Deep Learning Solutions for Soybean Leaf Infestation: A VGG19-Based Approach

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***Abstract*—After all, soybean crops are an essential constituent in world agriculture. These plants generally become easy prey to attacks by pests like Diabrotica speciosa and caterpillars. The early detection of these attacks is pretty significant in reducing the damage, from an economic point of view as well as an ecological one. This present study has been motivated by the above facts, proposing a newer deep learning-based solution using a transfer-learning approach with VGG19 CNN for efficient classification of soybean leaf images. In this work, we adopt the pre-trained VGG19 architecture for detecting pest infestation in soybean leaves and perform fine-tuning specific to the problem. In this work, employing transfer learning from VGG19 means utilizing the deep features learned from large-scale image datasets for adaptation in the specialized context of agricultural pest detection. This approach not only improves the model's accuracy but also reduces the dependency on huge amounts of training data, which is usually a bottleneck in agricultural applications. We test the performance of our model on a very challenging dataset of soybean leaf images, which yields a balanced accuracy of 99.5% on previously unseen test data.The contribution of this work can be both theoretical and practical. Theoretically, the study advances deep learning applications in plant pathology, showing how effective transfer learning will be in a new domain. In practice, our model is a potent tool for early detection of pest infestations that permits interventions in time and avoids huge economic and environmental losses.**

***Index Terms*—Deep learning architecture,Visual Geometry Group model with 19 layers,Crop pest detection,Legume crop,Insect pest species,Lepidopteran larvae**

I. Introduction

Indeed, agricultural productivity is the backbone to both global food security and economic prosperity yet simultaneously, it always faces this one constant, yet increasingly oppressive threat from plant diseases as well as pest infestations that are no mere minor irritation; however, they constitute a serious global threat. Plant pathogens and pests account for an estimated annual loss of 14% of crop yields around the globe[1]. The effects are massive economic setbacks that trickle down to farmers, the agricultural industry, and even the environment, all through the excessive usage of treatment measures[2]. The reason, therefore, calls for the formulating of innovative strategies meant at reducing these losses. Although this is a long overdue issue, traditional methods of pest control are in essence chemical pesticides. While such methods are quite effective in some ways, they are very expensive and pose severe health hazards to humans and to the environment as well. This therefore demands urgent necessity in the development of more sustainable, efficient, and environmentally friendly alternatives to pest management[3]. Most of the traditional detection methods of pests are labour-intensive and visual. The scale and complexity of issues facing modern agriculture cannot be handled by them. They are error-prone and inefficient, which makes such a method impractical when it is used in applications that require quick response for reducing losses caused by pests [3].

The most recent advances in deep learning, CNNs, in particular, seem promising for the solution of this problem. Here is a powerful classification model obtained from the application of the pre-trained VGG19 network for accurate identification of the infestation caused by pest in soybean leaves by binary classification between healthy leaves and infested ones, including Diabrotica speciosa or caterpillars[4].

This paper proposes a new model, with the design, development, and evaluation of the model proposed for the direction of creating a new benchmark in pest detection in agriculture[5]. Our study adopted the methodology used by data preprocessing, feature extraction, training of the model, and results analysis. We also further discuss our broader implications for the findings toward agricultural pest management and identify limitations for the present study along with potential directions in the future.

II. LITERATURE INSIGHT

A. Damage to Soybean Crops Caused by Lepidopteran Larvae and Rootworm Beetles

Soybean crops represent one of the critical components of the global agricultural industry. However, they are increasingly threatened by caterpillars and Diabrotica speciosa [4]. These are very destructive pests that cause a great deal of damage to the different soybean plant parts, from the leaves through the stems to the pods and grains[6]. Caterpillars are well-known damages—more precisely, the species Anticarsia gemmatalis, Chrysodeixis includens, Spodoptera, and Omiodes indicatus—are responsible for injuries to leaves by eating from the side towards the center of the leaf and causing typical cracks.

Traditionally, carbamates were used as insecticides for caterpillar control measures. However, the continued misuse and overuse of these chemicals have resulted in environmental degradation, health risks, and the development of resistance among pest populations. Alternative methods such as exploitation of the parasitic fungus Beauveria bassiana and entomopathogenic viruses have been fronted for better sustainability in pest control. These methods, however, largely rely on the level of infestation detected at an early stage and accurately.

Another widespread soybean pest in South America, mainly in Brazil, is Diabrotica speciosa, the green cow or patriot beetle. Control of Diabrotica speciosa can be controlled by using insecticides such as carbamates. pesticides applied by supporting its early detection and alternative control methods[7]. Precise, timely identification of pests is one of the major principles in IPM, and this results in interventions at the exact time when the effects on the environment and economy are the least possible. As the caterpillars and the Diabrotica speciosa[13] have similar treatment protocols, our research is focused on developing a binary model for identification that makes IPM feasible through early warning of an incipient infestation.

B. RELATED WORK

Integrated Pest Management (IPM) relies on reducing the amounts of As in every other agricultural field, for soybean growing, too, there is an urgent need for correct identification of pests during the early stages regarding measures relating to their control. Research lately in this area is increasingly based on the power of machine learning and deep learning in terms of plant disease and pest detection and classification[2]. Nicolas Drack conducted studies on soybean culture. Nicolas Drack introduced an approach for soybean leaf detection in soybean culture, using CNN. With such a method, an accuracy higher than 93.71% to 94.16% was reached with vgg19 convent architecture[4]. After that, the obtained results were compared to other classic machine learning methods applied to agriculture among those support vector machines, Adaboost-C4.5, and Random Forests, which proved CNN is very effective in agriculture.

Vimal Bhatia.Conducted research on using machine learning models to detect fungal-infected soybean seeds, where they obtained an accuracy of 97.72% using various techniques. This research ascertained the power of machine learning in predicting the disease outbreak in soybean farming. In a similar approach, Vimal Bhatia. Applied several deep learning architectures in detecting soybean leaf diseases and obtained high accuracies such as 97.72%, 94.31%, 98.86%, and 96.59% using ConvLSTM, SVM, KNN, and ANN, respectively[8].

These studies all prove that CNN and other methods of ML are effective in the identification of plant diseases and pests. In this work, we intend to make an even better model for correctly detecting soybean infestation by caterpillars and Diabrotica speciosa, thus setting a new benchmark among such research.

III. METHODOLOGY

This section will address, in sequence, an overview of Convolutional Neural Networks (ConvNets), an explanation of the deep learning architecture implemented for our research, and a method to be used for model evaluation.

A. Convolutional Neural Networks (ConvNets)

Amongst the classes of DL models that turned out to be particularly successful in image and video recognition, Convolutional Neural Networks take the lead. Majorly, these have become the cornerstones of computer vision applications since they are capable of automatically and efficiently extracting features from input data in order to predict the output[4].

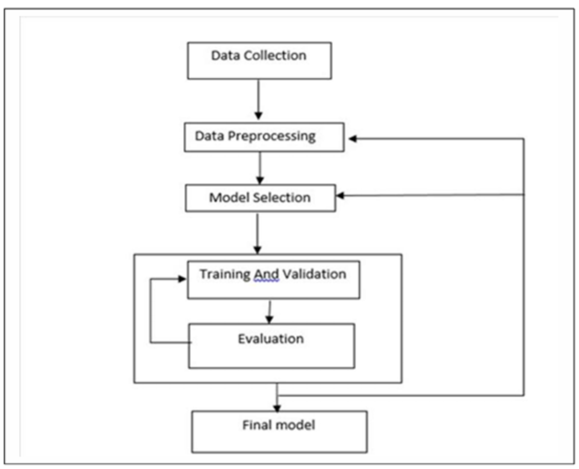
Now, the three basic kinds of layers that include ConvNets are convolutional layers, pooling layers, and fully connected layers[16]. Convolutional layers are at the core of any ConvNet, and the core task is feature extraction. They do this by scanning the input data with a number of filters or kernels. These are mostly small, like 3x3 or 5x5 pixels in size; however, it is employed to the whole input image through a sliding window technique. Many output features, called feature maps, are generated and captivate close trends of the input data in this process.

After that, the feature maps are passed through a series of layer pools that reduce the feature maps' dimensionality while preserving the most important data they include. maximum pooling is a popular pooling technique that downsamples the data and keeps only the most important features by taking a maximum value inside a predetermined window of the feature map[4]. The pooling process makes the network invariant to small translations of input data, improving the robustness of the model.

TABLE I
EVALUATION OF TECHNIQUES FOR IDENTIFYING AND CATEGORIZING SOYBEAN PESTS AND DISEASES

Author	**Year**	**Inquiry topic**	**Data collection**	**Approach and Exactness**
Nicolas Drack	2023	Detection of infested soybeans.	Acquisition under natural lighting conditions.	Vgg19 ConvNet (93.71%-94.16%)
Khalili et al.	2020	Identification of charcoal rot infection in soybean plants.	collected under laboratory conditions.	LR-l1 (95.92%) LR-l2 (95.58%) MLP (94.88%) RF (95.42%) GBT (96.2%) SVM (96.16%)
Tetila et al.	2020	Identification and categorization of different soybean pests.	Acquisition with UAV under natural conditions.	Inception-v3 (91.87%) Resnet-50 (93.82%) Vgg-16 (91.80%) Vgg-19 (91.33%) Xception (90.52%)
Tetila et al.	2020	Automated detection of soybean leaf infections.	Acquisition with UAV under natural conditions.	Inception-v3 (99.04%) Resnet-50 (99.02%) VGG-19 (99.20%) Xception (99.06%)
Ferentinos	2018	Identification of different plant infections.	Collected under laboratory and natural conditions.	AlexNet (91.87%) AlexNetOWTBn (93.82%) GoogleNet (91.80%) Overleaf (91.33%) VGG (90.52%)

Fig. 1. The steps involved in the model

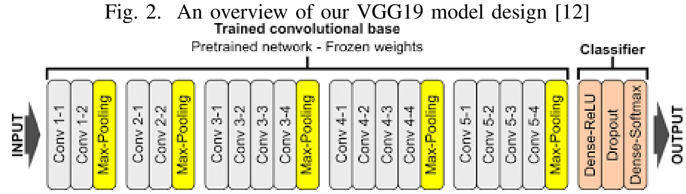


Finally, the reduced feature maps are flattened and passed through the fully connected layers, where every node connects to each node in the previous layer. The fully connected layers play the role of a decision-making part of the network, synthesizing extracted features to make final predictions.

B. Machine Learning Approach

Our proposed machine learning approach is based on VGG19, a 19-layer CNN that was originally proposed by Simonyan and Zisserman.Due to its effectiveness in a broad range of computer vision applications, from object detection to image classification, this has grown in popularity [9].

Fig. 2. An overview of our VGG19 model design [12]



VGG19 architecture needts the dimensions of the input image to be of fixed size 224 × 224 RGB pixels[4]. Architecture: The network is formed of convolutional and maxpooling layers followed by full-connected layers. The concrete network consists of five convolutional blocks. Each of the first and second blocks contains two convolutional layers, while each of the rest has four convolutional layers. Convolutional layers use a hierarchical approach to derive characteristics from the given input images, however layers of max-pooling downsample the resulting feature maps in space to decrease the dimensionality.

It is characterized by using small 3 × 3 convolutional filters and up to 512 filters in its deepest layers, whereby intricate and high-level features could be learned. The nonlinearity in the model comes through ReLU functions and amplifies the capability for learning the model[10].

We have taken the base model as VGG19 for transfer learning. To apply this base model for our specific task, we have added a global average pooling layer[16]. This calculates the average of all the spatial dimensions of the feature maps and thus gives us a 2D feature vector. This is followed by two fully connected layers: the first with 1,024 neurons, and the

Fig. 3. Healthy Plant

Fig. 4. Diabrotica Specosa attacked plant

Fig. 5. Caterpillar attacked plant

second with a single neuron and sigmoid activation function for a binary classification.

C. Evaluation Method

We would identify a complete model evaluation plan that would assess the performances of our model. In this case, we have followed a hold-out validation strategy for splitting data into training, test, and evaluation sets. In this work, we have divided the data set into 70% for training, 20% for testing, and 10% for evaluation [4]. This kind of strategy helps in having the model trained on one subset and tested for generalization on separate subsets. Indicators used for the model interpretation performance were as follows: 1. Accuracy:The ratio of correctly identified instances to all occurrences is determined by this general performance statistic. This gives a general view regarding model performance concerning classes in general. 2. Precision: It is another important metric that can be applied to gauge the accuracy of the model concerning the correctly identified positive cases.It is referred to as the ratio of real positive forecasts to all of the model's positive predictions. A high accuracy indicates a low rate of false positives for the model. 3. F1 Score: The F1 Score combines the precision and recall harmonic means into a single metric. This metric captures model performance related to identifying true instances while keeping false positives and false negatives as low as possible.

D. Data Preprocessing

The dataset comprises 6,410 RGB color images of healthy, Diabrotica speciosa-infested, and caterpillar-infested soybean leaves[13]. The data preprocessing methodology in the steps that would follow was put in place to prepare the dataset in readiness to train the deep learning model.

Data gathering or collection was the first process in the stages, in which images that were taken of soybean leaves that were categorized and differentiated into three classes : healthy plants, leaves damaged with caterpillars, and those attacked by Diabrotica speciosa, and for each category they were set in different folder to get a clear vision for subsequent processing and further analysis.

The images were further resized to a uniform dimension of 224x224 pixels. This resizing process was important because the input into the VGG19 model must be of a particular dimension. By resizing each image to this standard dimension, we ensured that every input image met the dimension requirement for the model to operate.

Once resized, images were cast into NumPy arrays. To process this in an optimal manner for either mathematical treatments or just compatible with processing by a machine learning frame, image data was in the form of a NumPy array.

After the conversion, the images were normalized. This will scale the pixel values to a range between 0 and 1, enabling the model to process this data more easily and fasten the convergence during training. Normalizing the data gives the model a chance to focus on the important features without being influenced by extreme variations in pixel intensity.

Having preprocessed the images, we moved to extract features. Relevant features have been extracted from the image using various processing techniques.

Following feature extraction, dimensionality reduction techniques were applied to select the most important features. Feature selection helps eliminate redundant or irrelevant data, making the classification process more efficient while retaining the most significant information needed for accurate predictions.

The last step of the preprocessing stage was the division of the dataset into three subsets. 70% of the data were allocated to the training set, which is used to fit the model. 10% was kept for the validation set that was to be used for assessing model performance and hyperparameter tuning during training. The rest, which constituted 20%, was to form the test set to be used for final model performance evaluation. The model was trained in a very representative and diversified dataset, following a meticulous pre-treatment, and the training set was augmented. Consequently, an increase in accuracy and generalization was realized.

E. Dataset

This study's dataset came from an open-source dataset made available by Mignoni [12][13] from the Mendeley website. It's comprised of 6,410 soybean leaf images, which have already been labeled and classified into three classes. The images have been shown in three different folders, classifying the images in accordance with their soybean leaf health and pest infestation.

- Healthy Soybean Leaves: First folder: Contains 896 images of healthy soybean leaves. Infested leaves are compared against these images. These images of healthy leaves will be very important in training the model to differentiate between healthy and infested conditions(fig4)[13].
- Leaves Infested with Caterpillars The second folder contains 3,309 images of soybean leaves that have been infested by caterpillars. These images show the different types of damage caused by different caterpillar species, such as Anticarsia gemmatalis, Chrysodeixis includens, Spodoptera, and Omiodes indicalus. The high number of images in this folder ensures that the learning model does learn properly(fig6)[13].
- 2,205 images of soybean leaves harmed by the soybean pest Diabrotica speciosa, sometimes known as the green cow or patriot, are included in the third folder. The images present the feature damage, including small round holes and cuts at the edge of the leaf, provoked by this specific pest(fig5)[13].

The images were captured over two soybean farms spread across the state of Mato Grosso, Brazil, in January 2021. To increase wider applicability, photos are taken under natural weather and field conditions. The dataset images were captured by a UAV-mounted camera and also by two 48MP AI-enabled smartphones with triple cameras, which are high-resolution visuals that enable proper analysis and classification.

IV. Results

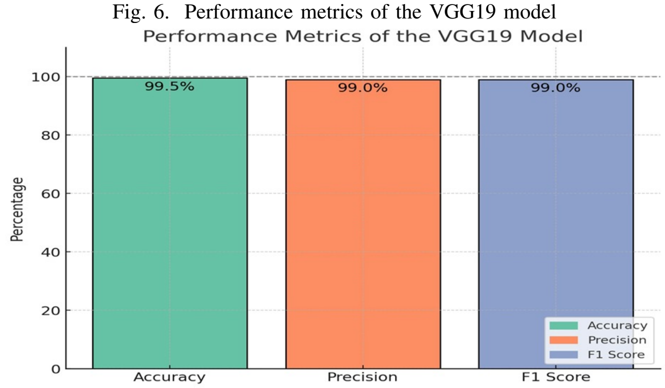
We have compared the performance of the VGG19 model on the Soybean leaf dataset, which contains a total number of 6,410 images[13]. These images are representative of three different classes: healthy soybean leaves, class A, which consists of 896 images; soybean leaves infested with caterpillar images, class B, which consists of 3,309 images; and soybean leaves infested with Diabrotica speciosa images, class C, consisting of 2,205 images[13]. The dataset was split into training, testing, and evaluation subsets in the ratio as described previously.

Most of the hyperparameters used in VGG19 for the soybean image classification task were picked by hand from the literature and standard practices. This model was trained over 100 epochs to ensure that it is adequately exposed to the data

TABLE II
Performance Metrics for Different Classes

Class	Accuracy	Precision	Recall	F1 Score
Healthy/Infested	99.5%	99%	98%	99%
Healthy/Caterpillars	99.5%	99%	100%	99%
Healthy/Diabrotica Speciosa	99.5%	100%	100%	100%

Fig. 6. Performance metrics of the VGG19 model



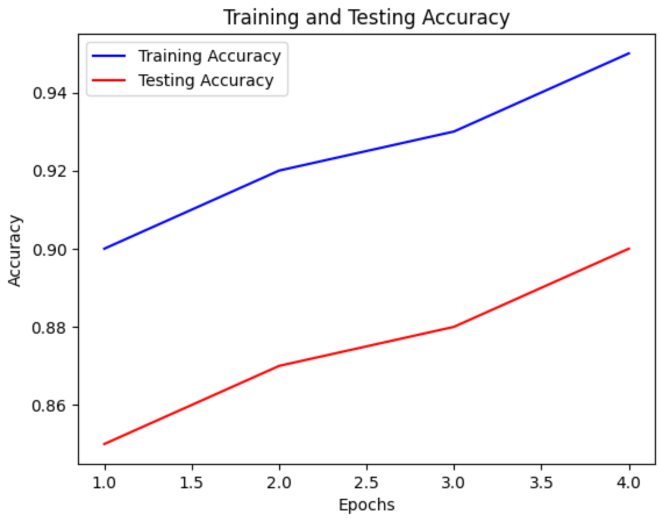
so that the risk of overfitting is avoided. For the optimization procedure, RMSprop was applied for adaptive learning rate per parameter for stabilizing the training process with a learning rate of 0.001[4]. This works for binary classification tasks. It used the VGG19 model, pre-trained on the dataset, removing its top layer and freezing all the rest to avoid updates on their weights; then added new layers, a Global Average Pooling 2D, a density of 1024 units with ReLU activation, and finally the output layer with a single unit and sigmoid activation for binary classification[8]. These are some of the hyperparameters and architectural adjustments that go a long way in serving the accuracy of the model on a classification task on soybean leaf image data across different categories.

The models developed to classify the images of soybean leaves, according to whether they are healthy or infested, yield quite good results, especially for the Healthy/Infested model[11]. This latter approach resulted in an accuracy of 99.5%, that is, almost all images were correctly classified. This means it identified 80% of the healthy plants correctly. The model precision was 99.0%, meaning that when the model classified a plant as infested, it was accurate 99.0% of the time. The F1 score, and balancing precision were 99.0%.

A. Results of the Models

We show the results of the Healthy and Infested model, where images were categorized as healthy soybean leaves versus leaves that are infested with either caterpillars or Diabrotica speciosa. We stress this model because of the practical relevance of determining whether there is an infestation of either type since both pests could be effectively controlled by similar methods. Models for the other two categories of infestation were also implemented. Results are presented in Table 2.

Fig. 7. Training and Testing accuracy of the model



Accuracy: The Healthy and Infested model achieved an impressive accuracy of 99.5%. This high accuracy in essence serves as proof of the overall viability of the model in correctly classifying soybean leaves into either a healthy or infested category.

Balanced Accuracy: Sensitivity and specificity averaged 99.5%. This metric defines a model's capability to identify both healthy and infested classes correctly, considering class imbalance.

Precision: The model gave 99.0% precision, meaning out of all those instances where it identified a plant as infested, it was correct about 99.0%, hence highly accurate in identifications.

F1 Score: This was 99.0%, which incorporates both precision and sensitivity into one measure. The fact that the F1 score is this high means performance concerning identifying and classifying both healthy and infested plants is well-balanced.

V. Future Work

It is further realized that deeper homogenization in the performance of the model for soybean leaf classification can be done by developing deep learning architectures, coupled with data augmentation techniques. Models, such as CaffeNet, AlexNet, GoogLeNet, and Xception, are therefore developed to compare the results of this work. For performance measures and generalization, other than what the model used, which is VGG19, in that case, another possible approach would be applying k-fold cross-validation, which could aid in coming up with more robust performance estimates.

VI. Conclusion

This work validated a VGG19 Convolutional Neural Network implementation that can be successfully used as a classifier of soybean leaves in healthy and infested classes, targeting Diabrotica speciosa and caterpillars. The results highlighted the high effectiveness of VGG19 for this task and further improved infestation detection on soybean leaves. That is to say that the accuracy and reliability of our model, confirmed through constant testing on a hold-out split, will truly make it very instrumental for IPM.

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