



Detection and Classification of Wilting in Soybean Crop using Cutting-edge Deep Learning Techniques

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ABSTRACT

Background: This paper employs deep learning in the classification of soybean wilting, a plant health indicator affected by external pressures, using a Convolutional Neural Network (CNN) with a pre-trained model. It highlights the promise of deep learning in agriculture by examining the relevance of wilting, evolution in the agricultural sector and applications in crop wellness monitoring.

Methods: A CNN is used in the study to classify soybean withering, with special attention to the VGG16 pre-trained model. Deep learning's ability to interpret complex data patterns is harnessed for intelligent and accurate wilting detection. A smart detection system tailored for soybean wilting is developed, incorporating recent advancements and addressing associated challenges.

Result: The CNN model, notably VGG16, achieves 76% overall accuracy in distinguishing healthy and wilted soybean leaves, signifying a transformative shift in soybean crop health management. The approach offers a precise, efficient and sustainable solution supported by state-of-the-art CNN technology, advancing soybean cultivation practices.

Key words: Accuracy, Convolutional neural network (CNN), Soybean wilting, VGG16 pre-trained model.

INTRODUCTION

The numerous issues involved with crop management in today's dynamic agricultural landscape demand the integration of advanced technologies. One of the main crops in the world, soybeans is subject to a variety of stresses that can have a big effect on crop productivity and health. Wilting is one of the most important signs of plant stress and physiological imbalance among them. The ability to accurately and promptly identify wilting in soybean leaves holds the key to implementing targeted interventions, optimizing resource usage and ultimately ensuring sustainable agricultural practices. However, because of water shortages, drought stress can have a significant impact on soybean yield (Deshmukh *et al.*, 2014). Drought stress lowers seed weight later in the process, but it also lowers the quantity of seed per soybean pod in the early stages of seed filling (Desclaux *et al.*, 2000). There is a pressing need to develop soybean cultivars with drought tolerance to sustain crop productivity under drought conditions (Comas *et al.*, 2013).

The core of this work is the application of state-of-the-art deep learning techniques, a branch of artificial intelligence that is distinguished by its capacity to learn on its own and recognize complex patterns in large datasets. Deep learning models, in contrast to standard methods, possess the ability to understand extensive relationships, which allows them to extract subtle features that are frequently undetectable to human observers. With its smart and sophisticated approach to wilting detection, this revolutionary technology has the potential to completely change the soybean production industry. Several methods have been proposed by researchers to reliably identify and categorize plant infections. Some rely on conventional image processing methods that combine manually executed

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extraction of features and segmentation (Daniya *et al.*, 2022; Dubey *et al.*, 2012) suggested a K-means clustering technique to segment the leaf portion that is infected and a multi-class support vector machine, or SVM, is used for the final classification.

Convolution neural networks, or CNNs, have drawn a lot of interest lately because of their capacity to extract intricate low-level characteristics from pictures and perform identification and classification tasks. As a result, since CNNs produce better results, they are recommended to replace conventional techniques in automated plant disease detection (Karthik *et al.*, 2019). Barbedo, (2018) has suggested a CNN-based prediction model for paddy plant image processing and categorization. Additionally, Vardhini *et al.* (2020) employed a CNN to identify diseases in rice fields. Convolutional neural networks with four to six layers are typically used by researchers to classify various plant species. Additionally, Mohanty *et al.* (2016) classified, recognized and segmented many plant diseases using a CNN and a transfer learning technique. The datasets

employed in these studies are not very diverse, despite the fact that many other types of study have been conducted with CNNs and improved results have been reported (Panigrahi *et al.*, 2020).

The development of a smart, deep learning-based system holds the potential to serve as a template for addressing similar challenges across diverse crops and agricultural contexts. The knowledge gained from this exploration not only contributes to soybean crop management but also paves the way for broader applications in the domain of smart agriculture. The convergence of agriculture and cutting-edge deep learning technologies in the pursuit of advancing soybean wilting classification signifies a pivotal moment in the evolution of modern farming practices. Through the utilization of artificial intelligence, this study aims to enhance crop health, empower farmers and make a positive impact on the sustainable and effective future of worldwide agriculture.

Related work

Improved crop management and reducing the negative effects of stressors on agricultural productivity are the main goals of the current wave of research inspired by the growing field of agriculture and artificial intelligence, especially deep learning. Breeders of soybeans have worked over the past 20 years to choose plants that exhibit the slow-wilting characteristic in drought-stressed environments by grading canopy wilting and ocular observations (Carter *et al.*, 2016; Kim and AlZubi, 2024). But in breeding programs requiring a lot of crossings and thousands of progenies to be screened, it is not possible to finish scoring canopy wilting on thousands of breeding progeny rows in a single day. Moreover, visual evaluations might be biased or prone to human mistakes, which could lower breeding programs' ability to choose the best genotypes (Bagherzadi, 2017). The aim of this study is to provide a comprehensive overview of the literature on the subject of smart detection with deep learning technologies for the progress of soybean wilting categorization. However, because to the high computational cost of training, deep CNN layers are challenging to implement. Several scholars have developed methods based on transfer learning to address these problems (Tan *et al.*, 2018; Andrew *et al.*, 2019; Andrew-Onesimu and Karthikeyan 2020; Mhathesh *et al.*, 2021; Maria *et al.*, 2022; Kusuma *et al.*, 2022). Several well-liked models for transfer learning include Inception, DenseNet, ResNet and VGG-16 (Too *et al.*, 2019; Min *et al.*, 2024). Multiple class data from the ImageNet dataset is used to train these models. Since the picture features such as edges and contours are shared by all datasets, these models may be trained on any kind of dataset. Therefore, the most appropriate and reliable model for picture classification has been determined to be the transfer learning strategy (Hussain *et al.*, 2018). A CNN was proposed by Jadhav *et al.*, (2021) to identify plant diseases. With this method, diseases in soybean plants were identified using CNN models that had already been trained. Better

results were obtained when pre-trained transfer learning techniques, including AlexNet and GoogleNet, were used in the tests; nonetheless, the model lagged behind in terms of classifying diversity. In their study, Abbas *et al.* (2021) suggested using the conditional generative adversarial networks to create a library of artificial photos of tomato plant leaves. Real-time data capture and collecting, which were previously costly, time-consuming and arduous, may now be accomplished with the help of generative networks. Anh *et al.* (2021) discovered that a previously trained MobileNet CNN model could effectively perform multi-leaf classification on a benchmark dataset, achieving a dependable accuracy of 96.58%. Furthermore, the authors of Kabir *et al.* (2021) assert that their study is the first to use a multi-label CNN to classify 28 different classes of plant diseases. The multi-label CNN was proposed for determining the classification of multiple diseases of plants using transfer learning approaches, including DenseNet, Inception, Xception, ResNet, VGG and MobileNet.

With the world population growing and environmental changes occurring quickly, crops are becoming increasingly important to guarantee people and animals' long-term health and welfare by providing sufficient and wholesome food supplies. Varieties of soybean that are resistant to drought are especially vulnerable to the negative impacts of weather and water stress, which results in significant physiological changes in the plants. This study aims to identify and evaluate the water stress levels in soybean crops, which is an important task. The study offers a contemporary and practical substitute for conventional manual surveillance techniques by combining a mechanized strategy with Unmanned Aerial Vehicles (UAVs) to increase efficiency and decrease time requirements. This approach promises to provide timely and accurate insights into the water stress levels of soybean crops, supporting more accurate and proactive agricultural management practices.

MATERIALS AND METHODS

Dataset description

For deep learning models to handle data effectively, large datasets are necessary. The data is collected with the help of experts in agriculture for this study. There are 1275 photos of soybeans taken in the fields. The pictures show five distinct stages of wilting in soybean plants and each image is annotated with a number between 0 and 4. In this dataset, class 0 denotes healthy leaves that are not wilting. class 1 denotes leaflets folding inward at the secondary pulvinus without any turgor loss in the petioles or leaflets. Class 2 denotes slight turgor loss in the petioles or leaflets in the upper canopy. While class 3 denotes moderate turgor loss in the upper canopy. Class 4 denotes severe turgor loss throughout the canopy. Fig 1 and Table 1 provide a classification of the dataset. In this study, the entire dataset was divided into training, testing and validation sets using an 80:10:10 ratio.

State-of-the-art algorithm

In this section, the architecture of the custom deep learning model is discussed to detect the wilting of soybean plants.

Image pre-processing and labeling

Image pre-processing played a crucial role in preparing the raw images for training a custom deep-learning classifier. These pre-processing steps are required because different sources of photos can have images with differing dimensions. Standardizing the size of all photos becomes essential to ensure reliability in the input data and to maximize the computational efficiency during the training phase. Resizing and rescaling are the two main operations in image pre-processing. To ensure that all of the photographs are suitable for the model's input requirements, resizing is necessary to get them all to the same dimension. This stage is crucial because different dimensions may adversely affect the performance of neural network models, which normally require input images to be a certain size.

In this study, the photos were first resized to 224×224 pixels followed by the conversion of images into grayscale. When using VGG16, which normally accepts RGB images with three channels, images are converted to greyscale to simplify and increase computational efficiency. Because greyscale images only have one channel, they require less memory and require less processing power. This method can also help concentrate on the important patterns and features in the images, as well as fulfill task-specific requirements. The next step was to classify the soybean plant pictures based on their types of healthy and wilting. After that, each image is labelled according to class from 0 to 4.

Custom deep-learning model implementation

A custom deep-learning model is implemented for the classification of Soybean crop images based on wilting. The model architecture is a combination of the VGG16 pre-

trained model, followed by additional convolutional, pooling and fully connected layers. The details of the model architecture are as follows:

- The VGG16 base model is initialized with pre-trained Image Net weights and used as the base model for feature extraction. The model's specified input shape is (224, 224, 3), indicating that it expects input images with dimensions of 224 pixels in height, 224 pixels in width and 3 RGB color channels.
- The model consists of a MaxPooling2D layer (3×3) after the Conv2D layer (512 filters, kernel size 5). Spatial dimensions are decreased by a GlobalAveragePooling2D layer. Dense layers (512, 256, 128, 64, 32) with dropout regularization and 'elu' activation are incorporated. Activations are normalized by batch normalization following a few Dense layers. Dense (5 units) is the last layer and it uses softmax activation for multi-class classification (Fig 2). Sparse categorical accuracy metric, sparse categorical cross-entropy loss and Adam optimizer are used in the compilation of the model.
- Data augmentation is performed on a subset of the training data to increase the diversity of the dataset. Augmentation includes horizontal flipping, adjusting saturation, brightness and rotating images.
- During each iteration of training, the model processes and updates its weights based on a batch of 64 samples from the training dataset and the number of epochs is 75. To add non-linearity and help the model recognize intricate patterns in the data, the "elu" activation function is employed in neural network layers (Fig 3).

Performance evaluation parameters

Accuracy

The accuracy measure, which is derived as the ratio of the total number of accurate predictions (including true positives and true negatives) to the total number of predictions, is one of the most widely used metrics for evaluating model

Table 1: Images classification detail.

Class	Label
0	Healthy or no wilting
1	Leaflets folding inwards at the secondary pulvinus, no turgor loss in leaflets or petioles.
2	Slight leaflets or petiole turgor loss in the upper canopy.
3	Moderate turgor loss in the upper canopy.
4	Severe turgor loss throughout the canopy.



Fig 1: Images from the dataset consisting of Soybean plants with healthy and 4 wilting classes.

performance. Accuracy not only shows how well the model performed overall, but it also shows whether or not the model was trained correctly. The following formula is used to calculate the accuracy.

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

Where:

TP= True positive.

TN= True negative.

FP= False positive.

FN= False negative.

Precision

The accuracy of the model's predictions is shown by this parameter. The calculation is performed by dividing the total number of positive labels by the number of correctly predicted positive outcomes.

$$\text{Precision} = \frac{TP+TN}{TP+FP}$$

Recall or sensitivity

The completeness of the classifier is measured by this metric. Its definition is the ratio of all positive reviews in the dataset to the number of positive observations that were accurately anticipated.

$$\text{Recall} = \frac{TP}{TP+FN}$$

F1-score

The F1-score ranges from 0 to 1, with 1 denoting total failure and 1 representing flawless performance. The F-measure is expressed as:

$$\text{F1-Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

RESULTS AND DISCUSSION

Artificial intelligence has benefited from the application of both new and traditional deep learning (DL) and machine learning (ML) approaches, which have produced new ways to interpret data collected in real-world scenarios (Lee *et al.*, 2018). These methods look for and identify biotic and abiotic stressors in plants, then forecast yield loss based on those metrics (Singh *et al.*, 2018). Image collection, storage, preprocessing, annotation, classification and trait extraction are common workflows for deep learning approaches. In this section, the study outcomes are expressed in terms of training loss and accuracy for each fold, along with the presentation of the confusion matrix and classification reports. The classification reports include precision, recall and F-Score

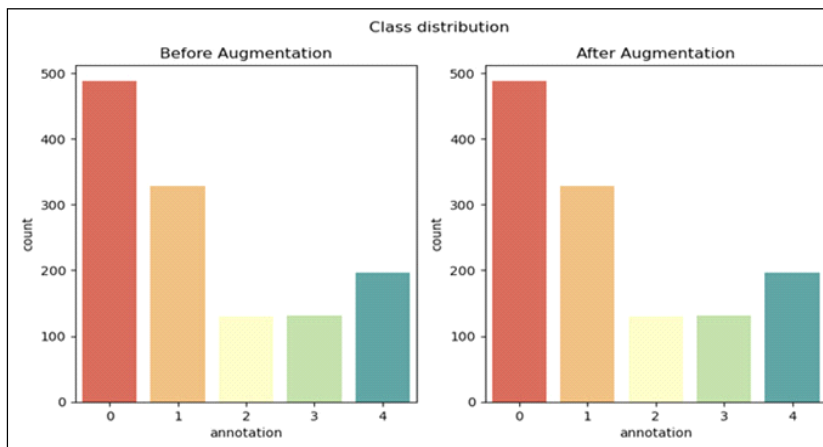


Fig 2: Class distribution before and after augmentation.

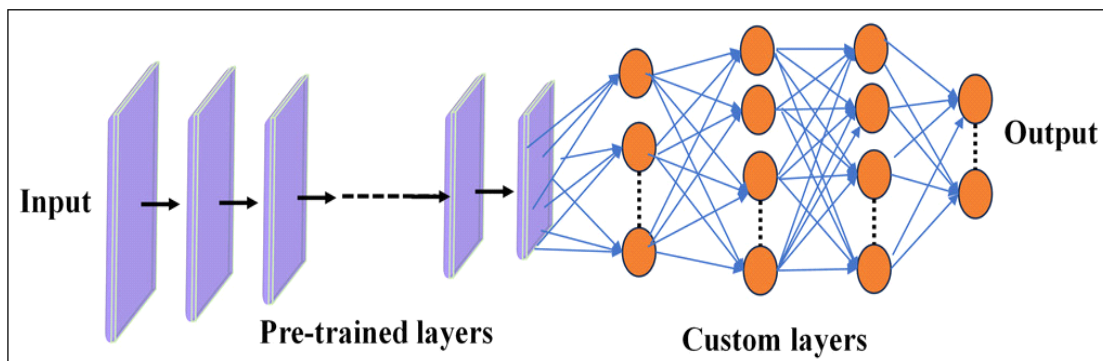


Fig 3: Custom deep-learning model architecture.

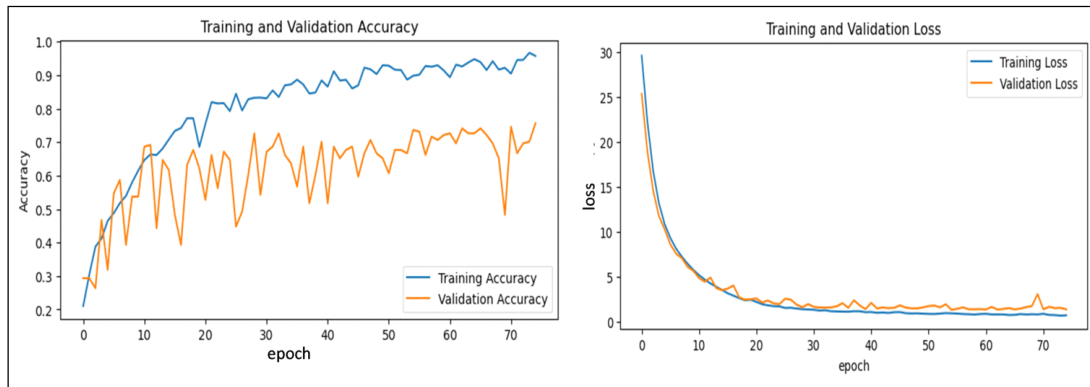


Fig 4: Training and validation accuracy and loss of the model.

Table 2: Classification accuracies, precision, F1 score and support.

Class	Precision	Recall	F1-score	Support
0	0.95	0.68	0.77	95
1	0.56	0.87	0.68	47
2	0.68	0.85	0.75	36
3	0.77	0.85	0.80	36
4	0.89	0.77	0.83	38
Accuracy			0.76	252
Macro avg	0.77	0.61	0.77	252
Weighted avg	0.81	0.78	0.76	252

metrics. Fig 4 (a, b) compare training and validation loss and accuracy of the model.

The training phase achieves an accuracy rate of 95.75% after 75 epochs. The slightly lower accuracy rate observed during the validation phase is 75.62%. This disparity implies that although the model performs well when trained on training data, it has difficulties when applied to unseen validation data. It is sensible to conclude that the observed trend would likely result in improved data accuracy when the number of repetitions (epochs) is increased. It is crucial to recognize that the number of epochs increases in direct proportion to the length of the training phase. The loss rate of the training phase is 71.24% after 75 epochs.

Classification report

The classification report offers a thorough evaluation of the model's performance over five classes (0 to 4). Class 0 has a particularly high precision of 0.95, meaning that 95% of the time the model predicts Class 0 correctly. The recall, at 0.68, is significantly lower, indicating that some Class 0 occurrences may be missed by the model. The F1-Score, which is computed to be 0.77, strikes a balance between recall and precision. The precision, recall and F1-Score pattern is examined for every class, offering valuable information about the model's capacity to accurately categorize cases within each category (Table 2).

The precision, recall and F1-Score unweighted means for all classes are combined to create the macro-average. This macro-average precision of 0.77 takes into account both the uneven class sizes and overall performance across

classes. With a weighted average precision of 0.81, the weighted average shows marginally better overall performance by taking into account each class's contribution according to its support. When taken as a whole, these metrics provide a thorough assessment of the model's recall, accuracy, precision and F1-Score, offering insightful information for improved classification result interpretation and development. Few false positives or false negatives occur in the model, which has a well-balanced precision and recall. As a result, the majority of the images might be correctly classified by the model. However, the model performed slightly better in certain classes than others. Compared to classes 3 and 4, class 1 exhibits slightly less precision. This may be caused by a variety of things, including the quantity of photos in each class or the inherent difficulty of distinguishing between some groups. The number of actual events or instances of each class in the dataset is referred to as support. It provides a numerical representation of the class distribution, showing the number of samples that fall into each specific group. Class 0 in the provided classification report has a support of 95, indicating that the dataset contains 95 instances of this class. In the same way, the supports for classes 1, 2, 3 and 4 are 47, 36, 36 and 38, respectively. The overall accuracy of the performance of the model is 76%. Finally, the CNN model is a powerful tool for image categorization of diseases in plants.

Similarly, the classification of drought-induced soybean leaf wilting using UAV-based imagery was reported by Zhou *et al.* (2020). Overall classification accuracy was 76% for the SVM model that used all seven image features as predictors. Sarkar *et al.* (2023) used UAV imagery and machine learning to perform a study on the evaluation of soybean lodging. According to the results, the overall accuracies of RF, ANN, KNN and XGBoost were 0.80, 0.79, 0.77 and 0.73, respectively. Finally, the diseases in plants can be identified using deep learning methods.

CONCLUSION

In summary, the developed deep learning model uses a hybrid architecture with pre-trained VGG16 layers to efficiently classify images of soybean crops based on wilting.

The model's performance on unseen validation data indicates that more generalization is required, even though it achieved a high accuracy rate during training. The selected architecture supports efficient feature extraction by combining layers such as MaxPooling2D, Conv2D and GlobalAveragePooling2D. Utilizing data augmentation methods enhances the model's ability to ensure changes in soybean crop images. The model's strengths and potential areas for improvement are highlighted by a thorough evaluation that takes accuracy, recall and F1-score into account. This analysis offers insightful information for future improvements in the multi-class classification environment. Future research can involve a wider range of diseases that may impact various soybean parts. Hybrid machine learning approaches such as support vector machines, decision trees and random forests can also be used in the future to compare and improve the model's overall performance.

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Authors' contributions

Both authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all aspects of this work.

Data availability statement

The database generated and /or analyzed during the current study are not publicly available due to privacy but are available from the corresponding author on reasonable request.

Declarations

Author(s) declare that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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