Optimization in Agriculture

Journal Homepage: sciencesforce.com/oia

Optimization Agri. Vol. 1 (2024) 81–93

Paper Type: Original Article

An Interpretable Deep Learning for Early Detection and Diagnosis of Wheat Leaf Diseases

Ahmed Tolba [1,*], **and Nourhan Talal** [1]

[1] Department of Computer Science, Faculty of Computers and Informatics, Zagazig University, Zagazig 44519, Egypt.
Emails: a.tolba24@fci.zu.edu.eg; N.Talal22@fci.zu.edu.eg.

Received: 03 Jan 2024 **Revised:** 07 Apr 2024 **Accepted:** 05 May 2024 **Published:** 09 May 2024

Abstract

Wheat is a strategic crop that ensures food security and sustainability. Due to climate change, Egypt faces many challenges in the context of wheat disease. This led the government to set goals to achieve sustainable development, represented by Egypt's Vision 2030. Automated systems using artificial intelligence can help in the early identification of wheat diseases and reduce effort and time as well. In this paper, we introduce a novel deep learning model (Mobile-DNN-Net) to identify wheat diseases. The mobile-DNN-Net model is evaluated using a wheat disease dataset between 15 different classes. Our model (Mobile-DNN-Net) is a hybrid between MobileNet and Deep convolution neural network (DCNN). Also, Grad-Cam techniques into a convolutional neural network (CNN) defect detection model to enhance its transparency and comprehensibility. Grad-CAM precisely identifies the precise regions of the input image that exert the greatest influence on the model's prediction, thereby enhancing the clarity and comprehension of the detection process. The mobile-DNN-Net model is compared to other DL models such as Xception, MobileNet, InceptionV3, and VGG19. The proposed model shows superior results compared to other models.

Keywords: Wheat Disease Identification; Deep Learning (DL); Grad-CAM; Explainable AI.

1 | Introduction

The global wheat crop represents a major aspect of food security and environmental sustainability. According to FAOSTAT report [1] wheat production in Egypt is constantly increasing. Unfortunately, climate change would reduce global wheat production by 1.9% by mid-century, with Africa and South Asia bearing the brunt of the damage. Studies have already shown that wheat yields fell by 5.5% between 1980 and 2010, due to rising global temperatures. Climate change threatens wheat crop spreading and affects environmental sustainability and global food security [2].

The utilization of machine learning (ML) and Deep learning (DL) techniques in the detection of plant diseases has become increasingly popular and has demonstrated promising outcomes in accurately identifying plant diseases based on digital images. Conventional ML techniques, such as SVM, random forest, and decision trees have been extensively employed in the domain of wheat disease detection. These techniques utilize various algorithms to extract distinct characteristics from images, including color, texture, and shape. These

Corresponding Author: a.tolba24@fci.zu.edu.eg
https://doi.org/10.61356/j.oia.2024.1257
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extracted features are then used to train a classifier that can accurately distinguish between healthy plants and those that are diseased [3].

In recent times, advanced DL techniques like convolutional neural networks (CNNs) and deep belief networks (DBNs) have been suggested to detect plant diseases. These techniques entail training a neural network to acquire knowledge about the fundamental characteristics of the images, allowing for the detection of subtle disease symptoms that conventional image processing methods may fail to identify[4, 5]. DL models are capable of processing intricate and sizable images, rendering them appropriate for high-resolution images. Nevertheless, these techniques necessitate a substantial quantity of annotated training data and may not be appropriate for novel illnesses [6]. Moreover, DL models incur significant computational costs, which can pose limitations for certain applications.

In this study, we introduce a novel DL model (Mobile-DNN-Net) to identify 15 different wheat diseases from the Wheat Plant Diseases Dataset. The dataset consists of 14,155 high-resolution images. Grad-Cam techniques in a CNN-based defect detection model to improve its transparency and comprehensibility. A comparison between the Mobile-DNN-Net model and other 4 DL models such as Xception, MobileNet, InceptionV3, and VGG19, has been maintained in terms of accuracy, precision, recall, F1-Score, and area under the curve (AUC). Additionally, these models offer visual representations that aid in diagnosis and facilitate comprehension. Through the utilization of techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping), we have effectively generated comprehensible results that provide valuable insights into the decision-making process of CNN models.

The main contributions of the present study can be succinctly summarized as follows:

- An integration between MobileNet and Deep Neural Network (DNN) to introduce the Mobile-DNN-Net model.
- A novel Mobile-DNN-Net model is introduced to classify a wide range of wheat diseases.
- An investigation of the effectiveness of different DL models such as (Xception, MobileNet, InceptionV3, and VGG19) has been evaluated between 15 classes of wheat disease.
- The mobile-DNN-Net model achieves superior results compared with other DL models.
- The grad-CAM visual explanation method is utilized to troubleshoot the prediction procedure for each model and to emphasize the noteworthy parts in the wheat leaf image that are accountable for the conclusion.
- The validity of the models was assessed using a range of metrics, such as accuracy, precision, recall, F1-score, and AUC. In exploratory data analysis using the ROC Curve.

The rest of this paper is organized as follows. Section 2 reviews related work. Section 3 presents materials and methods. Section 4 presents the proposed model. Section 5 presents results and discussion Section 6 managerial implications and Section 7 presents the conclusion and future work.

2 | Related Work

Recently, the manual process of visually inspecting plants to identify diseases is frequently characterized by being time-consuming, requiring a significant amount of labor, being costly, and subject to personal interpretation. These factors are among the primary motivations for researchers to investigate alternative methods. Several ML methodologies have been suggested to address this issue. With a high level of precision, as well as a decrease in expenses and subjectivity.

Singh et al. [7] examine the utilization of ML methods, such as DL, in the context of high-throughput stress phenotyping in plants. The authors investigated the utilization of different omics technologies, such as genomics, transcriptomics, proteomics, and metabolomics, for stress phenotyping. They emphasized the vast capabilities of ML Methods for managing the large and complex datasets generated by these technologies, allowing for efficient analysis and interpretation.

Boulent et al. [8] proposed a sophisticated plant disease detection system by leveraging DL techniques and implementing a CNN. The system underwent training using a comprehensive dataset consisting of 54,306 photographs that covered 15 different types of plant diseases. The model demonstrated an impressive level of accuracy, reaching a remarkable 95% in correctly identifying and categorizing plant diseases. Gogolev et al. [9] Developed an autonomous system for detecting and diagnosing plant diseases by analyzing leaf images using a CNN. The dataset consisted of 3,795 images representing 10 different plant diseases. The accuracy rate achieved was 95.5%. Also, Feng et al. [10] Devised a technique for identifying plant leaf diseases by fine-tuning the parameters of CNN. Using a dataset of 2,376 images that represent 11 different plant diseases, the researchers achieved an accuracy rate of 98.8%.

Rubio et al. [11]Suggested a DL methodology for categorizing and diagnosing plant ailments by employing transfer learning and fine-tuning techniques. The dataset consisted of 54,306 images depicting 15 distinct plant diseases, achieving an accuracy rate of 99.2%.

Feng et. al [12] Suggested a technique that combines ML and multispectral imaging to identify and diagnose plant diseases. By employing a random forest classifier, the researchers achieved a commendable accuracy rate of 93.3% when analyzing a dataset consisting of 480 multispectral images of apple trees affected by fire blight.

Song et. al [13] proposed a technique for detecting tomato diseases by utilizing DL algorithms and hyperspectral images. The researchers achieved an accuracy of 93.6% on a dataset consisting of 1,080 hyperspectral images representing six different tomato diseases.

Arjmand et. al [14] Explored the use of ML methods to enhance agriculture, specifically by analyzing omics data and sensor data for crop phenotyping and disease diagnosis. They emphasized the capacity of ML techniques to expedite crop improvement and tackle global food security concerns.

Fu et. al [15] Examined the latest progress in the application of DL methods, such as CNNs, Recurrent Neural Networks (RNNs), and autoencoders, for the diagnosis of plant diseases. The author explored a wide range of data types used for diagnosing plant diseases, including images, omics data, and sensor data. Moreover, the discussion illuminated the difficulties faced in this domain and emphasized the possibilities for future research endeavors. Kuswidiyanto et al. [16] Developed a plant disease identification system utilizing CNN technology. When applied to a collection of 1,625 images representing four distinct plant diseases, their efforts resulted in an impressive accuracy rate of 98.34%.

Furthermore, there is a strong need among plant pathologists and cultivators for the creation of accessible tools and platforms that streamline. Streamlined data gathering and analysis from plant omics. The application of recent advancements in cloud computing, the Internet of Things (IoT) Sayed et al. [17], and mobile technology can enable seamless monitoring and instantaneous decision-making. DL methods that make use of plant omics data have significant potential to enhance plant disease control and contribute to the advancement of global food security. By conducting ongoing research and development, these methods can aid in the creation of a durable and adaptable agricultural system that can effectively address the challenges of the twenty-first century.

3 |Materials and Methods

This study investigates four DL models: Xception [18], MobileNet [19], InceptionV3 [20] and VGG19 [21].

3.1 |MobileNet Architecture

MobileNet is a specific sort of CNN that has been specifically developed to be used in mobile and embedded vision applications. These networks are constructed using depthwise separable convolutions, which results in a streamlined design. This allows for the creation of lightweight deep neural networks that have low latency, making them suitable for usage in mobile and embedded devices [19].

The MobileNet architecture is enhanced with Separable Convolutions, Drop-Activation, and Random Erasing techniques to reduce its size. Modification 4 removes redundant layers 9 to 13, along with the other enhancements. Access the network for a streamlined version of MobileNet. Table 1 shows the core elements of the Thin MobileNet model.

Table 1. MobileNet body architecture.

Type / Stride		Filter Shape	Input Size
Conv / s2		3 × 3 × 3 × 32	224 × 224 × 3
Conv dw / s1		3 × 3 × 32 dw	112 × 112 × 32
Conv / s1		1 × 1 × 32 × 64	112 × 112 × 32
Conv dw / s2		3 × 3 × 64 dw	112 × 112 × 64
Conv / s1		1 × 1 × 64 × 128	56 × 56 × 64
Conv dw / s1		3 × 3 × 128 dw	56 × 56 × 128
Conv / s1		1 × 1 × 128 × 128	56 × 56 × 128
Conv dw / s2		3 × 3 × 128	dw 56 × 56 × 128
Conv / s1		1 × 1 × 128 × 256	28 × 28 × 128
Conv dw / s1		3 × 3 × 256 dw	28 × 28 × 256
Conv / s1		1 × 1 × 256 × 256	28 × 28 × 256
Conv dw / s2		3 × 3 × 256 dw	28 × 28 × 256
Conv / s1		1 × 1 × 256 × 512	14 × 14 × 256
5×	Conv dw / s1	3 × 3 × 512 dw	14 × 14 × 512
	Conv / s1	1 × 1 × 512 × 512	14 × 14 × 512
Conv dw / s2		3 × 3 × 512 dw	14 × 14 × 512
Conv / s1		1 × 1 × 512 × 1024	7 × 7 × 512
Conv dw / s2		3 × 3 × 1024 dw	7 × 7 × 1024
Conv / s1		1 × 1 × 1024 × 1024	7 × 7 × 1024
Avg Pool / s1		Pool 7 × 7	7 × 7 × 1024
FC / s1		1024 × 1000	1 × 1 × 1024
Softmax / s1		Classifier	1 × 1 × 1000

3.2 | Grad-Cam Technique

In this study, we focus on Interpretable DL by applying Grad-Cam methods with Transfer Learning Models. The models used in this experiment are Xception, MobileNet, InceptionV3, and VGG19 in addition to the Proposed Model. The gradient-weighted class activation mapping (Grad-CAM) technique [22] is employed to investigate issues with any CNN model and assess its effectiveness in task classification. This technique provides a visual representation of how the model examines the image during processing and identifies the pixels that have the most significant information. The Grad-CAM approach involves calculating the significance weights of neurons in the last convolutional layer's feature map, namely over the width and height dimensions denoted by i and j. The algorithm calculates the gradient of the score y^c for class c in relation to the feature map activation $A^k$of the convolutional layer. Eq. (4) illustrates the computation of neuron significance weights.

$$\alpha_k^c = \frac{1}{N}\sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}^k} \tag{1}$$

Where N is the number of pixels in the concerned feature map. Figure 1 explains the most important components of the Grad-CAM working process. This methodology offers a heat map that allows us to visually represent how the model is analyzing the wheat dataset and identify the specific areas of the images that have the most impact on the prediction conclusion. This strategy involves monitoring the prediction process by utilizing the last convolutional layer. A weighted total of the feature maps is calculated for each prediction to identify the main regions of the original image that have a significant impact on the model's choice. The outcome is a heat map that may be linked to the original image for display purposes. This technique aids in ascertaining if the model accurately predicts cases of wheat diseases based on the correct diseased region of the leaves.

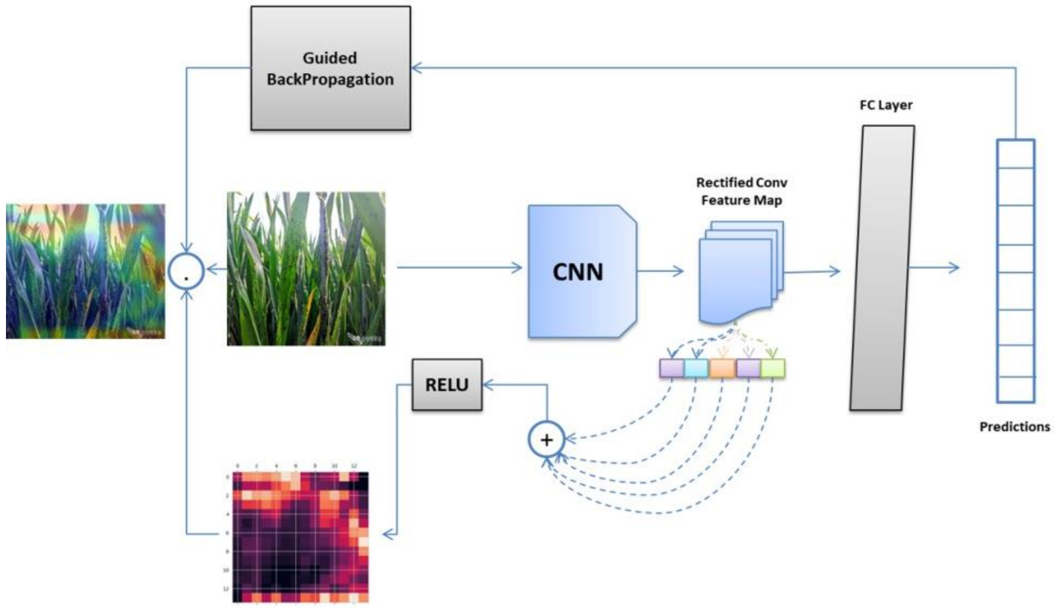

Figure 1. Grad-Cam visual explanation mechanism.

4 | Proposed Model

4.1 | Pre-Processing Stage

MobileNet is a specific sort of CNN that has been specifically developed to be used in mobile and embedded vision applications. These networks are constructed using depthwise separable convolutions, which results in a streamlined design. This allows for the creation of lightweight deep neural networks that have low latency, making them suitable for usage in mobile and embedded devices [19].

The normalization process has been done over the wheat disease dataset. Image normalization is solely relied upon to expedite the convergence speed. This is achieved by transforming the input images into a range of values between 0 and 1, as determined by the following formula:

$$image' = image/255 \tag{2}$$

Where $image'$ is a normalized image and $image$ is the input image. The input image is divided by 255 to convert the image from RGB to Grayscale so that the image becomes composed of range 0 and 1.

4.2 | Proposed Architecture

The proposed model is a fusion of the MobileNet architecture and two layers of a deep neural network. The architecture of the proposed model is illustrated in Figure 2. The MobileNet architecture functions as a feature extractor, efficiently capturing essential patterns and characteristics from the input data. The tiny size of the model is achieved by using depth-wise separable convolutions, which reduces both the model size and computational requirements. The subsequent two layers of the deep neural network enhance the model's learning and abstraction capabilities, allowing it to capture more intricate and advanced representations. The Rectified Linear Unit (ReLU) activation function introduces non-linearity, hence enhancing the model's capacity to acquire knowledge and generalize.

The main component of the proposed model is:

- Streaming Block: which has a Conv layer followed by batch normalization and Relu Activation function.
- MobileNet Block: which has a depth-wise convolutions layer followed by batch normalization and Relu Activation function. then Conv layer followed by batch normalization and Relu Activation function.
- DNN Block: Two Dense layers with Relu activation function.

Regarding the loss function, the proposed model adopts the categorical cross-entropy loss, Categorical cross-entropy is a loss function often used in classification tasks involving several classes. It evaluates the dissimilarity between predicted values probabilities and the true values labels. The goal is to minimize this dissimilarity during training, helping the model learn to effectively classify new data into the correct categories.

$$\text{Minimize: loss} = -\sum_{i=1}^{M} y_i \cdot \log \check{y}_i \tag{3}$$

Where y_i represent real values and $\check{y}_i$ represent predicted values.

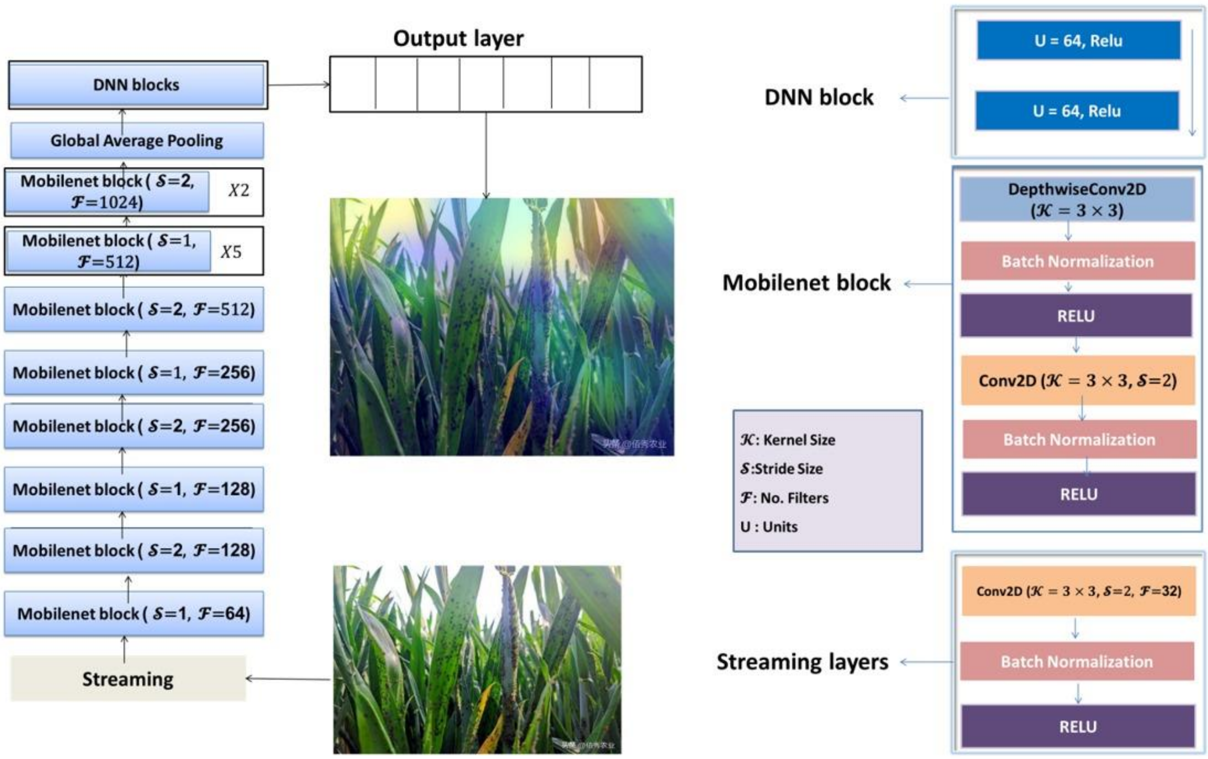

Figure 2. Mobile-DNN-Net model (proposed model).

4.3 | Training DL Model

Phase 1: The dataset is partitioned into several sets for training, validation, and testing so we process each partition alone by dividing it by 255 for normalization, image normalization is solely relied upon to expedite the convergence speed. This is achieved by transforming the input images into a range of values between 0 and 1.

Phase 2: The utilization of a training dataset is employed for training DL models then evaluating performance and checking epochs and early stopping, if a defect occurs in any of them, the model stops because it has finished the training process or is unable to learn, so it stops to prevent the overfitting, otherwise it completes the learning and development process.

Phase 3: The validation dataset is utilized to evaluate the performance of the model and adjust its parameters.

Phase 4: Lastly, the testing dataset is employed to analyze the final performance and generalization ability of the trained model on unknown data.

Phase 5: Display Explanation Results by using Grad-Cam on Original images for helping people who specialize in agriculture understand the disease and help them make decisions easily.

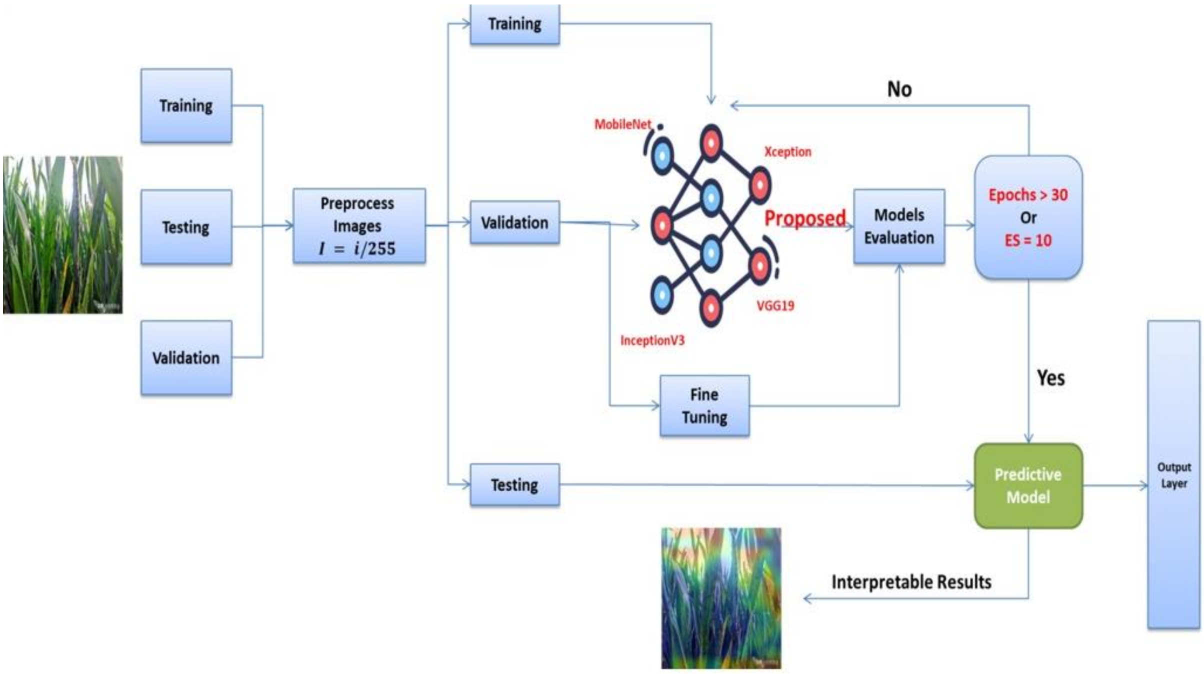

Figure 3. DL pipeline for wheat disease data classification.

5 | Experimental Results

This part includes the wheat image dataset overview, evaluation metrics, and statistical, and computational complexity analysis related to wheat image identification.

5.1 | Dataset Description

This study utilizes a publicly accessible dataset called Wheat Plant Diseases[23], obtained from several sources, The purpose of this dataset is to provide researchers and developers with the necessary tools to create strong ML models that can accurately classify different diseases affecting wheat plants. The collection features high-resolution photographs that display authentic wheat diseases in their natural state, without any artificial enhancement methods. The dataset has a total of 15 distinct classifications. Among the 15 classes, one was healthy and the remaining 14 represented different diseases of wheat leaf such as (Aphid, Black Rust, Blast, Brown Rust, Common Root Rot, Fusarium, Head Blight, Leaf Blight, Mildew, Mite, Septoria, Smut, Stem fly, Tan spot, Yellow Rust), The Dataset distribution as shown in Table 2 where the dataset contains a significant number of 14,154 high-quality images, which serves as a solid basis for training and evaluating DL models. The dataset is distributed into three separate folders: training, testing, and validation sets. The dataset has a well-balanced distribution, making it appropriate for developing a DL model capable of predicting a specific disease in wheat leaves and then classifying them accordingly.

Table 2. Dataset distribution.

	Classes	Pest			Rusts			Smut	Common Root Rot	Leaf Blight	Blast	Fusarium Head Blight	Mildew	Septoria	Tan Spot	Healthy
Training		Aphid	Mite	Stem Fly	Yellow Rust	Brown Rust	Black Rust									
	Count	903	800	234	1301	1271	576	1310	614	842	647	611	1081	1144	770	1000
	Total	13104														
Testing	Classes	Pest			Rusts			Smut	Common Root Rot	Leaf Blight	Blast	Fusarium Head Blight	Mildew	Septoria	Tan Spot	Healthy
		Aphid	Mite	Stem Fly	Yellow Rust	Brown Rust	Black Rust									
	Count	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50
	Total	750														
Validation	Classes	Pest			Rusts			Smut	Common Root Rot	Leaf Blight	Blast	Fusarium Head Blight	Mildew	Septoria	Tan Spot	Healthy
		Aphid	Mite	Stem Fly	Yellow Rust	Brown Rust	Black Rust									
	Count	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
	Total	300														

Figure 4. Depiction of infected and healthy images in this dataset.

5.2 | Evaluation Metrics

This section investigates the performance of the proposed model using a widely used dataset, Wheat diseases. In addition, it is compared to several DL models, such as Xception, InceptionV3, VGG19, MobileNet, and our Proposed Model**.** All DL models are implemented in Python using the Kaggle platform and Keras API. The Adam optimizer was used to train the weights of those models for 30 epochs. In addition, the early stopping with a patience of 10 was used in our experiments, and applying mini-batch gradient descent technique with batch size 64 to decrease the error calculated from the loss function (Categorical Cross Entropy).

The performance indicators used to evaluate the performance of those models are described as follows:

- **Accuracy:** The definition of this metric is the proportion of correctly predicted samples to all samples in a particular dataset.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}. \tag{4}$$

- **Precision:** Precision is a metric that quantifies how accurate positive predictions produced by a certain model are. The percentage of correctly detected positive instances to all anticipated positive instances is quantified by the statistic.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{5}$$

- **Recall:** This metric, which is also known as true positive rate or sensitivity, assesses how well the model can identify positive samples out of all the real positive samples.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{6}$$

- **F1-score:** The F1 score offers a fair evaluation of model performance by integrating recall and precision into a single metric.

$$\text{F1} - \text{score} = 2 * \frac{Precision \cdot Recall}{Precision + Recal}. \tag{7}$$

- **AUC:** It shows how well the model can discriminate between positive and negative examples; a greater AUC denotes superior performance.

$$\textbf{AUC} = \frac{1 + \frac{\text{TP}}{\text{TP} + \text{TN}} - \frac{\text{FP}}{\text{FP} + \text{TN}}}{2} \tag{8}$$

TP, TN, FP, and FN represent the abbreviations for True Positive, True Negative, False Positive, and False Negative, respectively.

- **Confusion Matrix:** A confusion matrix is a graphical representation that provides a concise overview of the performance of a ML or DL model on a certain dataset. It is a method of presenting the frequency of correct and incorrect events based on the model's forecasts. It is customary to evaluate the efficacy of classification models using metrics such as F1-score, accuracy, precision, and recall. When all the true values reach their maximum magnitude, the model achieves its optimal performance.

- **ROC Curve:** The receiver operating characteristic (ROC) curve shows how well a model performs in classification. At various classification thresholds, it plots the specificity (1 - false positive rate) against the sensitivity (true positive rate). A greater ROC curve denotes better performance, and it is used to assess the model's ability to distinguish between positive and negative cases.

5.3 | Statistical Analysis

As shown by the data in Table 3, the proposed model demonstrates the highest accuracy among the compared DL models, achieving an accuracy score of 90.1% after being trained for 20 epochs. It is closely followed by MobileNet, Xception, InceptionV3, and then VGG19, with an accuracy of 84.8%, 83.6%, 82.9%, and 48.5%. This confirms the superiority of the proposed model in terms of accuracy, followed by MobileNet, among the evaluated architectures. Figure 5 illustrates the confusion matrix, which displays the number of cases in which the actual class matches the estimated class. We notice that the main diagonal is filled with numbers, and the rest of the matrix elements are zeros. This means that the model can predict with high accuracy, except for Class No. 6. In Figure 6, the receiver operating characteristic (ROC) curve for a 15-class classification model shows an overall mean area under the curve (AUC) of 95%, with most classes having AUC values greater than 95%. However, it should be noted that classes 3 and 6 scored 93% and 53%, respectively.

The results of the prediction of the proposed model show that it correctly predicted the case, and the Grad-CAM visualization confirmed that the prediction was based on the correct regions in the wheat, which is demonstrated in Figure 7.

Table 3. Comparison between the Mobile-DNN-Net model and others in terms of various performance indicators.

Model Name	# Epochs trained	Accuracy	Precision	Recall	F1-Score	AUC
Proposed Model	20	0.901	0.893	0.901	0.884	0.947
MobileNet	30	0.848	0.852	0.848	0.834	0.918
Xception	30	0.836	0.840	0.836	0.820	0.912
InceptionV3	30	0.829	0.842	0.829	0.816	0.908
VGG19	30	0.485	0.506	0.485	0.469	0.724

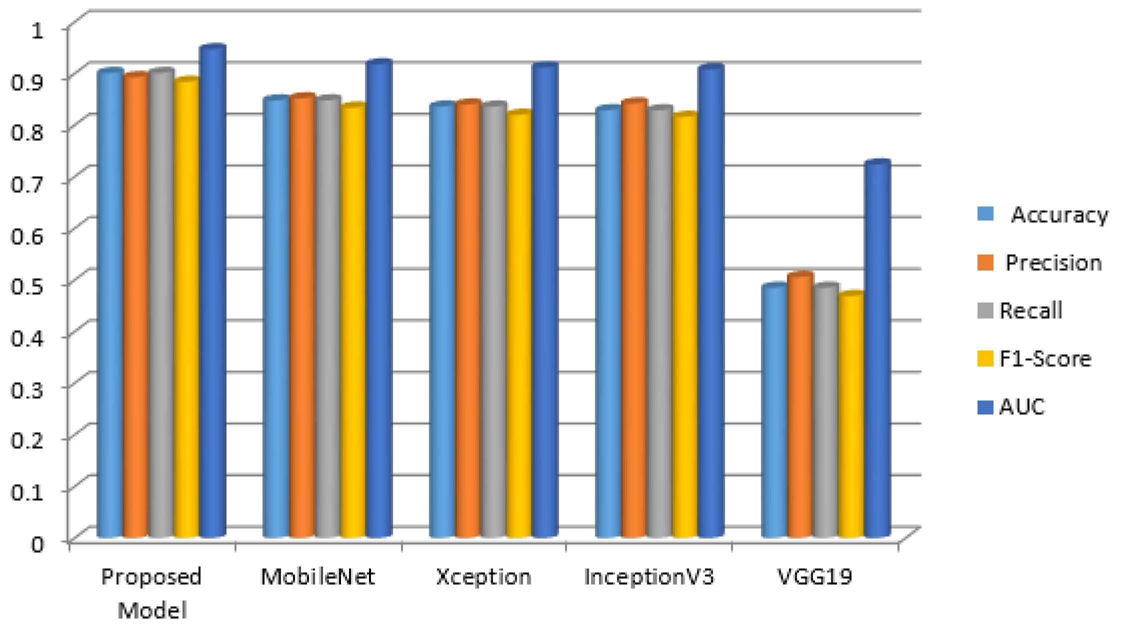

Figure 5. Comparison between Mobile-DNN-Net model and other DL models.

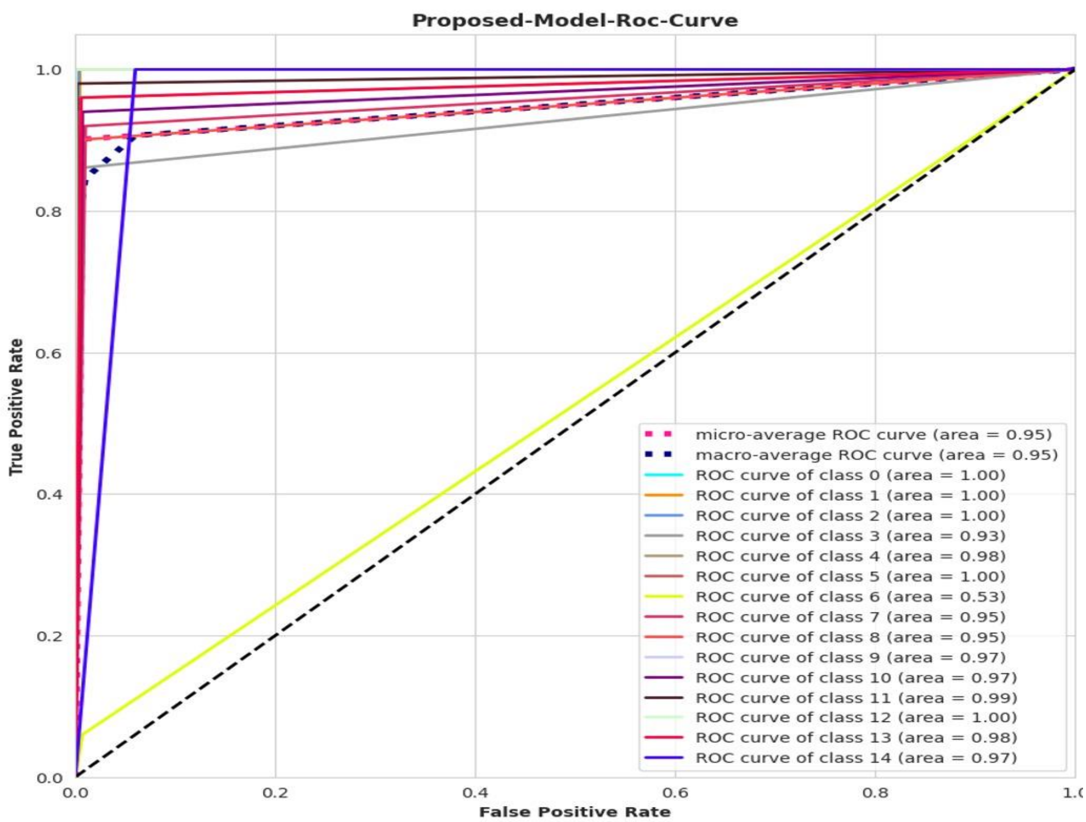

Figure 6. Roc Curve for Mobile-DNN-Net model.

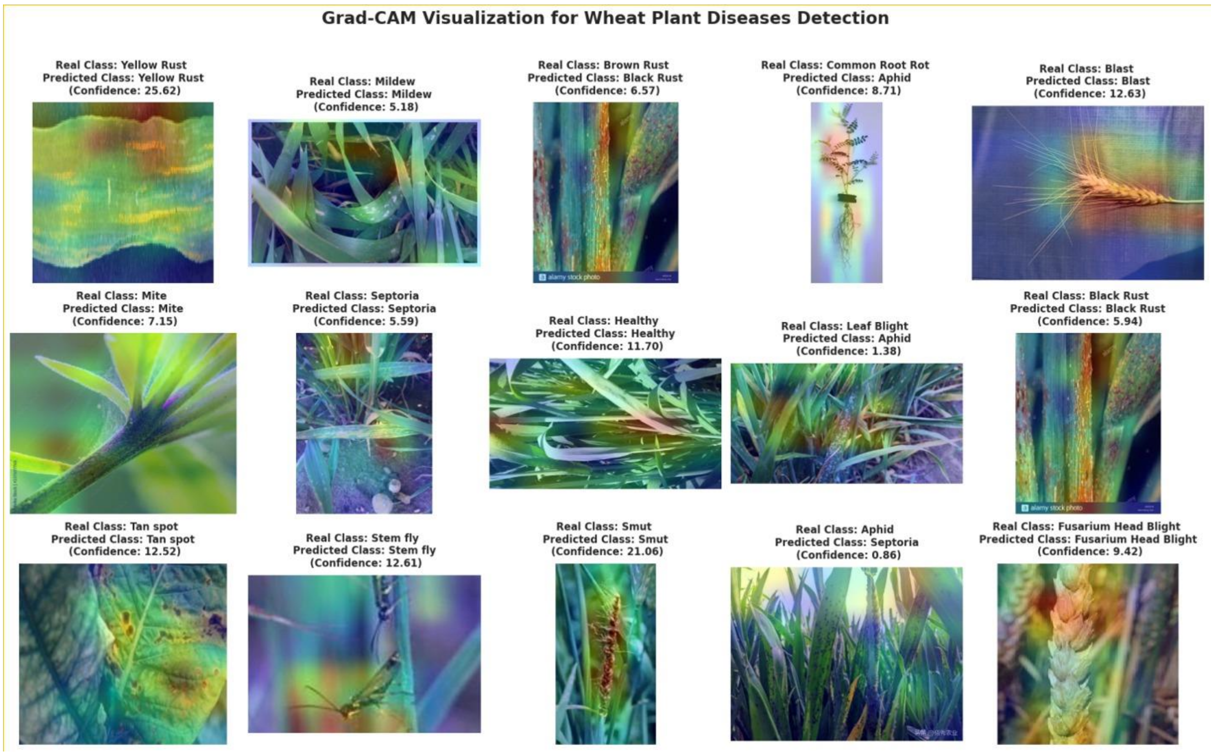

Figure 7. Grad-CAM visualization for predicting a real.

6 | Managerial Implications

Egypt must achieve the goals set forth in Vision 2030 in order to establish a strong agricultural sector. Implementing interpretable DL methods for early identification and diagnosis of wheat leaf diseases can result in more efficient and environmentally friendly agricultural methods, benefiting both farmers and the wider agricultural ecosystem.

Utilizing DL for the detection and diagnosis of wheat leaf diseases has the potential to enhance agricultural services and the precision of diagnoses. DL models that can be easily understood and analyzed offer valuable insights into the factors that contribute to the development of diseases. Farmers can utilize this information to comprehend the fundamental reasons behind disease outbreaks, recognize patterns of disease transmission, and formulate enduring strategies for disease control and prevention.

This paper showcases the integration of Grad-Cam techniques into a convolutional neural network (CNN) defect detection model to enhance its transparency and comprehensibility.

Grad-CAM precisely identifies the precise regions of the input image that exert the greatest influence on the model's prediction, thereby enhancing the clarity and comprehension of the detection process. This study can be utilized to enhance the process of accurately identifying wheat diseases. The proposed work has the potential to benefit and support the agricultural sector in achieving Egypt's vision for the year 2030.

7 | Conclusion and Future Work

This study introduces a Mobile-DNN-Net model for identifying wheat diseases. The proposed model is an integration between MobileNet and deep convolutional neural networks (DCNN). The model identifies 15 classes of diseases by utilizing the Wheat Plant Diseases dataset, which consists of 14,155 images. The Mobile-DNN-Net model is compared with the Xception, MobileNet, InceptionV3, and VGG19 models in terms of accuracy, precision, recall, F1-score, and AUC. The Mobile-DNN-Net model achieves results of 0.901, 0.893, 0.901, 0.884, and 0.947 for accuracy, precision, recall, F1-score, and AUC, respectively. Furthermore, Grad-CAM (Gradient-weighted Class Activation Mapping) was applied to effectively generate interpretable results that provide valuable insights into the decision-making process of CNN models. Grad-CAM precisely identifies the precise regions of the input image that exert the greatest influence on the model's prediction, thereby enhancing the clarity and comprehension of the detection process. Our proposed DL analysis of plant data can fundamentally transform the field of plant pathology. It provides a quicker, more accurate, and more economical substitute for conventional approaches to diagnosing plant diseases. Future endeavors will concentrate on improving the model, evaluating its efficacy on larger and more diverse datasets, and investigating its suitability in real-world scenarios.

Acknowledgments

The author is grateful to the editorial and reviewers, as well as the correspondent author, who offered assistance in the form of advice, assessment, and checking during the study period.

Author Contributaion

All authors contributed equally to this work.

Funding

This research has no funding source.

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.

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