IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 20 June 2023, accepted 29 August 2023, date of publication 11 September 2023, date of current version 18 September 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3313978

RESEARCH ARTICLE

A Deep Learning-Based Approach for the Detection of Infested Soybean Leaves

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This work was supported in part by Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Grant 491183248; and in part by the Open Access Publishing Fund of the University of Bayreuth.

ABSTRACT We address the soybean leaves infestation problem by proposing a robust classification model that can reliably detect infests by Diabrotica speciosa and caterpillars. Our transfer-learning based model uses a VGG19 convolutional neural network to classify the soybean leaves and we achieve balanced accuracies between 93.71% and 94.16% on unseen testing data. This sets a new benchmark and outperforms previous work using the same dataset. Our work has theoretical and practical implications. The soybean plays a crucial role in the agricultural industry. Infestation of soybeans leads to enormous economic and environmental losses. With our model presented here, an early and accurate detection to control the spread of plant pests is possible, which reduces economic and ecological damages.

INDEX TERMS Convolutional neural network, VGG-19, plant infestation, soybean, Diabrotica speciosa, caterpillars.

I. INTRODUCTION

Plant diseases and infestations are leading to major ecological and economic losses in the agricultural industry. 14% of global crop yields are lost due to plant diseases, weeds and insects, which not only leads to smaller revenues for the agricultural industry but also causes expenses for crop treatment [1], [2], [3], [4]. Furthermore, it is necessary to develop efficient controls to enhance crop production to meet the increasing demands of the growing world's population [5], [6]. It is estimated that the production of global crops will have to be doubled by 2050 making it more important to reduce losses [1]. Besides the economic impact, the treatment of plant infestations, also affects the environment [1], [7], [8]. To control plant infestations, cultural, biological and chemical techniques are in use [1], [7], [8]. Cultural practices include, for example, crop rotation or soil solarization. However, this is often not enough and is therefore combined with chemical and biological methods [1]. As a result, the use of chemical substances continues to be the most important [7]. Soil, water and air contamination are possible consequences of excessive pesticide use. In addition, pesticides are harmful to healthy plants, animals and microorganisms due to their toxins [8], [9]. This also has implications for human health, as pesticides can enter the human body through, for example, inhalation of polluted air [10]. In conclusion, the early detection of plant diseases is essential to minimize economic and ecological losses, reduce pesticide residues and enhance the crop quality [2]. Therefore integrated pest management (IPM) was founded and implemented in the 1970s [7], [11]. IPM as one of the most successful programs of pest management focuses on reducing pesticides and protecting the environment and declares early pest detection as a key factor in selecting and developing appropriate countermeasures [7], [11].

In South America, especially in Brazil, damages in the soybean production caused by Diabrotica speciosa and caterpillars were detected [12]. Soybeans as a crop are very important in the agricultural industry since the crop is used for oil and protein consumption for humans and livestock, as well

The associate editor coordinating the review of this manuscript and approving it for publication was Jeon Gwanggil.

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as feedstock for bio-fuel production [5]. In recent years, the production of soybeans already increased enormously: The crop quantity for 2022/23 stands at 383,011 thousand metric tons which is an increase of over 40% compared to 2012/13, when approximately 269,000 thousand metric tons of soybeans were harvested [13], [14]. As Brazil is one of the major soybean-producers and the leading export country of soybeans worldwide the damage caused by Diabrotica speciosa and caterpillars has an enormous impact [13], [15].

With approximately 153,000 thousand tons, Brazil is predicted to have a share of about 40% of the world's soybean production in 2022/23 [13]. About 92,000 thousand tons will be exported, making Brazil the largest exporter of soybeans in the world [13]. As a result, pest infestation in soybeans affects not only the Brazilian economy, but also the global supply [16].

To identify infested soybeans effective classification methods are required. Traditional crop management that rely on human identification of diseases and pests are often no longer sufficient. It requires skilled and experienced personnel and hence significant investment in resources. At the same time, the method is time-consuming, labor-intensive and inefficient. Additionally it carries a high risk of false detection and poor monitoring [17].

Previous work has demonstrated the successful use of deep learning models in object detection, especially in the detection of various plant pests and diseases [2], [6], [18], [19], [20], [21], [22], [23], [24]. Specifically, Badgujar et al. [24] have already used the same dataset and adopted a multiclass-approach to classify healthy soybeans, soybeans infested with Diabrotica speciosa and soybeans infested with caterpillars. We address this approach and improve its results. Our objective was to use image classification to detect plant infestations. We followed a transfer learning approach by using the pre-trained model VGG19 and assume that the model will deliver accurate results that can support IPM or pest management in general. To improve the results, we chose a binary approach and focused on distinguishing between healthy and infested soybean leaves. As a result, the most important contributions of this study are the following:

- We develop a model to outperform the existing bench-mark regarding the detection of soybeans infested with caterpillars or Diabrotica speciosa by Badgujar et al. [24].
- We adopt a transfer learning approach using the pre-trained deep learning model VGG19.
- We followed a binary approach to improve the results. We developed three cases to be able to differentiate between healthy and infested soybeans in general, between healthy and caterpillar infested and between healthy and Diabrotica speciosa infested soybean leaves.
- We contribute to improving pest management and thereby help to reduce economic and ecological damage.

Therefore, this paper is structured as follows: The second chapter presents the theoretical background regarding the pests in the dataset and current approaches to early plant disease detection. In the third chapter our methodological approach is described in detail followed by the presentation of the results in the fourth chapter. Afterwards, we discuss their implications, the limitations of our work as well as possible future research. Finally, the work is summarized in the conclusion in the sixth chapter.

II. RESEARCH BACKGROUND

A. SOYBEAN PLANTS DAMAGES BY CATERPILLARS AND DIABROTICA SPECIOSA

Caterpillars cause damage to various parts of the soybean plants. Depending on their gender, they attack leaves, stems, pods and grains. The damage is in the form of cracks that are eaten from the sides to the center of the leaf [12]. There are various different types of caterpillars, like Anticarsia gemmatalis, Chrysodeixis includens, Spodoptera and Omiodes indicalus [12]. In recent years, Spodoptera caterpillars have become increasingly common and have caused enormous damage, especially in some Brazilian states [11]. Specifically the species Spodoptera frugiperda has emerged as a soybean pest in Brazil, with increased infestations and observed damage [25], [26]. As a result, there are various strategies to control the damage. Traditionally caterpillars were controlled by the use of insecticides such as carbamate [26]. The misuse use of these insecticides led to undesirable effects on the environment and human health. In addition the caterpillar became mostly resistant to these insecticides. Other techniques had to be established such as the use of parasitic fungus called Beauveria bassiana or the use of entomopathogenic viruses [26]. Nevertheless successful control depends on the spread of the pest and therefore on the detection of the pest [26].

Diabrotica speciosa, also called green cow or patriot, has been detected in most crops in South America. In Brazil, the adult pest is considered an important pest infesting some extensive crops, such as soybeans [27], [28]. The pest that prefers the softer leaves and damages plants by eating small round holes in the leaf or making incisions on the leaf edges [12]. To control damages in soybean crops, insecticides like carbamates can be used [27]. In addition, also biological approaches promise success. Soybean fields damaged by Diabrotica speciosa can also be treated with the fungi Beauveria bassiana or entomopathogenic viruses [27], [28]

Both pests are considered and observed in IPM. One of the objectives of IPM is to reduce the amount of pesticides, for this reason it is important to use as much as necessary and to use only as little as possible making the accurate and early pest detection and alternative control techniques more important [11]. As a result, according to the principles of IPM early pest detection is a key factor and constitutes the basis for further actions: After identifying pests, sampling them, and considering their economic impact and natural mortality, there are different strategies to control pests [11]. Since both pests can be treated with similar procedures, this emphasizes our approach of binary identification model. In particular, it is

TABLE 1. Concept matrix of related work.

Reference	Year	Research subject	Image acquisition	Methodology	Accuracy
Dos Santos Ferreira et al [19]	2017	Weed detection in soybean crops	Acquisition with UAV under natural conditions	CaffeNet	> 98%
Khalili et al. [2]	2020	Detection of Charcoal Rot Disease in soybeans	Acquisition under laboratory conditions	LR-L1 LR-L2 MLP RF GBT SVM	95.92% 95.58% 94.88% 95.42% 96.79% 96.04%
Tetila et al. [6]	2020	Automatic recognition of soybean leaf diseases	Acquisition with UAV under natural conditions	Inception-v3 Resnet-50 VGG-19 Xception	99.04% 99.02% 99.02% 98.56%
Tetila et al. [20]	2020	Detection and classification of various soybean pests	Acquisition with UAV under natural conditions	Inception-v3 Resnet-50 VGG-16 VGG-19 Xception	91.87% 93.82% 91.80% 91.33% 90.52%
Mohanty et al. [21]	2016	Classification of various plant diseases	Acquisition under laboratory conditions	AlexNet GoogLeNet	91.87% 93.82%
Sladojevic et al. [22]	2016	Detection of leaf diseases from various plants	Dataset collection by downloading various images from the internet	CaffeNet	91.87%
Ferentinos [23]	2018	Recognition of various plant diseases	Acquisition under laboratory and natural conditions	AlexNet AlexNetOWTBn GoogLeNet Overfeat VGG	91.87% 93.82% 91.80% 91.33% 90.52%

more important to detect an infestation than to classify the type of infestation and therefore improve IPM.

B. RELATED WORK

The basis of pest management is early and accurate identification of pests. This is important not only in the crop of soybeans, but in the entire agricultural economy. Consequently, there are several studies that focus on the identification of plant diseases by using machine learning methods. Table 1 summarizes the following studies and gives an overview of related work.

Dos Santos Ferreira et al. [19], Khalili et al. [2] and Tetila et al. [6], [20] all researched in the soybean agriculture. While Dos Santos Ferreira et al. [19] and Tetila et al. [6], [20] used images taken with an Unmanned Aerial Vehicles (UAV) under natural conditions, Khalili et al. [2] used a dataset with images taken under laboratory conditions.

Specifically, dos Santos Ferreira et al. [19] developed a Convolutional neural network-based approach for weed detection in soybean crops. Their study achieved over 98% average accuracy using the CaffeNet architecture. To evaluate their results, they compared the results of the CaffeNet with SVM, Adaboost - C4.5 and RF and were able to achieve the best results with the Convolutional neural network (ConvNet) CaffeNet. The study therefore demonstrated the feasibility of using a ConvNet for weed control in soybean fields.

In addition to pest and weed detection, machine learning techniques have also been used to predict diseases in soybean crops. Khalili et al. [2] investigated the use of machine learning models to predict Soybean Charcoal Rot Disease. Their study achieved between 95.92% and 96.79% accuracy with different machine learning techniques, indicating that machine learning models can effectively predict disease occurrence.

Similarly, Tetila et al. [6] used different deep learning architectures to detect leaf diseases in soybeans. They achieved accuracies of 99.04%, 99.02%, 99.02% and 98.56% for Inceptionv3, Resnet-50, VGG19 and Xception.

Tetila et al. [20] considered the five deep learning models Inception-v3, Resnet-50, VGG16, VGG19 and Xception for classifying images of various soybean pests. The accuracies were 91.87% (Inception-v3), 93.82% (Resnet-50), 91.80% (VGG16), 91.33% (VGG19) and 90.52% (Xception).

Mohanty et al. [21], Sladojevic et al. [22] and Ferentinos [23] classified various diseases of different plants. The applicability of deep learning in 14 plant species with 26 diseases was tested using both AlexNet and GoogLeNet architectures. With regard to the achieved accuracies of 91.87% and 93.82% it should be noted that the image dataset was acquired under laboratory conditions [21]. Sladojevic et al. [22] used CaffeNet to detect 13 leaf diseases of different plants. The dataset was collected by downloading various images from the internet. This led to an accuracy of 91.87%. The architectures AlexNet (91.87% accuracy), AlexNetOWTBn (93.82%), GoogLeNet (91.80%), Overfeat (91.33%) and VGG (90.52%) have been used to detect plant diseases based on their leaves. The dataset is composed of images under laboratory and natural conditions [23].

Badgujar et al. [24] already used the same dataset as in this study. For the annual international meeting of the American Society of Agricultural and Biological Engineers, they produced an overview of classifying images of soybean leaves infested with pests using deep learning techniques. The authors followed a multi-class approach to classify the healthy, caterpillar infested and Diabrotica speciosa infested plant images. To do so, they used the four different deep learning techniques DenseNet201, VGG16, Inception-v3 and ResNet50 and achieved accuracies of 88%, 86%, 84% and 74%.

Overall, the studies reviewed in this section demonstrate the potential of ConvNets and other machine learning techniques in plant disease and infestation detection. Since related studies achieved great results of over 90%, we would like to address this and develop an accurate model for the detection of caterpillar and Diabrotica speciosa infested soybeans and therefore outperform the existing benchmark.

III. METHODOLOGY

In the following, the methodological steps are explained. First, we provide a brief description of ConvNets, followed by the presentation of our deep learning architecture. Afterwards, the evaluation method is explained. Finally, we describe the data pre-processing and the underlying dataset.

A. CONVOLUTIONAL NEURAL NETWORKS

ConvNets are a type of deep learning model commonly used for image and video recognition tasks. ConvNets are designed to automatically extract features from input data, which are then used to make predictions about the output [29], [30].

ConvNets consist of three different types of layers: convolutional layers, pooling layers and fully-connected layers [29]. As the name suggests, the use of convolutional layers plays an important role in the architecture of ConvNets. These are layers that apply a set of adaptive filters to the input data. The filters are typically small (e.g. 5×5), but are applied to the input data using a sliding window approach, resulting in a set of output features (also referred to as feature maps) that capture local patterns in the input data [29], [31]. These features are then pooled (e.g., using max-pooling) to reduce their dimensionality, and the resulting features are passed to a fully connected layer that makes the final prediction [29].

B. MACHINE LEARNING APPROACH

The VGG19 model is a 19-layer ConvNet introduced by Simonyan and Zisserman [32]. This model was trained in general on the ImageNet dataset and is capable of performing a wide range of computer vision tasks, including image classification and object recognition [32].

VGG19 requires a fixed image size 224×224 RGB as input. The architecture then consists of a series of convolutional layers and max-pooling layers, followed by several fully connected layers. Specifically, the model has five convolution blocks, the first and the second block consists of two layers, while the remaining blocks each have four convolutional layers [32]. The convolutional layers are used to extract features from the input image, while the max-pooling layers are used to downsample feature maps and reduce their spatial extent. The fully linked layers then use these features to perform the final classification or recognition. The VGG19 model is characterized using very small 3×3 convolutional filters and up to 512 filters in each layer. To activate the hidden layers, the ReLU function is implemented [32]. This architecture allows the model to learn many complex features from the input image. In addition, the model uses a deep-network architecture that allows it to capture hierarchical representations of the input image [32].

The VGG19 model has been widely used as a pre-trained model for transfer learning, where it is used to extract features from an input image and then serves as a starting point for a

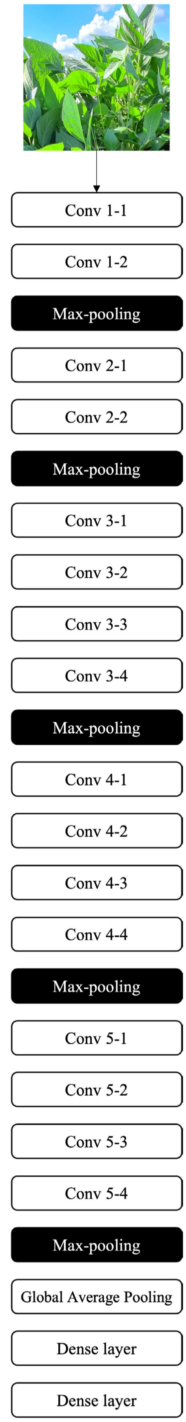

FIGURE 1. A simple representation of our VGG19 architecture.

new task [33]. The pre-trained weights of the model can be fine-tuned on a new dataset to learn task-specific features.

Fig. 1 shows our approach, which uses the VGG19 base model up to and including the last max-pooling. We then configured the three final layers. At first we implemented a global average pooling layer. This layer computes the average of the feature maps across all spatial dimensions and generates a 2D feature vector [34]. Afterwards the model consists of two dense layers. The first dense layer has 1024 neurons and the second dense layer has a single neuron with a sigmoidal activation function.

C. EVALUATION METHOD

In order to evaluate the quality of our predictions, the dataset was split into a testing and training dataset before training the model. The hold-out validation randomly divides the dataset according to a defined ratio. The training set trains the model while the test set is used to estimate the performance of the model [35]. In our case, the entire dataset was split into 70% training data and 20% testing and 10% evaluation data.

To evaluate and interpret the performance of the model, we use the following performance indicators: Accuracy, Balanced Accuracy, True Positive Rate, True Negative Rate, Precision and the Cohen's Kappa. In addition, the Receiver Operating Characteristic (ROC)-curve and the Area Under the Curve (AUC) give an overview of the quality of the model. Finally, we also provide a Confusion Matrix for evaluation.

The Accuracy determines the overall effectiveness of a model [36]. However, especially for imbalanced distributed classes, the Balanced Accuracy is considered. It indicates how well a model correctly recognizes both classes by taking the average of the correctness for both classes [37]. While the True Positive Rate (or Sensitivity, or Recall) focuses on how well the model recognizes positive examples by measuring the proportion of examples correctly classified as positive among all actual positive examples, the True Negative Rate (or Specificity) calculates how well the model recognizes negative examples. In this case, it measures the proportion of examples correctly classified as negative among all actual negative examples [36]. The Precision determines what proportion of positive identification was actually correct [36]. Cohen's kappa describes the reliability of the model and therefore measures the agreement between two judgments. It varies from -1 to 1, with a Cohen's kappa of -1 representing complete disagreement. A Cohen's kappa of 1 means that the same result is expected when the model is repeated [38]. The ROC-curve is a graphical representation used to evaluate the performance of binary classifiers. The ROC-curve shows the classifier's ability to distinguish between positive and negative examples by plotting the true positive rates against the false positive rates [39]. The AUC is the corresponding metric that indicates how good a classifier is at distinguishing between positive and negative examples. An AUC of 1 means that the classifier differentiates perfectly, while an AUC of 0.5 shows that the classifier is no better than random guessing [39]. The F1 score combines the precision and the true positive rate of the model using their harmonic mean. It describes the ability of the model to detect positives cases and be accurate in the detected cases. The value fluctuates in the interval 0 and 1 and is better the higher it is [36].

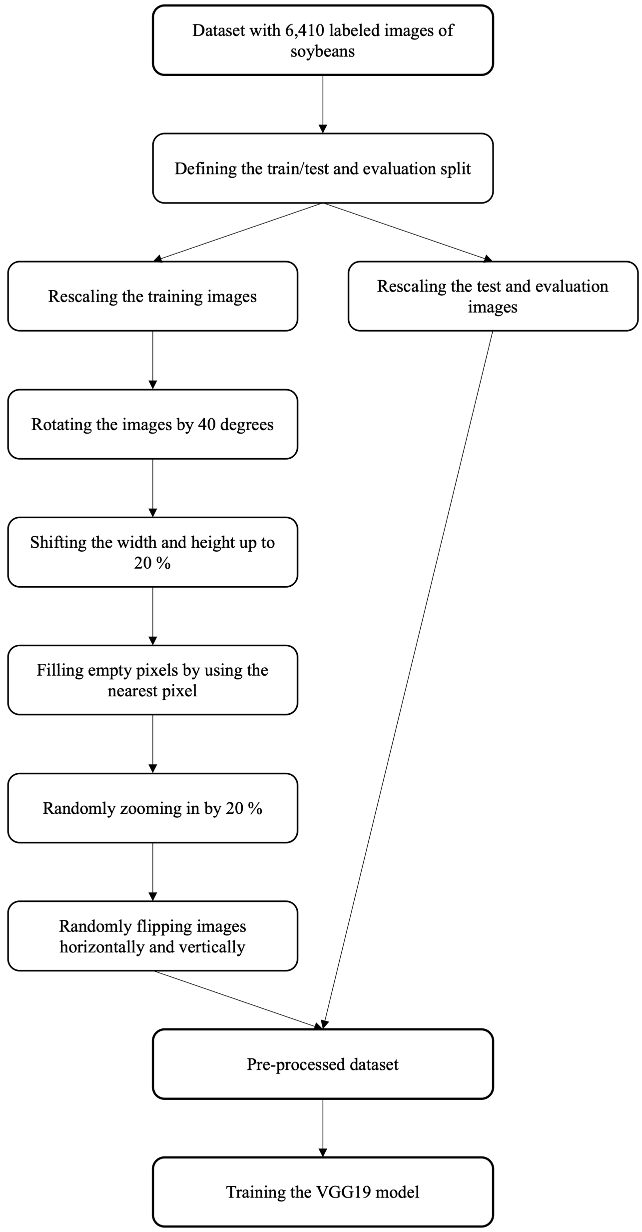

FIGURE 2. Data Pre-Processing.

D. DATA PRE-PROCESSING

The dataset used in this study consisted of a total of 6,410 RGB color images divided into three categories: Healthy, Diabrotica speciosa and caterpillars. To preprocess the data, the images were first resized to 224 $\times$ 224 px for faster processing and then scaled to a range of [0, 1] for normalization using the rescale parameter with a value of 1/255. In addition, data expansion techniques were applied to the

FIGURE 3. Healthy plant.

images in the training set using the ImageDataGenerator class from the Keras library, which provides several options for image expansion.

In particular, the following data augmentation techniques were applied to the training images: The images were rotated randomly by up to 40 degrees, and random horizontal and vertical flipping was applied, as well as random zooming of up to 20% [40]. Empty pixels due to applied scale shifts were filled using the nearest neighbor method. Additionally, random width and height shifts of up to 20% were also applied to the images to expand the training data [40]. The application of these techniques helps to increase the variability of the training data, which can lead to improved performance of the trained model.

To evaluate the performance of the model, a hold-out cross-validation approach was used. The entire dataset was first divided into training (70%), testing (20%), and validation (10%) datasets. The evaluation dataset was never shown to the model during training and was only used to calculate performance scores after training was completed. This prevented the model from overfitting to certain image sequences.

The training dataset was used to train the model. Once the model training was complete, the performance metrics were calculated using the previously mentioned validation dataset.

E. DATASET

The VGG19 network just described, combined with the data pre-processing steps, was then applied to a dataset provided by Mignoni [12]. This dataset is freely available online on Mendeley website. The dataset includes a total of 6,410 images which had already been annotated and divided into three folders. Fig. 3 represents the first folder that provides 896 images of healthy soybean leaves. The second one contains 3,309 images of caterpillar attacked leaves (Fig. 4). Finally, the third folder stores 2,205 images of plants damaged by Diabrotica speciosa (Fig. 5) [12]. The images were captured with two smartphones equipped with a 48mp AI triple camera and a UAV camera in January 2021 on two soybean farms in the State of Mato Grosso in Brazil under natural weather and field conditions [12].

IV. RESULTS

In this section, we present the results of the experiments conducted to evaluate the performance of the VGG19 model on the soybean leaf dataset. We trained and tested the model on a dataset consisting of 6,410 images of soybean leaves belonging to three classes: healthy soybean leaves (896 images), soybean leaves infested with caterpillars (3,309 images), and soybean leaves infested with Diabrotica speciosa (2,205 images). The classes were divided into a training dataset with 70%, a test dataset with 20% and a evaluation dataset with 10% as already described above.

FIGURE 4. Caterpillar attacked plant.

FIGURE 5. Diabrotica speciosa attacked plant.

A. HYPER-PARAMETERS

We trained the VGG19 model with different hyper-parameters, which are parameters, that are not directly learned within the estimators but pre-determined by the authors [41]. The batch size of a model, i.e. the number of training examples propagated through the model in one step, was 16 in the used model in this paper [42]. The number of epochs, i.e. the number of times the entire training data set was passed through the model during the training process, was 100 [43]. We used Root Mean Square Propagation (RMSprop) as an optimizer that adjusts the learning rate for each weight in the model based on the moving average of the squared gradient. The learning rate, that controls the size of the optimization steps and affects the speed and accuracy of the training process, was 0.001, which is the predefined rate of the RMSprop-optimizer [44]. We used a binary cross-entropy loss function, which measures the dissimilarity between the predicted probability distribution and the actual distribution of the target variable [45].

In summary, we used a VGG19 model pre-trained on an ImageNet dataset. First, the top layer of an existing model was removed, and the remaining layers were frozen to prevent their weights from being updated during training. New layers were then selected, including a "Global average pooling2D"

TABLE 2. Performance metrics of the VGG19 model for the soybean leaf dataset.

Class	Accuracy	Balanced Accuracy	Sensitivity	Specificity	Precision	Cohen's Kappa	AUC	F1 Score
Calculation formula	(True Pos + True Neg) / Total	(Sensitivity + Specificity) / 2	True Pos / (True Pos + False Neg)	True Neg / (True Neg + False Pos)	True Pos / (True Pos + False Pos)			
Healthy/Infested	93.71%	83.64%	97.62%	69.66%	95.19%	72.03%	95.48%	96.39%
Healthy/Caterpillars	94.00%	90.46%	96.65%	84.27%	95.77%	81.92%	95.95%	96.21%
Healthy/Diabrotica speciosa	94.16%	92.56%	96.35%	88.76%	95.48%	85.68%	97.68%	95.91%

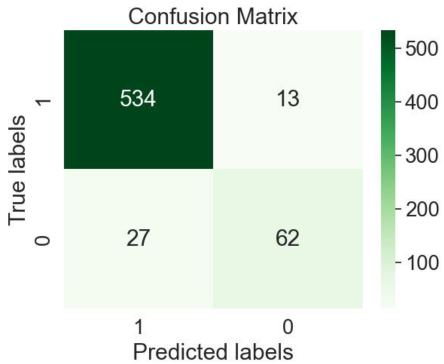

FIGURE 6. Confusion Matrix - Healthy/Infested.

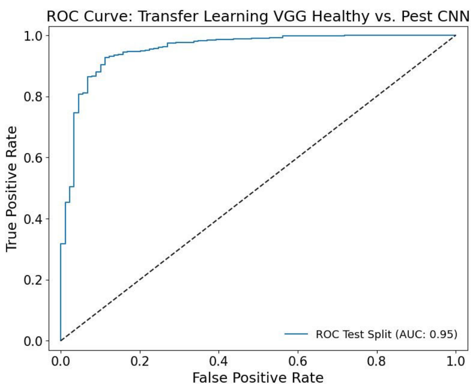

FIGURE 7. ROC - Healthy/Infested.

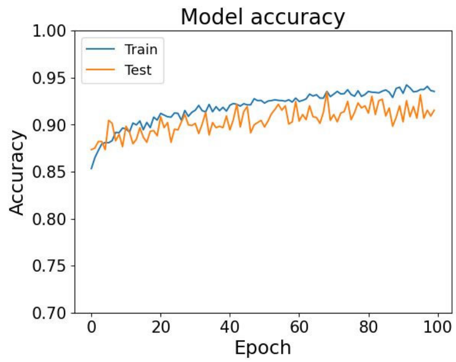

FIGURE 8. Model Accuracy - Healthy/Infested.

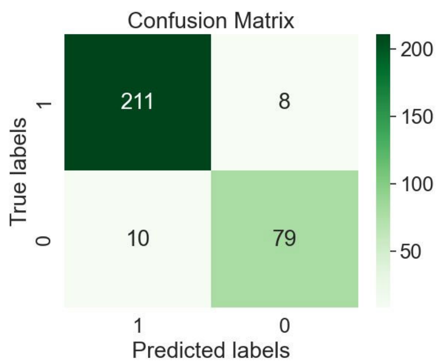

FIGURE 9. Confusion Matrix - Healthy/Diabrotica speciosa.

layer to reduce the spatial dimensions of the input feature maps, a "Dense" layer with 1024 units and ReLU activation function to extract high-level features, and an output layer with one unit and sigmoid activation function to predict binary classification results. These layers were added to the existing model, replacing the excluded top layer.

B. RESULTS OF THE MODELS

As an example, we present the results of the Healthy/Infested model, which includes both the caterpillars and Diabrotica speciosa. As already described, models were also created for the individual infestations. The exact values of the three models are shown in Table 2. Since both caterpillars and Diabrotica speciosa can be controlled with the same methods [26], [27], [28], we decided to emphasize the Healthy/Infested model because it is the recognition of the infestations that is needed, not the classification of what pest it is.

The Healthy/Infested model achieved an accuracy of 93.71%. The balanced accuracy, taking the average of sensitivity and specificity, was 83.64%. The sensitivity of the model was 97.62%, meaning that the model correctly identified 97.62% of the infested plants in the dataset. The specificity was the lowest metric at 69.66%, indicating that the model correctly identified 69.66% of the healthy plants. The model's precision was 95.19%, indicating that when it classified a plant as infested, it was correct 95.19% in the cases. The Cohen's kappa coefficient was 72.03%, indicating substantial agreement between the model's predictions and the actual labels. The AUC was 95.48%, indicating that the model had good discrimination between healthy and infested

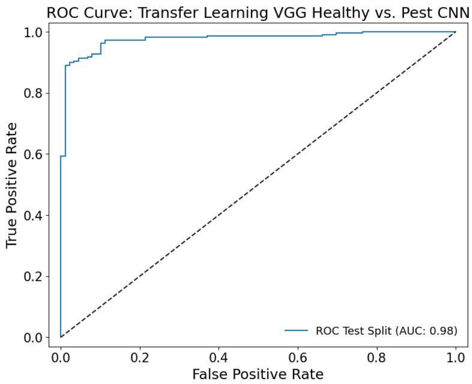

FIGURE 10. ROC - Healthy/Diabrotica speciosa.

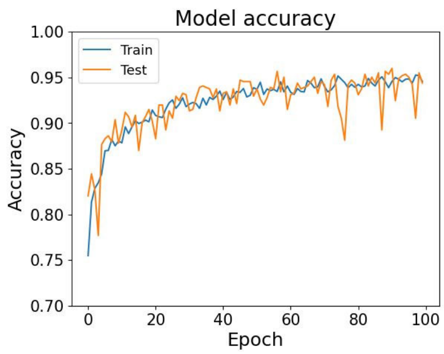

FIGURE 11. Model Accuracy - Healthy/Diabrotica speciosa.

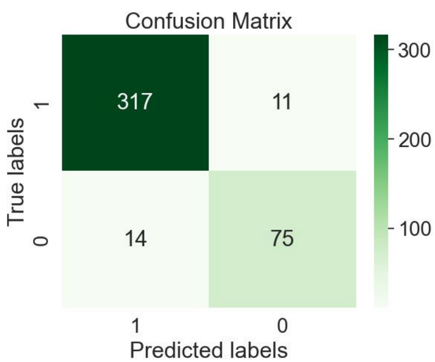

FIGURE 12. Confusion Matrix - Healthy/Caterpillars.

plants. The F1 score, which measures the balance between precision and sensitivity, was 96.39%.

The model accuracies over the training, respectively testing period are shown in Fig. 8 for the Healthy/Infested model, in Fig. 12 for the Healthy/Diabrotica speciosa model and in 16 for the Healthy/Caterpillars model. They demonstrate that the model can improve at the beginning of the epochs, but reaches stable results at the end.

V. DISCUSSION

Table 2 and the corresponding confusion matrices shown for the three models in Fig. 6, 10 and 14, clearly demonstrate that the model based on the VGG19 network accurately predicts whether the soybean leaves under consideration are healthy

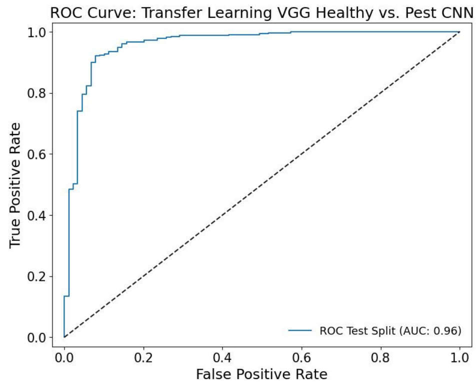

FIGURE 13. ROC - Healthy/Caterpillars.

or infested. We attribute this improvement to the deeper and more complex architecture of the VGG19 model, which allows it to capture more complicated features and patterns in the images. The distinct advantages of the VGG19 method are its ability to learn complex and diverse features in images and its pre-trained weights in a large dataset. In addition, VGG19 is known for its high accuracy rates in various image classification tasks.

Our model outperformed the study that had previously used image recognition on the same dataset. The benchmark they had previously set was therefore exceeded and the results presented in our paper can be seen as a new benchmark.

A. LIMITATIONS

Although this work provides a good overall result, it has limitations. The first issue that needs to be addressed is the generalisability of the results. We used a dataset published in the Data of Brief Journal containing images of soybean leaves [12]. Although we wanted to ensure the best possible validation of the data through a hold-up split, the result of our model should also be confirmed with other datasets to ensure the generalisability of the results.

The second limitation is the imbalanced dataset. There is a majority of images representing soybean leaves infested with caterpillars (3,309 images), followed by soybean leaves infested with Diabrotica speciosa (2,205 images), and a minority of images representing healthy soybean leaves (896 images).

Finally, the absence of external validation constitutes a limitation. This should be considered and is part of the future work.

B. FUTURE WORK

Further research could explore the use of other deep learning models or additional data augmentation techniques to improve the performance of the classification model.

Possible alternative models that have not been tried yet on this dataset are, for example, CaffeeNet [46], AlexNet [47] GoogLeNet [48] or also Xception [49].

Additionally, future research could use the k-fold cross-validation instead of the hold-out validation. K-fold

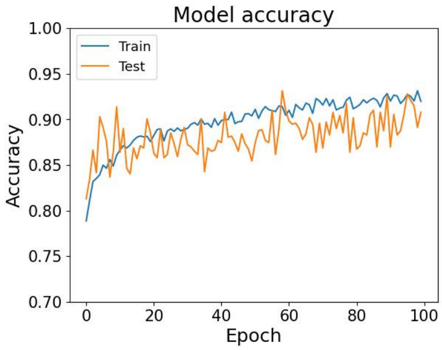

FIGURE 14. **Model Accuracy - Healthy/Caterpillars.**

cross-validation offers several advantages, including more efficient use of data, better estimation of model performance, more generalisable results and reduced bias [50]. This could improve the performance of the model even more.

VI. CONCLUSION

In this study, we successfully applied the VGG19 ConvNet to classify images of soybean leaves as healthy or infested with Diabrotica speciosa or caterpillars. The results show that VGG19 is a very suitable convolutional network for this task and could improve and support IPM. The VGG19 model therefore provides a new benchmark in the detection of caterpillar or Diabrotica speciosa infested soybeans.

Our results were validated by a hold-out split, which confirmed the reliability of our model. The accuracy and reliability of our model suggest that it has the potential to be a valuable tool for the soybean industry, enabling more targeted use of pesticides or alternative techniques and helping to reduce the cost and environmental impact of treating infested soybean leaves.

ACKNOWLEDGMENT

(Niklas Farah, Nicolas Drack, Hannah Dawel, and Ricardo Buettner contributed equally to this work.)

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