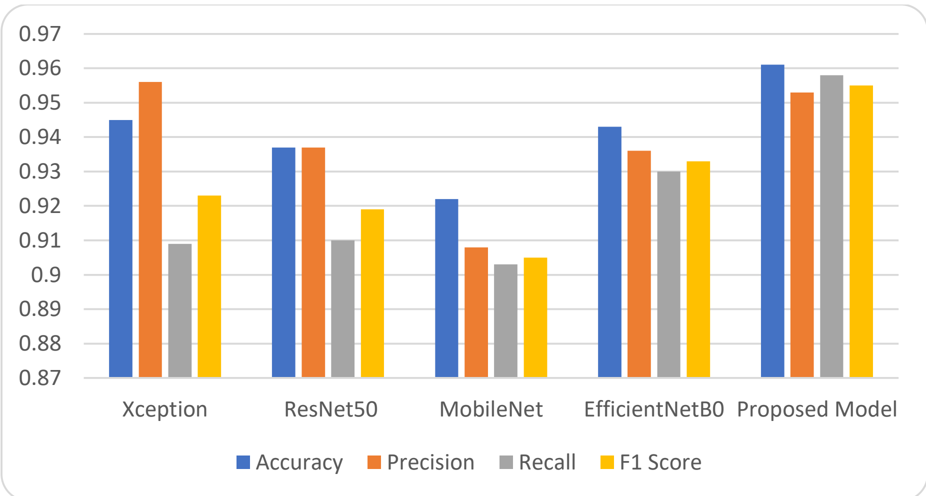

Figure 2. The proposed model Performance against other models.

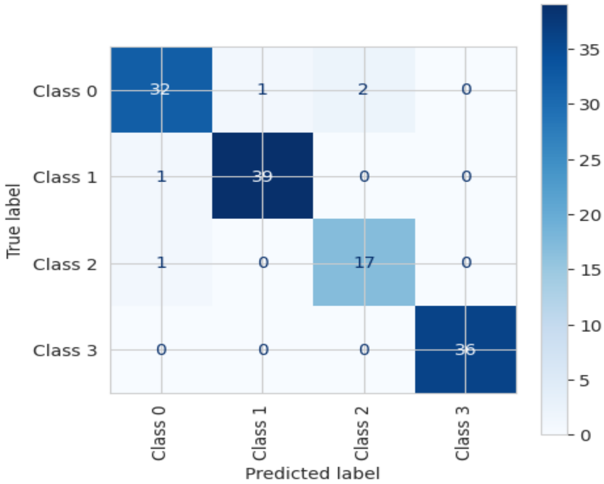

Figure 4. Confusion matrix of the proposed model.

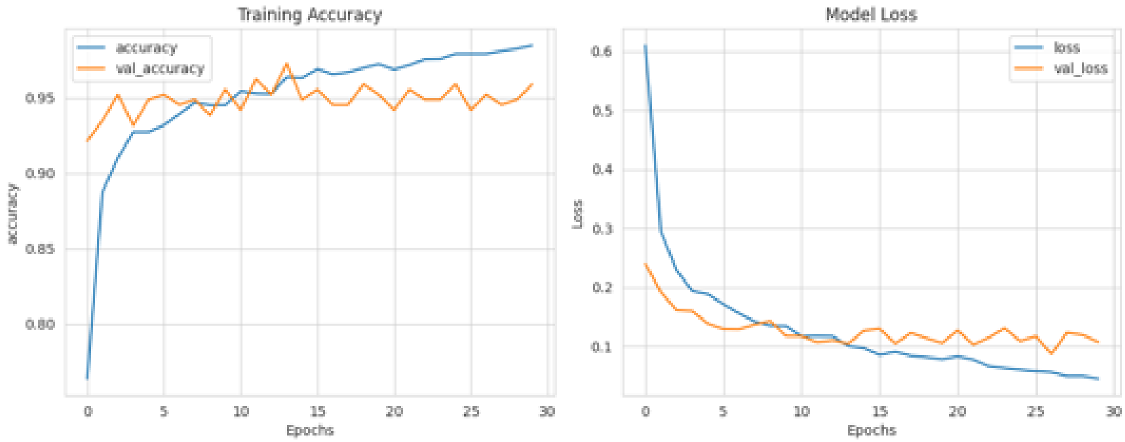

Figure 5. Loss and accuracy curves of the proposed model on the utilized dataset.

Finally, in our analysis of Grad-CAM visualizations, we found compelling evidence of the model's ability to focus on disease-specific regions within corn plant images. The highlighted areas consistently aligned with known symptoms of the respective diseases, indicating the model's capacity to learn relevant features for accurate disease detection. Figure 6 Sample images of Grad-Cam-based analysis for the proposed model (DenseNetDNN).

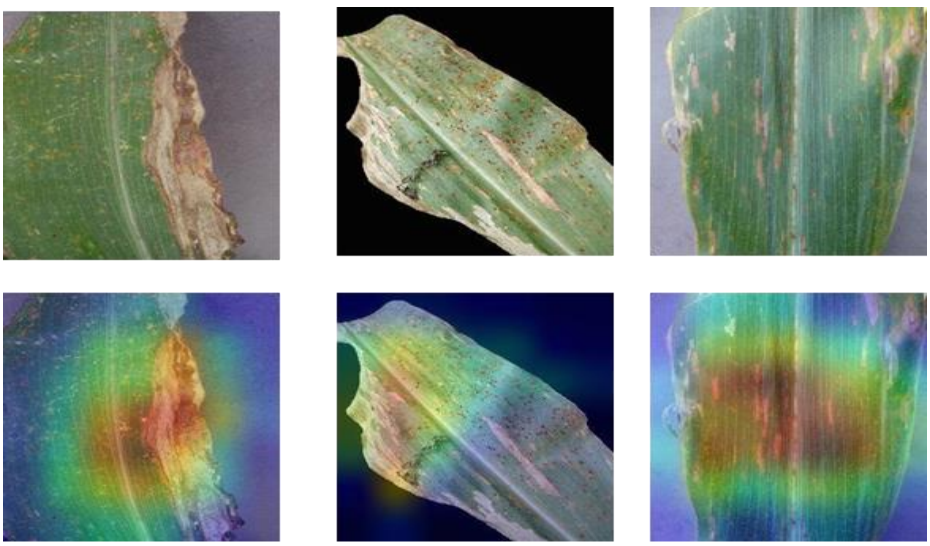

Figure 6. Grad-CAM results visualization.

5 | Implication

Ensuring the corn crop's health and early detection of leaf diseases play a very important role in agriculture's productivity and the global economy. Automating the process of disease detection using new technologies such as artificial intelligence techniques, specifically DL models, can help save time, minimize crop loss, ensure food security, and have significant economic implications for the agriculture industry and trade.

This study works on leveraging DL techniques for corn disease detection, which aligns with several Sustainable Development Goals (SDGs) [29] outlined by the United Nations. Specifically, our work contributes to Goal 2: Zero Hunger, by enhancing agricultural productivity and food security, Goal 8: Decent work and economic growth by minimizing crop loss, which increases agriculture productivity. Goal 9: Industry, Innovation, by fostering technological advancements and promoting sustainable agricultural practices, and Goal 13: Climate Action: By preventing yield losses due to diseases, our model contributes to achieving Egypt Vision 2030.

6 | Conclusion

In this study, we proposed a novel approach for detecting corn diseases by combining DenseNet121 with a deep neural network (DNN) classifier, named the DenseNetDNN model. The proposed model's performance was compared against four pre-trained CNN models, namely ResNet50, MobileNet, EfficientNetB0, and Xception. Experimental results demonstrate the superior performance of the DenseNetDNN model using four evaluation metrics accuracy, precision, recall, and F1 score. The results indicate that the integration of DenseNet121 with DNN classifiers achieves an accuracy of 96.1% and an F1 score of 0.955. the results demonstrated the effectiveness of deep learning techniques, particularly when leveraging powerful feature extraction capabilities combined with robust classification algorithms. Moreover, this study utilizes the GradeCam algorithm for performance evaluation, enhancing the reliability and reproducibility of our results. This underscores the importance of employing advanced tools and methodologies in agricultural research to ensure accurate and consistent assessments.

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Author Contribution

All authors contributed equally to this work.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

References

[1] FAOSTAT, F., Agriculture organization of the united nations FAO statistical database. 2023.

[2] Abdullah, H.M., et al., Present and future scopes and challenges of plant pest and disease (P&D) monitoring: Remote sensing, image processing, and artificial intelligence perspectives. Remote Sensing Applications: Society and Environment, 2023: p. 100996.

[3] Wan, L., et al., Hyperspectral sensing of plant diseases: Principle and methods. Agronomy, 2022. 12(6): p. 1451.

[4] Alam, S., P. Raja, and Y. Gulzar, Investigation of machine learning methods for early prediction of neurodevelopmental disorders in children. Wireless Communications and Mobile Computing, 2022. 2022.

[5] Anand, V., et al., Weighted average ensemble deep learning model for stratification of brain tumor in MRI images. Diagnostics, 2023. 13(7): p. 1320.

[6] Gulzar, Y., et al., OCA: ordered clustering-based algorithm for e-commerce recommendation system. Sustainability, 2023. 15(4): p. 2947.

[7] Malik, I., et al., Estimation of the extent of the vulnerability of agriculture to climate change using analytical and deep-learning methods: A case study in Jammu, Kashmir, and Ladakh. Sustainability, 2023. 15(14): p. 11465.

[8] Khan, U., et al., A Systematic Literature Review of Machine Learning and Deep Learning Approaches for Spectral Image Classification in Agricultural Applications Using Aerial Photography. Computers, Materials & Continua, 2024. 78(3).

[9] Abourabia, I., et al., Enhancing Deep Learning-Based Semantic Segmentation Approaches for Smart Agriculture, in Engineering Applications of Artificial Intelligence. 2024, Springer. p. 395-406.

[10] Ayoub, S., et al., Generating image captions using bahdanau attention mechanism and transfer learning. Symmetry, 2022. 14(12): p. 2681.

[11] Hamid, Y., et al., An improvised CNN model for fake image detection. International Journal of Information Technology, 2023. 15(1): p. 5-15.

[12] LeCun, Y. and Y. Bengio, The handbook of brain theory and neural networks. chapter Convolutional Networks for Images, Speech, and Time Series. MIT Press, Cambridge, MA, USA, 1998. 3: p. 255-258.

[13] Pahlawanto, R.D.S., H. Salsabila, and K.R. Pratiwi, Detection and prediction of rice plant diseases using convolutional neural network (CNN) method. Journal of Student Research Exploration, 2024. 2(1): p. 22-33.

[14] Yao, J., et al., Deep Learning for Plant Identification and Disease Classification from Leaf Images: Multi-prediction Approaches. ACM Computing Surveys, 2024. 56(6): p. 1-37.

[15] Suharto, D.N. and R. Mandala. Identification of Diseases on Corn Leaves Using CNN Denoising (DeCNN). in Proceeding International Conference on Religion, Science and Education. 2024.

[16] Selvaraju, R.R., et al. Grad-cam: Visual explanations from deep networks via gradient-based localization. in Proceedings of the IEEE international conference on computer vision. 2017.

[17] Haque, M.A., et al., Recognition of diseases of maize crop using deep learning models. Neural Computing and Applications, 2023. 35(10): p. 7407-7421.

[18] Singh, E., et al. Maize Disease Multi-Classification: Leveraging CNN and Random Forest for Accurate Diagnosis. in 2024 International Conference on Automation and Computation (AUTOCOM). 2024.

[19] P, B.R., A. Ashok, and A.V. S. H. Plant Disease Detection and Classification Using Deep Learning Model. in 2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA). 2021.

[20] Amin, H., et al., End-to-End Deep Learning Model for Corn Leaf Disease Classification. IEEE Access, 2022. 10: p. 31103-31115.

[21] Li, E., et al., A novel deep learning method for maize disease identification based on small sample-size and complex background datasets. Ecological Informatics, 2023. 75: p. 102011.

[22] Ashwini, C. and V. Sellam, An optimal model for identification and classification of corn leaf disease using hybrid 3D-CNN and LSTM. Biomedical Signal Processing and Control, 2024. 92: p. 106089.

[23] Olivas, E., et al., Chapter 11: Transfer Learning, Handbook of Research on Machine Learning Applications. 2009, IGI Publishing: Hershey, PA, USA.

[24] Chollet, F. Xception: Deep learning with depthwise separable convolutions. in Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

[25] He, K., et al. Deep residual learning for image recognition. in Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

[26] Tan, M. and Q. Le. Efficientnet: Rethinking model scaling for convolutional neural networks. in International conference on machine learning. 2019. PMLR.
[27] Howard, A.G., et al., Mobilenets: Efficient convolutional neural networks for mobile vision applications. 2017.
[28] Chollet, F., Deep learning mit python und keras: das praxis-handbuch vom entwickler der keras-bibliothek, MITP-Verlags GmbH & Co. KG: Frechen, Germany, 2018.
[29] Nations, U., Transforming our world: The 2030 agenda for sustainable development. New York: United Nations, Department of Economic and Social Affairs, 2015. 1: p. 41.