A Leaf Disease Detection Using Machine Learning and Deep Learning: Comparative Study

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Abstract: This study aims to provide innovative methods and additional suggestions for detecting plant diseases using deep learning techniques. The study focused on identifying diseases affecting major daily consumed plants, such as tomatoes, corn, and potatoes. The detected diseases included rust, early and late spots, mildew, and bacterial spots. The study relied on machine learning and deep learning algorithms, such as Support Vector Machine and VGG19 algorithm, to detect plant diseases. SIFT and Gabor filters were also incorporated into the work and tested using SVM algorithm. The study reached highly accurate results, as the accuracy rate reached 98% using SVM, and 97% using VGG19 algorithm, which are satisfactory results compared to previous studies, confirming the effectiveness of the methods used in detecting plant diseases.

1 INTRODUCTION

Agricultural crops are among the most important basic pillars of human life, which they depend on completely in their lives. For thousands of years, humans have paid attention to agricultural crops, especially in some developing countries that depend for their economic components on agriculture because it is the basic resource in human life, and it also provides a large portion of Work for some people.

Sometimes, agricultural crops are afflicted by diseases, which can be a significant cause of their complete or partial destruction. Any disease affecting these plants negatively impacts their quality, either in terms of health or economic aspects, leading to a decrease in their value. Farmers often incur substantial losses, resorting at times to agricultural experts and pesticides to combat diseases. This is where artificial intelligence comes into play in diagnosing diseases affecting medicinal plants. It has achieved remarkable success in diagnosing and distinguishing certain diseases, attempting to limit the spread of diseases among other agricultural crops, and improving the agricultural and economic sectors simultaneously by reducing the cost of diagnosing plant diseases. A large number of machine learning algorithms have been employed to produce better crops, training on a wide range of data related to the agricultural sector to mitigate diseases (Goralski & Tan, 2020).There are many studies that have proven its efficiency in detecting plant diseases and working on them seriously and extensively (Shruthi, Nagaveni, & Raghavendra, 2019). In this study, we tried to discover diseases that affect corn, tomatoes, and potatoes using CNN deep learning algorithms. These particular plants were selected due to their status as fundamental crops essential for people's daily sustenance, ones they frequently find indispensable (Mohanty, Hughes, & Salathé, 2016). Research was conducted on the identification of plant diseases employing both the SVM algorithm and the VGG19 algorithm.

Each of these attempts led to a high score in some type of plant, with accuracy reaching approximately 98% in some algorithms.

In this paper, we looked at three main types of plants that affects human life, as we mentioned

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previously, which are corn, potatoes, and tomatoes. There were a number of nematode diseases that affect these plants, including common rust, leaf spot, and northern leaf blight in corn plants, and then early blight and late blight in potatoes, in addition to the bacterial spot that affects tomatoes and Spectura leaves, which are among the targeted diseases in tomato plants.

Work was done on deep learning algorithm, compared with traditional machine learning methods such as SVM. These algorithms were chosen because they achieved good results in detecting and classifying diseases in many studies (Arora & Agrawal, 2020). Furthermore, it can be used in many areas including image classification, and object detection (Song et al., 2019).

The structure of the paper was as follows: In the second section, we provided an overview of prior studies, discussing various research endeavors and advancements in the scientific field. Following that, the third section detailed the methodology employed in conducting our study, transitioning to the subsequent stage. Here, we presented and analyzed the results we obtained. The research work concluded by summarizing our findings and outlining the intended objectives for future work.

2 RELATED WORKS

Tomato an individual consumes approximately 42 kilograms, especially in North America, and in order to preserve that plant efforts are made to preserve it (Albawi, Mohammed, & Al-Zawi). Artificial intelligence has been used to discover potential diseases on tomatoes and use some artificial intelligence applications and algorithms for to an early detection of those diseases that affect those plants and classify the condition if the disease is found or not (Laranjeira et al., 2022).

In (Natarajan, Babitha, & Kumar, 2020), researchers worked on developing techniques used in deep learning to detect diseases in a number of plants, including tomatoes. The most common diseases in that plant were bacterial spot, leaf curl, bacterial spots, and early and late end blights of that plant. A number of techniques were adopted in deep detection of the plant. Including: Single Shot Detectors (SSD), VGG, and AlexNet. In addition to the ResNet algorithm for detecting diseases that affect plants. In that study, a small number of real images containing a number of diseases were worked on, and they were detected in a number of early, intermediate, and final stages of the disease. The results in that case showed that the accuracy rate reached 95.71%.

In (Shijie, Peiyi, & Siping, 2017), the researcher worked on developing a CNN model with transfer learning algorithms in the VGG16 algorithm to detect a number of diseases related to plants, such as spider mite, gray spot, mosaic viruses, targeted bacterial spots, and leaf spot. A healthy leaf is considered healthy disease, but there is no injury. A number of real photographs (7040) were used in this study. The researcher extracted features from the original images using VGG16 and compiled them into the Support Vector Machine algorithm to classify them to determine the disease and its type. The average accuracy obtained was 89%, and the deep learning framework Keras/TensorFlow was used in that study.

Furthermore, in (Arora & Agrawal, 2020) researchers worked on proposing a new approach to classify corn leaf diseases through the application of a number of algorithms, such as Deep Forest. They used something new to discover three diseases, which are: leaf spot and rust disease common in plants. In addition to leaf spot disease, work has been done on a small dataset consisting of only 400 images, and these studies have shown good results. The accuracy in that study in describing and identifying the disease in corn plants reached 96.25%, while in the algorithm LeNet5 reached 83.46% accuracy, and finally the CNN algorithm reached 91.25% accuracy. From there, the researcher arrived at the approach he proposed that is capable of competing with traditional deep learning methods and is a good alternative to image-based applications.

In (Al-Shalout, Elleuch, & Douik, 2023), the study employed several algorithms, including VGG16, VGG19, and CNN utilizing around 25000 images. Among these algorithms, VGG19 demonstrated superior performance, achieving a remarkable accuracy rate of 95%. The CNN algorithm also yielded promising results, with an accuracy rate of 90%, while the accuracy rate for the VGG16 algorithm reached 86%.

In (Reis & Turk, 2024), a novel approach to plant disease classification is introduced, utilizing the Integrated Deep Learning (IDLF) and Ensemble Learning (EL) framework. This methodology integrates pre-trained deep neural networks, including the ImageNet-based model, with 13 distinct deep learning architectures (DLA), comprising models trained from scratch and hybrid variations. Various image quality enhancement techniques, such as hypercolumn, contrast stretching, and Contrast Limited Adaptive Histogram Equalization (CLAHE), were applied. The primary objective is to attain robust classification performance. In experimental trials, the RegNetY080 model trained from scratch achieved an accuracy of 97.64% on the original dataset, which increased to 98.33% with CLAHE optimization.

In (Alzahrani & Alsaade, 2023), the pressing issue of early detection of tomato leaf diseases, vital for sustaining crop quality and yield, was tackled. Utilizing computer vision and advanced artificial intelligence, the study utilizes three deep learning models - DenseNet169, ResNet50V2, and Vision Transformer (ViT) - to classify tomato diseases.

3 METHODOLOGY

In this section, we present the proposed processes and methodologies that we worked on (See Figure 1).

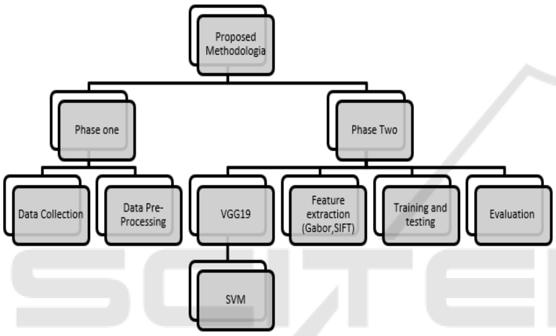
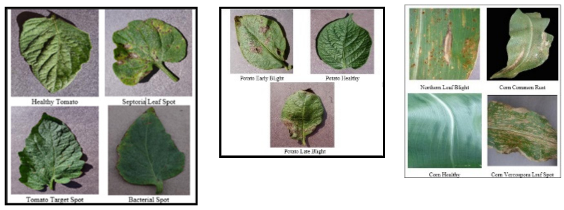


Figure 1: Proposed Methodology.

3.1 Phase One: Data Collection and Data Pre-Processing

3.1.1 Data Collection

The data utilized in our research was sourced from the Kaggle dataset, comprising 25272 images. These images encompass various plant diseases, with a specific focus on three types: tomatoes, corn, and potatoes, as mentioned earlier. The targeted images represent authentic plant leaves, featuring both healthy and diseased specimens within each category. The observable symptoms on these leaves encompass leaf spot diseases, bacterial spots, and target spots on tomato plants, as depicted in Figure 2(a). On corn plants, the symptoms include leaf blight, common rust, and leaf spot, as shown in the respective figure 2(b). The figure also illustrates advanced and late blight, along with bacterial spots on potato plants in Figure 2(c). The images given in figure 2 illustrate real pictures of both diseased and healthy plant leaves.



(a) (b) (c)

Figure 2: (a) Tomato Disease, (b) Potato Disease and (c) Corn Disease.

3.1.2 Data Pre-Processing

Central processing is one of the key procedures necessary for extracting data from images. The data extraction process is defined as a data extraction method that works to convert raw data into a format for the purpose of determining the data you are working with. Before initiating the data extraction process in images, it is crucial to perform a significant pre-processing step, primarily involving the central processing unit. This step is essential because the data often tends to be perplexing or ambiguous, lacking accurate and meaningful values necessary for training, extraction, and obtaining reliable results. To enhance the quality of the data and achieve optimal outcomes, thorough cleaning and processing of the images are carried out prior to the commencement of the work, as emphasized in (Lazzeri, Bruno, Nijhof, Giorgetti, & Castoldi, 2015).

Our research involves a three-stage data processing approach: Labels and image unification in addition to data normalization.

Labels: This process involves transforming labels and images into digital representations, enabling easy comprehension and interpretation by the program. It facilitates instructing the machine in reading, defining the utilized control, and managing digital components.

Table 1: Label encoding.

Tree	Label	Disease
Corn (4 Classes)	0	Vercospora leaf spot
	1	Common_rust
	2	Northern Leaf Blight
	3	Corn healthy
Potato (3 Classes)	0	Early Blight
	1	Late Blight
	2	Healthy
Tomato (4 Classes)	0	Bacterial Spot
	1	Healthy
	2	Septoria Leaf Spot
	3	Target Spot

This constitutes a fundamental step in handling structured data, serving a supervisory role (Singh & Singh, 2020). Table 1 displays the encoding present in the specified dataset.

Data Normalization: It is the process of converting image pixel values into a more common or familiar meaning. In this process, image data pixels (intensity) are projected onto a specific scale or the data is rescaled (usually (0,1) or (-1,1)). This process is used when the dataset contains many image formats and only one algorithm will be applied to it (Reis & Turk, 2024).

Image Standardization: defined as the process of controlling the image and its remainder (height with width), that is, controlling the pixels of the image, whose goal is to improve quality, standardize measurements, and maintain consistency for all images.

Image Data Generation from the Kera's Library provides a sample for each image and data set, which is obtained from the average and standard deviation statistics necessary to standardize the values in the images, and is done through the individual pixel values in each image or the groups as a whole (Weinberger, Seroussi, & Sapiro, 2000).

3.2 Phase Two: Training and Testing Dataset, Applied ML and DL Algorithms and Evaluation Process

3.2.1 Training and Testing Dataset

To train the data according to our study, we used the Python TensorFlow package and divided the data into two groups, a training group and a test group, in ratios of 8:2, according to the table 2 explanation for the training and testing processes for the data sets.

Table 2: Traning and Testing Dataset.

Tree	Diseases	Training	Testing
Corn	Common Rust	1907	477
	Vercospora Leaf Spot	1642	410
	Northern Leaf Blight	1908	477
	Healthy	1859	465
Potato	Early Blight	1939	485
	Late Blight	1939	485
	Healthy	1824	456
Tomato	Bacterial Spot	1702	425
	Septoria Leaf Spot	1745	436
	Target Spot	1827	457
	Healthy	1926	481

3.2.2 Applied ML and DL Algorithms

In this section, artificial intelligence algorithms, specifically the VGG19 algorithm and the Support Vector Machine (SVM) algorithm, were presented. They are used for the detection and classification of plant diseases. Additionally, we incorporated SIFT and the Gabor filter in our work to enhance the results obtained with the Support Vector Machine algorithm. The outcomes demonstrated significant improvements compared to our previous studies (Al-Shalout et al., 2023).

VGG19

The primary contribution of the VGG network lies in its focus on augmenting the depth of the convolutional neural network to improve accuracy (Yin, Wortman Vaughan, & Wallach, 2019). This is accomplished by replacing a single 5×5 convolution layer with two layers of size 3×3, and substituting one 7×7 convolutional layer with three 3×3 convolutional layers. This structural adjustment not only increases the network's depth but also minimizes the number of parameters needed for the model (Qi, 2024). The architecture of the VGG19 network is depicted in Figure 3.

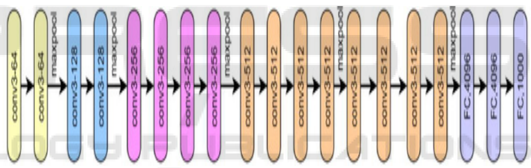


Figure 3: VGG 19 Network Structure (Qi, 2024).

SVM Classifier

Support Vector Machine (SVM) (Vapnik, 1998) is a supervised machine learning algorithm used for both classification and regression tasks. It's particularly effective in scenarios where the data is not easily separable through linear boundaries. SVM works by finding the optimal hyperplane that maximally separates different classes in the feature space (see Figure 4).

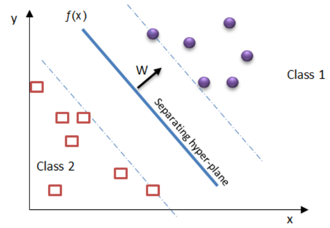


Figure 4: Principle of Support Vector Machine; two-class hyper-plane example (Elleuch, Maalej, & Kherallah, 2016).

SIFT

Scale-Invariant Feature Transform (SIFT) is a computer vision algorithm that was introduced by David G. Lowe in 1999 (Lowe, 1999). It is widely used for object recognition, image stitching, and other applications in computer vision and image processing. SIFT is particularly powerful because it is invariant to changes in scale, rotation, and illumination, making it robust in various real-world scenarios.

Gabor Filters

Gabor filters have become prominent in the domain of pattern recognition. The primary focus of Gabor filters is their ability to remain invariant to translation, rotation, scale, and illumination variations. We directly derive features from gray-level images using Gabor filters, allowing us to extract pertinent information in both spatial and frequency domains (Daugman, 1985; Jain & Farrokhnia, 1991).

3.2.3 Evaluation Process

In this paper, we used many metrics to evaluate the effectiveness of the proposed approach, and we adopted Accuracy, loss function, and Recall, in addition to F1 score, Precision and finally Confusion Matrix.

- **Accuracy**: ACC= (TP+TN)/(TP+FP+FN+TN)
- **Precision**: Precision = TP/(FP+TP)
- **Recall**: Recall =TP/(TP+FN)
- **F1 score**: F1 Score= 2*(Recall*Precision) / (Recall + Precision)
- **Loss Function**:

$$\text{Mean Squared Error } = \left(\sum_{i=1}^{n} (y_{true} - y_{predected})^2 / \text{ n} \right)$$

4 EXPERIMENTAL RESULTS AND DISCUSSION

In this study, we conducted many experiments to verify the proposed algorithms for predicting diseases of target plants, namely potato, tomato, and corn. First of all, we performed the operations via the VGG 19 algorithm. The study was carried out on the entire number of images, i.e. 25272 real images. The results are shown in Table 3.

The results showed that the algorithm works excellently, as the accuracy rate in corn plants reached 97%, while in potatoes it reached 96%, and finally in tomatoes it reached 95%, which is considered an excellent result in relation to the number of data.

Table 3: Experimental results using VGG19 algorithm.

Tree	Recall	Recall	F1	Accuracy
Corn	Common Rust	0.99	0.92	0.97
	Vercospor Leaf Spot	0.79	1.00	
	Northern Leaf Blight	0.66	0.98	
	Healthy	0.89	0.29	
Potato	Early Blight	0.78	0.96	0.96
	Late Blight	0.99	0.62	
	Healthy	0.87	0.99	
Tomato	Bacterial Spot	0.92	0.95	0.95
	Septoria Leaf Spot	1.00	0.88	
	Target Spot	0.98	0.79	
	Healthy	0.29	0.44	

Non-trainable parameters refer to the number of parameters in a neural network model that are not updated or learned during the training process. In this study, we mention that there are 20024384 non-trainable parameters in our VGG19 model (see Table 4).

Table 4: Parameters of VGG19 Model.

Layer (type)	Output Shape	Param #
vgg19 (Functional)	(None,7,7,512)	20 024 384
flatten (Flatten)	(None,25088)	0
dense (Dense)	(None , 4)	100 356
Total params: 20 124 740		
Trainable params: 100 356		
Non-trainable params: 20 024 384		

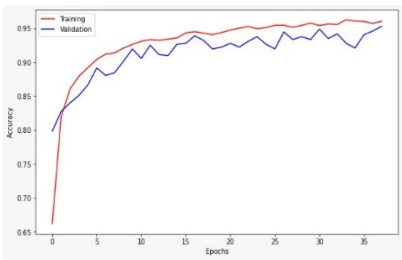


Figure 5: Performance of our proposed Model (VGG19).

Figures 5 and 6 illustrate the effectiveness of the VGG19 algorithm in detecting diseases in potato plants. The figure visually represents the significant enhancement in results, with 35 Epoch of successful disease detection in the study, achieving a remarkable accuracy rate of 96% for this plant.

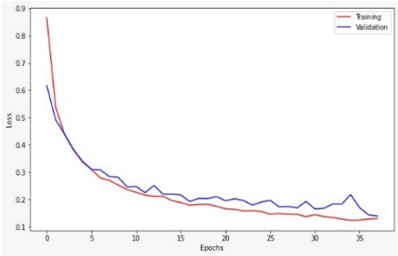


Figure 6: Trainig and validation Loss function (VGG19).

The second experiment using the SVM, where the feature was extracted through SIFT and Gabor Filter, achieved excellent results, more than expected, and with the same number of images, we obtained an accuracy rate that reached 96% in the tomato plant, 98% in the corn plant, and finally 97% in potato plants. The algorithm clearly excelled in detecting diseases that affect plants, and the Table 5 shows the results that appeared in the study and the experiments.

Table 5: Experimental results for SVM algorithm.

Tree	Recall	Recall	F1	Accuracy
Corn	Common Rust	0.94	0.95	0.98
	Vercospora Spot	0.98	0.99	
	Northern Leaf Blight	0.99	0.98	
	Healthy	0.91	0.93	
Potato	Early Blight	1.00	0.88	0.97
	Late Blight	0.91	0.92	
	Healthy	0.89	0.98	
Tomato	Bacterial Spot	0.98	0.95	0.96
	Septoria Leaf Spot	0.96	0.98	
	Target Spot	0..87	0.93	
	Healthy	0.92	0.94	

Table 6 describes the model summary for SVM algorithm used in experiments.

Table 6: Summary details for SVM Model.

Train Data - Train Labels		Test Data - Test Labels
features shape	(5702, 25088)	(1426, 25088)
labels shape	(5702)	(1426)
Splatted train and test data		
Train data	(5702, 25088)	
test data	(1426, 25088)	
Train labels	(5702)	
test labels	(1426)	

Figures 7 and 8 depict the model's performance in detecting plant diseases using an SVM algorithm specifically for potato plants. The figure 7 visually demonstrates the improvement in results in terms of the number of epochs, with the study yielding 18 epochs. The accuracy percentage for this plant reached 97%, indicating a slight improvement compared to the previous algorithm, where it was 96% for potato plants.

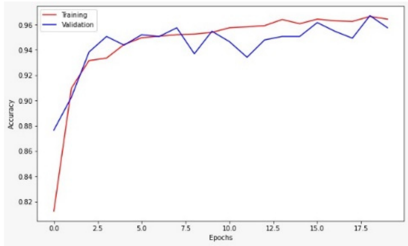


Figure 7: Performance of our proposed SVM Model.

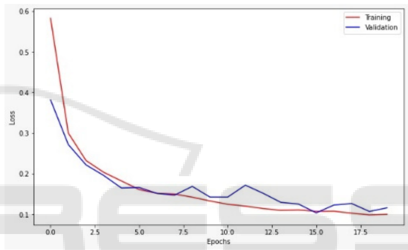


Figure 8: Training and validation Loss function (SVM).

Figures 9 and 10 display the confusion matrix regarding tomato plants, with an accuracy rate of 96%. Upon integrating the Gabor filter, the accuracy improved, reaching 97%. This visualization highlights the efficacy of the proposed system in categorizing tomato plants across four distinct classes.

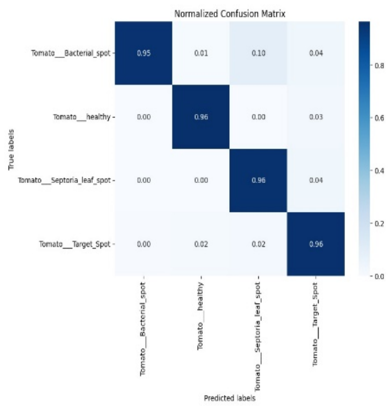


Figure 9: Confusion matrix about VGG model.

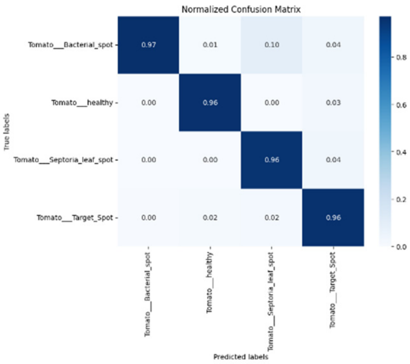


Figure 10: Confusion matrix about SVM model.

The results were notably favorable, particularly with the Support Vector Machine algorithm achieving an impressive accuracy rate of 98% on our dataset across multiple classes in a single stage. This high accuracy rate is commendable. Meanwhile, the VGG19 algorithm achieved an accuracy rate of 97% on the same dataset, representing a notable improvement compared to earlier studies using the VGG16 algorithm, where the accuracy was 89% (Shijie et al., 2017).

Several researchers have utilized diverse models, incorporating CNN algorithms along with Transfer Learning, AlexNet, and ResNet. Their results have shown a range of accuracies, varying from 83.46% to as high as 95.71%. These findings highlight the significance of numerous studies focused on identifying plant diseases, underscoring the crucial role of plants in human life (see Table 7).

Table 7: Comparative results.

Id	Dataset	Algorithms	Accuracy
(Natarajan et al., 2020)	1090 real images	ResNet, AlexNet, and Squeeze Net	95.71%
(Shijie et al., 2017)	7040 images	CNN model with transfer learning and VGG16	89%
(Arora & Agrawal, 2020)	12332 images	LeNet5	83.46%
		CNN	91.25%
(Mohanty et al., 2016)	54306 images	CNN	99.35%
Current work	25272 images	SVM (Gabor filters & SIFT)	98%
	25272 images	VGG19	97%

5 CONCLUSION

In this study, we targeted three types of plants in the study and a number of diseases that affect them, which were leaf spot, northern leaf blight, early and late blight, in addition to rot and bacterial rust on the plants.

The results showed that the proposed methods, which were added manually to improve the images using the Gabor filter in addition to Sift, achieved a high accuracy rate in detecting diseases that affect plants, reaching 98%, which is a good thing, especially since the number of data used in the study is large, Furthermore, an additional step in the future involves employing data augmentation to augment the number of images, thereby enhancing the results further.

5.1 Future Work

Based on the findings, future work could focus on enhancing disease detection algorithms to improve their efficiency and accuracy in dealing with diverse and large datasets. This could be achieved by exploring advanced techniques such as transformers or incorporating ensemble learning methods to improve model performance. Furthermore, the study could be expanded to include a wider range of plant diseases and species, with a focus on early detection at the initial stages before visible symptoms appear, enabling faster and more effective interventions. The integration of advanced technologies such as edge computing and the Internet of Things could facilitate real-time data collection and analysis, contributing to the development of smart systems that leverage AI for automated disease detection. These systems could be designed for practical field use through mobile applications or dedicated devices, making them accessible to farmers. In addition, these systems could support sustainable agriculture by reducing reliance on chemical pesticides and achieving more sustainable improvements in agricultural productivity. Finally, it is recommended to enhance collaboration with experts in plant science and agriculture to develop comprehensive and integrated solutions, leveraging modern technologies to create a clear improvement in the agricultural sector.

REFERENCES

Al-Shalout, M., Elleuch, M., & Douik, A. (2023). *Detection Plant Diseases Using Deep Learning Algorithms.* Paper presented at the 2023 International Conference on Cyberworlds (CW).

Albawi, S., Mohammed, T., & Al-Zawi, S. Understanding of a convolutional neural network. In2017 international conference on engineering and technology (ICET) 2017 Aug 21 (pp. 1-6): IEEE.

Alzahrani, M. S., & Alsaade, F. W. (2023). Transform and deep learning algorithms for the early detection and recognition of tomato leaf disease. *Agronomy, 13*(5), 1184.

Arora, J., & Agrawal, U. (2020). Classification of Maize leaf diseases from healthy leaves using Deep Forest. *Journal of Artificial Intelligence and Systems, 2*(1), 14-26.

Daugman, J. G. (1985). Uncertainty relation for resolution in space, spatial frequency, and orientation optimized by two-dimensional visual cortical filters. *JOSA A, 2*(7), 1160-1169.

Elleuch, M., Maalej, R., & Kherallah, M. (2016). A new design based-SVM of the CNN classifier architecture with dropout for offline Arabic handwritten recognition. *Procedia Computer Science, 80*, 1712-1723.

Goralski, M. A., & Tan, T. K. (2020). Artificial intelligence and sustainable development. *The International Journal of Management Education, 18*(1), 100330.

Jain, A. K., & Farrokhnia, F. (1991). Unsupervised texture segmentation using Gabor filters. *Pattern recognition, 24*(12), 1167-1186.

Laranjeira, T., Costa, A., Faria-Silva, C., Ribeiro, D., de Oliveira, J. M. P. F., Simões, S., & Ascenso, A. (2022). Sustainable valorization of tomato by-products to obtain bioactive compounds: Their potential in inflammation and cancer management. *Molecules, 27*(5), 1701.

Lazzeri, F., Bruno, G., Nijhof, J., Giorgetti, A., & Castoldi, P. (2015). *Efficient label encoding in segment-routing enabled optical networks.* Paper presented at the 2015 International Conference on Optical Network Design and Modeling (ONDM).

Lowe, D. G. (1999). *Object recognition from local scale-invariant features.* Paper presented at the Proceedings of the seventh IEEE international conference on computer vision.

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science, 7*, 1419.

Natarajan, V. A., Babitha, M. M., & Kumar, M. S. (2020). Detection of disease in tomato plant using Deep Learning Techniques. *International Journal of Modern Agriculture, 9*(4), 525-540.

Qi, J. (2024). *Efficiency study of VGG networks in autonomous driving tasks.* Paper presented at the Fourth International Conference on Computer Vision and Data Mining (ICCVDM 2023).

Reis, H. C., & Turk, V. (2024). Integrated deep learning and ensemble learning model for deep feature-based wheat disease detection. *Microchemical Journal, 197*, 109790.

Shijie, J., Peiyi, J., & Siping, H. (2017). *Automatic detection of tomato diseases and pests based on leaf images.* Paper presented at the 2017 Chinese automation congress (CAC).

Shruthi, U., Nagaveni, V., & Raghavendra, B. (2019). *A review on machine learning classification techniques for plant disease detection.* Paper presented at the 2019 5th International conference on advanced computing & communication systems (ICACCS).

Singh, D., & Singh, B. (2020). Investigating the impact of data normalization on classification performance. *Applied Soft Computing, 97*, 105524.

Song, Z., Fu, L., Wu, J., Liu, Z., Li, R., & Cui, Y. (2019). Kiwifruit detection in field images using Faster R-CNN with VGG16. *IFAC-PapersOnLine, 52*(30), 76-81.

Vapnik, V. (1998). Statistical learning theory. *John Wiley & Sons google schola, 2*, 831-842.

Weinberger, M. J., Seroussi, G., & Sapiro, G. (2000). The LOCO-I lossless image compression algorithm: Principles and standardization into JPEG-LS. *IEEE Transactions on Image processing, 9*(8), 1309-1324.

Yin, M., Wortman Vaughan, J., & Wallach, H. (2019). *Understanding the effect of accuracy on trust in machine learning models.* Paper presented at the Proceedings of the 2019 chi conference on human factors in computing systems.