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A Review on Plant Leaf Disease Classification Using Deep Learning

Zahraa Y. Younes [1]*, Elham Mohammed Thabit A. Alsaadi [2]

[1]*Department of Computer Science, College of Computer Science and Information Technology, University of Kerbala, Karbala, Iraq*

[2]*Department of Information Technology, College of Computer Science and Information Technology, University of Kerbala, Karbala, Iraq*

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Abstract

The Food and Agriculture Organization (FAO) claims that plants provide more than 80% of the world's food supply. The report (2023), found that plant diseases are responsible for an estimated 40% of global crop losses each year. Therefore, it was necessary to find a solution that detects and classifies plant diseases early in the plant growth stage, using deep learning techniques. In this review, we will discuss the techniques for detecting plant diseases using leaves that have been studied in previous years. An overview of the articles cited in this review reveals that EfficientNet outperforms all other CNN models for plant leaf disease classification. It achieves an impressive accuracy rate that surpasses even the best-performing VGG, ResNet, and DenseNet models. DenseNet is also a good option, especially when computing resources are limited.

Keywords: Deep learning, DenseNet, ResNet, VGG, EfficientNet, Plant disease, classification, KNN, CNN, SVM.

تصنيف أمراض النبات على أساس الأوراق باستعمال التعلم العميق

زهراء ياسين يونس[1]*, الهام محمد ثابت السعدي[2]*

[1]قسم علوم الحاسوب, كلية علوم الحاسوب وتكنولوجيا المعلومات, جامعة كربلاء, كربلاء, العراق

[2]قسم تكنولوجيا المعلومات, كلية علوم الحاسوب وتكنولوجيا المعلومات, جامعة كربلاء, كربلاء, العراق

الخلاصة

تقول منظمة الأغذية والزراعة (الفاو) أن النباتات توفر أكثر من 80% من الإمدادات الغذائية في العالم. ووجد التقرير العام الماضي (2023) أن الأمراض النباتية مسؤولة عن ما يقدر بنحو 40% من خسائر المحاصيل العالمية كل عام. ولذلك كان من الضروري إيجاد حل لاكتشاف وتصنيف أمراض النبات في وقت مبكر من مرحلة نمو النبات، وذلك باستعمال تقنيات التعلم العميق. سنناقش في هذه المراجعة تقنيات الكشف عن أمراض النبات باستعمال الأوراق التي تمت دراستها في السنوات السابقة. نظرة عامة على المقالات المشار إليها في هذه المراجعة يشير بشكل عام أن أداء Efficient Net أفضل من جميع نماذج CNN الأخرى لتصنيف أمراض أوراق النبات، مع معدل دقة مثير للإعجاب يفوق حتى نماذج VGG و ResNet

* Email: zahraayaseen1997@gmail.com

و DenseNetالأفضل أداءً. لكن DenseNet يعد أيضًا خيارًا جيدًا، خاصة عندما تكون موارد الحوسبة محدودة.

1. Introduction

The Food and Agriculture Organization (FAO) of the United Nations projects that there will be 9.1 billion people on Earth by 2050. In order to meet the nutritional needs of this enormous population [1], food production must rise by 70% by 2050. Simultaneously, plants are responsible for 20–40% of the annual loss in the world food trade [2]. If not promptly identified, plant diseases can have a detrimental effect on agricultural production and increase food insecurity. Consequently, given the extensive distribution of plants on Earth, advances in their proper cultivation are imperative. In agriculture, recognizing and treating plant diseases is essential, particularly for crops like rice, tomatoes, potatoes, and peppers. Thus, in order to significantly reduce crop disease outbreaks, a more stringent approach to early detection and management of losses is needed. Plant diseases must be identified in order to preserve plant life, protect human and animal health, and guarantee both the quantity and quality of crop production [3]. For instance, the yellow leaf curl virus causes yellowing in tomato plant leaves; early blight affects older plants with brown or black spots; and late blight impacts new growth. Similar characteristics apply to other diseases as well. This is crucial because even experienced individuals in disease classification can sometimes make mistakes, leading to incorrect treatment and pesticide application, which can result in crop and economic loss [4, 5]. However, in many cases, this approach is considered unfeasible because of long processing times and a lack of experts at farms, even though it frequently yields good outcomes. Additionally, visual classification can be erroneous due to leaf noise or missing portions [6]. This necessitates the use of automated classification methods such as deep learning [7, 8], particularly when diseases impact older plants. Deep learning is critical to solving the disease classification problem while also addressing plant losses. As such, the identification and classification of plant diseases are essential. To address this problem, an automatic leaf disease detection system is required. To address the previously mentioned issues, continuous utilization of an integrated deep learning algorithm [9] is needed. Our research contributes to the study of plant disease detection techniques, utilizing deep learning models like AlexNet, VGGNet, GoogLeNet, and others, as well as machine learning techniques like SVM, KNN, and others. This contribution provides insights into the mechanisms for detecting plant diseases as well as how to minimize agricultural crop losses through early disease detection. Diseases can appear in the roots, stems, leaves, and fruits of rice, tomato, potato, and pepper plants, among other plant parts. Growing rice is one of those crops that is particularly susceptible to early and late blight, while peppers may face bacterial issues. When it comes to tomatoes, there are a variety of diseases to contend with. Figure 1 displays examples of diseases that impact tomato plants.

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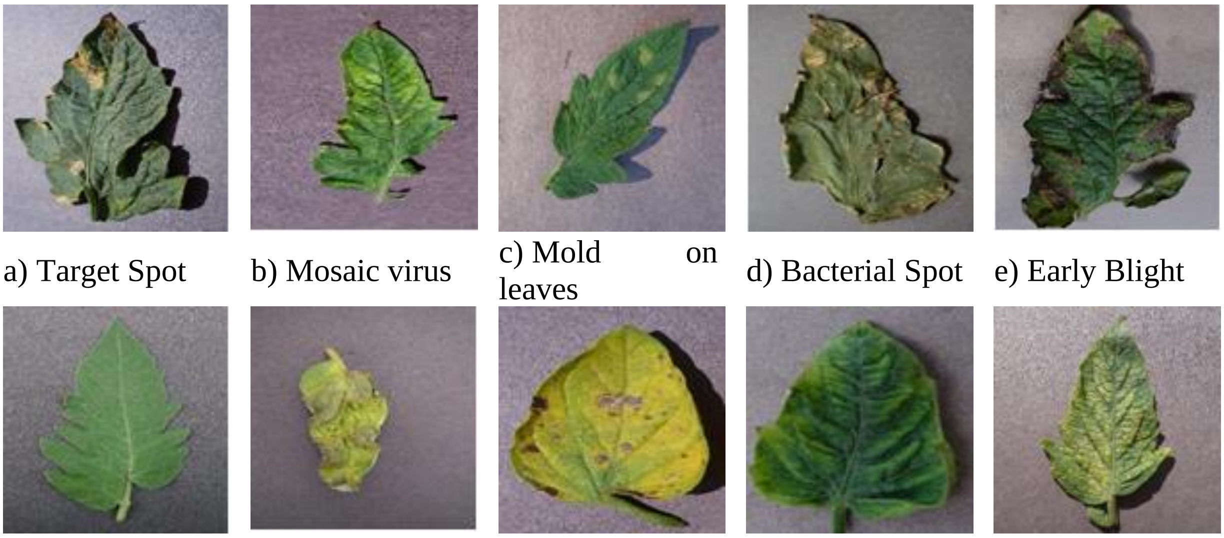

a) Target Spot | b) Mosaic virus | c) Mold on leaves | d) Bacterial Spot | e) Early Blight

f) Healthy | g) Blight late | h) Septoria leaf | i) Curl virus yellow leaf | j) Spider mites two-spotted spider mite

Figure 1: Types of plant diseases tomato

2. Related Works

This section provides a brief overview of the existing related works on plant leaf disease classification and detection.

In [10], Atila et al. proposed the EfficientNet model, which was trained on plant leaves infected with various diseases for classification purposes. The study concluded that EfficientNet outperformed models like VGG16 and Inception V3 in terms of accuracy rates. In particular, the EfficientNet B5 and B4 models achieved the highest accuracy values of 99.91% and 99.97%, as well as 98.42% and 99.39%, respectively. These studies are considered superior to the ones included in this review and serve as the foundation for our research.

In [11], Sardogan et al. used a CNN model alongside a Learning Vector Quantization (LVQ) algorithm-based method for identifying and categorizing diseases of tomato leaves. In this method, filters were applied to three color channels based on the RGB components of the images. One of the challenges that authors have faced is that leaves infected with different diseases are very similar to each other, representing one of the biggest obstacles to attempts to discover and classify diseases. Thus, some papers may be folded into incorrect chapters as a result of this similarity. The LVQ algorithm was trained using the output feature vectors generated by the convolutional part of the network. The experimental outcomes demonstrate that this method successfully identifies and classifies four different tomato leaf disease types with an 86% accuracy rate.

In [12], Rahman et al. used a segmentation technique that combined morphological operations and thresholding into the classification stage. DNN was used. A high accuracy of up to 99.25% was achieved when applied to the Plant Village dataset, which includes three types of plants. The tomato category includes ten types of diseases; the potato plant consists of three categories; and the pepper plant consists of two categories.

In [13], Jasim et al. used CNN to identify and classify diseases of plant leaves. The training data's accuracy was 98.29%, and the test data's accuracy was 98.29%.

In [14], Uğuz et al. proposed using CNN in addition to the VGG16 and VGG19 architectures. The main goal of this study was to assess the impact of data augmentation on these models' performance. When increasing the data on olive plants, the highest accuracy rate of 95% was reached, according to many experiments, but when the techniques were tried without increasing the data, the highest accuracy was reached, which is only 88%.

In [15], Tiwari et al. introduced the model, which extracted pertinent features from ensemble data by fine-tuning pre-trained models like VGG19 via transfer learning. Afterwards, the researchers used several classifiers, with logistic regression emerging as the most successful, demonstrating a notable advantage in classification accuracy with a test dataset success rate of 97.8%. This method was used to discover potato plant leaf diseases. The researchers encountered difficulties collecting images. They struggled to obtain accurate and clean images that were free of dirt and stains.

In [16], Al-Akkam et al. used a deep learning model known as a plant disease detector by analyzing plant leaves to identify various diseases using a neural network, and data augmentation techniques were used to increase its size. The accuracy of testing the proposed model was remarkably high, reaching 98.3%.
Jiang et al. [17] used the Leaky-ReLU activation function and the Resnet-50 model to find diseases in tomato leaves. They changed the convolutional layers' kernel size to an 11x11 architecture. Test accuracy reached 98.0%, and training accuracy reached 98.3%. The model achieved high results. Crops with similar disease characteristics pose a challenge to researchers, who address this issue by capturing a specific number of images and processing them.

In [18], Marzougui et al. used CNN (ResNet). The authors applied it to a dataset of plant leaves, removing the background from the images, thereby verifying the efficacy of deep learning technology through high accuracy. One of the challenges the authors encounter involves manually cutting each sheet and placing it on a uniform background, such as white paper or the same capture area, while also defining the entire base in the same manner. The model's primary objective was to classify images into diseased and non-diseased plant leaves. The developed system attains 98.96% accuracy.

In [19], Guo et al. proposed a model that involves using a region proposal network (RPN) to identify the infection location in complex environments. The images can then be segmented using Chan-Vese (CV) to highlight symptoms and VGG-16 for classification .Researchers face difficulties when retrieving leaves, and one of these challenges is accurately identifying factors such as soil and lighting in a complex environment. The proposed approach showed an impressive accuracy rate of 83.57%.

In [20], Akshai et al. concluded during this study that the DenseNet model reached the highest accuracy among the models used in this study, such as VGG and ResNet. The accuracy reached 98.27%. The suggested method outperforms the traditional method of manually observing every leaf on a plant in terms of speed and accuracy. By integrating such a model into a mobile application, farmers can use their smartphones' cameras to identify various plant diseases and take preventative measures to stop the disease from spreading. The vanishing gradient problem is a major issue that larger neural networks encounter and a significant research challenge.

Sharma et al. used potato and rice plants in their study [21]. Plant diseases are being identified through the application of both traditional machine learning-based image classification techniques and deep learning-based computer vision techniques such as convolutional neural networks (CNN). This paper proposes the CNN model for the classification of leaf diseases in rice and potato plants. Diseases like brown spot, blast, bacterial blight, and tungro are identified in rice leaves. Images of potato leaves are divided into three categories: disease-free leaves, early blight, and late blight. The study uses 1500 images of potato leaves and 5932 images of rice leaves. The suggested CNN model demonstrated 99.58% accuracy in classifying rice images and 97.66% accuracy in classifying potato leaves by uncovering hidden patterns from the raw images. It was found that the proposed model achieved the highest percentage compared to Random Forest, SVM, CNN, and Decision Tree.

In [22], Ksibi et al. proposed MobiRes-Net mode, which concatenates the MobileNet and ResNet5 models, which are two modern pre-trained CNN models. One drawback is that, due to the models' intricate internal structure, the training and testing run times are longer than for other models. Another drawback is the requirement for high-performance hardware to process the models. The accuracy of the proposed model was 97.08%, which is very good. It outperforms MobileNet and ResNet50, which obtained accuracies of 95.63% and 94.86%, respectively. Researchers proposed it for the diagnosis of olive leaf diseases.

In [23], Al-Akkam et al. used an innovative deep learning-based method for the identification and classification of plant leaf diseases, utilizing image processing techniques in conjunction with convolutional neural networks (CNNs). They carefully implemented data-augmentation techniques to enhance model generalization and prevent overfitting. Furthermore, the model was optimized through the application of the Adam optimization method. With a testing stage accuracy of 98.08% and a training stage accuracy of 99.24%, the performance results were noteworthy. To enhance the baseline model, early stopping was used. This led to a rise in accuracy; accuracy rose on the testing set to 98.34% and on the training set to 99.64%. Table 1 lists the relevant works in summary form.

Table 1: A summary of the related works

Study	Detection or Classification	**Accuracy**	**Year**	**Dataset Used**	**Algorithm Used**	**Advantages**	**Disadvantages**
[10]	Classification	Accuracy: 99.91% (B5), 99.97% (B4)	2020	PlantVillage (All Plants)	Efficient Net (B5 and B4)	reached maximum accuracy levels of 99.97%.	**Not remember**
[11]	Detection and Classification	86%	2018	Not specified	CNN + LVQ	with 86% accuracy correctly recognizes and categorizes four distinct tomato leaf diseases.	Different diseases can misclassify leaves because they are so similar.
[12]	Classification	99.25%	2019	PlantVillage database	Improved Segmentation (Thresholdin+ Morphologica	On the Plant Village dataset, a high accuracy of up	Not remember

					l Ops)	to 99.25% was attained.	
[13]	Detection and Classification	Training: 98.29%, Testing: 98.029%	2020	Plant Village (Tomatoes, Peppers, Potatoes)	CNN	high accuracy on both test and training data (98.029% and 98.29%).	Not remember
[14]	Classification	95% (with data augmentation). 88% (without data augmentation)	2021	Olive Leaves dataset (3400 samples)	Transfer Learning (VGG16, VGG19, CNN)	With data augmentation, accuracy reached 95%.	Accuracy without data augmentation was only 88%.
[15]	Classification	97.8%	2020	Potato Plants	CNN (VGG19 + Logistic Regression)	97.8% classification accuracy for potato plants was attained.	difficulties in gathering precise and pristine photos.
[16]	Detection Classification	Testing: 98.3%	2020	PlantVillage	CNN	high accuracy of testing (98.3%).	Not remember
[17]	Detection	Training: 98.3%, Testing: 98.0%	2020	Not specified	Resnet-50 + Leaky-ReLU	high accuracy in training (98.3%) and tests (98.0%).	Challenges arise from similar disease characteristics.
[18]	Classification	98.96%	2020	Augmented Dataset	CNN (ResNet)	Achieved a high accuracy of 98.96% through manual background removal.	a labor-intensive manual background removal procedure
[19]	Detection and localization of the disease	%83.57	2020	Not specified	Region Proposal Network (RPN), Chan-Vese (CV) algorithm	accurately detects the location of infections in complex environments with 83.57%.	Accurately identifying elements such as soil and lighting is difficult.
[20]	Classification	98.27%	2021	Plant Village	CNN (DenseNet and others)	98.27% accuracy was the highest compared to VGG and ResNet.	Vanishing gradient problem in larger neural networks.
[21]	Classification	Rice: 99.58%,	2022	Rice Leaves,	CNN	High classification	Not remember

		Potato: 97.66%		Potato Leaves		accuracy for potato (97.66%) and rice plants (99.58%).	
[22]	Classifica tion	%97.08	202 2	5400olive leaf images	MobiResNet (a concatenation of ResNet50 and MobileNet)	High accuracy (97.08%), outperforms MobileNet and ResNet50.	Longer training/testin g times and requires high-performance hardware.
[23]	Detection and classificat ion	testing:98.34 % trainin:99.64 %	202 1	Plant Village dataset (15 classes)	Convolutional Neural Network (CNN), Adam optimization	High accuracy after optimization: testing (98.34%), training (99.64%).	Not remember

3. The origins of deep learning

Deep learning (DL) falls under the umbrella of machine learning (ML). Its inception dates back to 1943 [15], and its development can be delineated into three distinct stages:

1. McCulloch-Pitts (MCP) (1943–1969) marked the inception of the first generation of neural networks. The initial phase, which began in 1943, introduced the McCulloch-Pitts model. This model was predominantly linear and focused on addressing linear classification problems.
2. Back Propagation (BP) (1986–1998): The Second Generation of Neural Networks—Back Propagation. Geoffrey Hinton introduced the Back Propagation (BP) algorithm in 1986, specifically designed for multi-layer perceptrons (MLP). By incorporating the sigmoid function for non-linear mapping, this era addressed the challenge of non-linear classification and learning. In 1991, issues related to the vanishing gradient problem were identified.
3. DL (2006-present) The Third Generation Neural Network: The third generation, spanning from 2006 onwards, brought forth solutions to the gradient-vanishing problem initially proposed by Hinton. Although these solutions lacked robust experimental validation and attention, it wasn't until 2011 that the ReLU activation function, which effectively mitigated the gradient vanishing issue, was introduced. This breakthrough led to a resurgence in 2012 when the Hinton team's deep learning model, known as AlexNet, achieved victory in the renowned ImageNet image recognition competition, surpassing the second-best method, Support Vector Machines (SVM). This success significantly elevated the prominence of convolutional neural networks (CNN) among researchers. With the advent of AlexNet [16], the architecture of deep learning began to evolve over time. Various advanced deep learning models and architectures were subsequently employed, with notable applications in the detection of plant diseases. These models were used for tasks such as image detection, segmentation, and classification.

4. Classification Algorithms

Deep learning in the fields of medical diagnostics and healthcare widely uses classification algorithms to classify and predict diseases. These algorithms leverage neural networks and deep learning methods to examine health data and forecast the existence or absence of illnesses. Figure 2 shows the different types of classification algorithms.

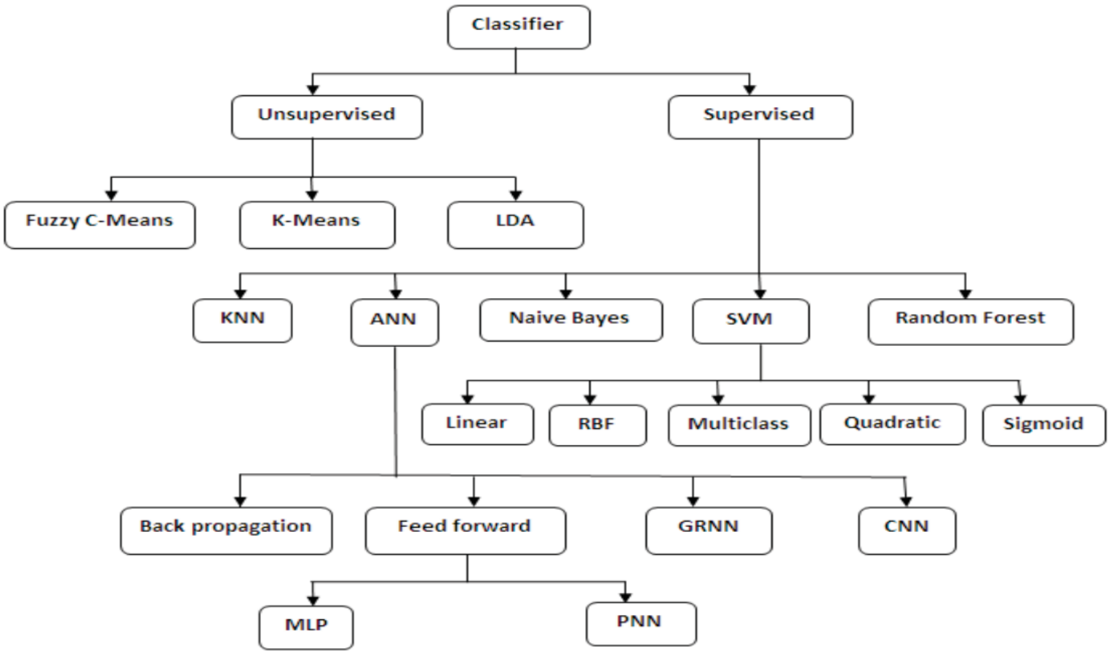

Figure 2: Types of classification algorithms [24]

4.1 Supervised classification algorithms

These algorithms are powerful tools for solving a wide range of problems [25]. The algorithm will not be able to generate precise predictions if the training data is not representative of the real-world data. The most commonly used algorithms for classification are supervised algorithms [26].

4.2 Unsupervised classification algorithms

These algorithms are powerful tools for discovering hidden patterns in data. Note that these algorithms have no prior data knowledge [27], so they may not always produce the best results. It is important to carefully evaluate the results of any unsupervised classification algorithm before using them to make decisions [28].

5. Plant Diseases Classification Based on Leaves Using Deep Learning

We will provide a simple summary of the practical steps of our work.

- Step 1: Getting the Data Ready
- Step 2: Image Preprocessing
- Step 3: Feature Extraction
- Step 4: Classifier

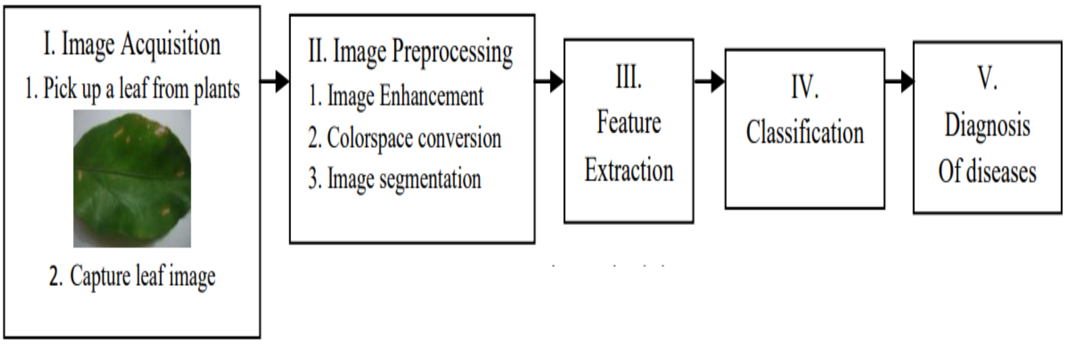

Figure 3: The Basic Methodology [29]

Step 1: Preparing the Data

This step is also called the image acquisition step. Every deep learning project needs an input image set. Image acquisition is the procedure by which the desired output format is obtained and converted. In this step, they can be obtained either by obtaining them via the Internet or by taking high-resolution photos of the plants with a digital camera. All healthy and diseased images are saved in RGB color format in the image database [30, 31]. Most researchers utilized the Botanical Village dataset, capturing images in a controlled environment. However, when the model is tested in an uncontrolled environment and then trained in a controlled environment, its accuracy is very low. To improve accuracy, there is a need to experience images in real time. So the authors have to pay attention to the real-time image dataset. Recently, the hyperspectral dataset has been used by some researchers in this field, showing better accuracy. Figure 1 shows pairs of tomatoes suffering from different plant diseases randomly selected from the plant village.

Step 2: Image Pre-processing

Image preprocessing is the second step in leaf disease classification. The purpose of image preprocessing is to extract the desired content from images, which typically contain a significant amount of noise, including background. Therefore, the image preprocessing stage must have the ability to remove background and noise. Additionally, if the captured images differ in size, pre-processing must resize and crop the selected images to ensure uniformity in size. Noise is the presence of insects, dust, and dew drops on plant leaves that affects classification accuracy [26]. To solve these problems, the input RGB image is converted to a grayscale image to obtain the correct results, or a filter is used to remove noise, as shown in Figure 4. All applications in this field require a reduction in the input image size due to its excessive size, which also serves to lower the memory size [32, 33].

(a) Noisy image (b) Image after median filter

Figure 4: Image Pre-processing [34]

Step 3: Feature Extraction

Color images are used to extract color features. The standard deviation and mean are two of the color features of RGB and HSV components' gray values, respectively. Additionally, include the color ratio in the RGB color model [34, 35]. Properties like entropy, variance, homogeneity, and contrast can be put together to create texture.

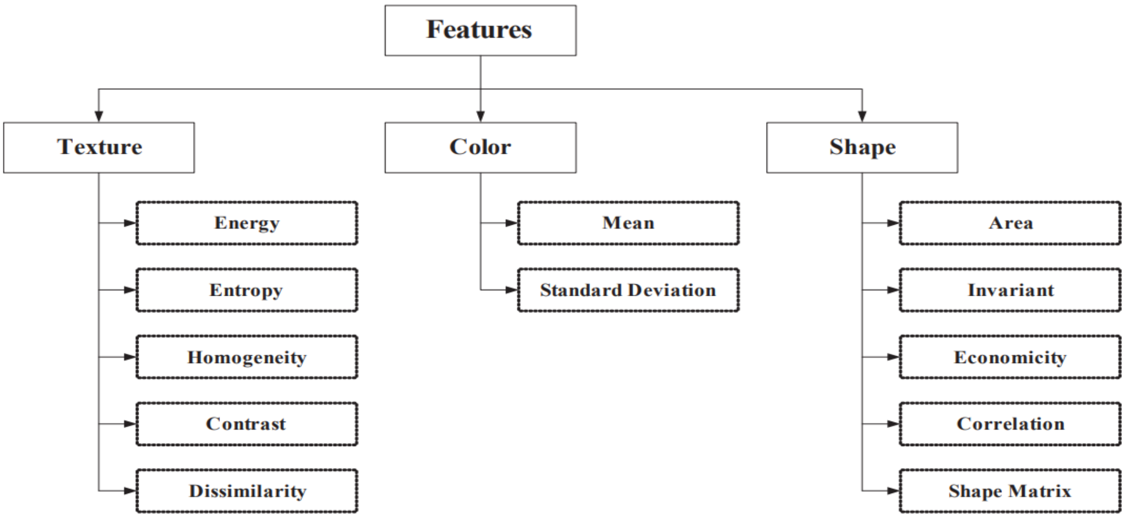

Figure 5: Features extraction techniques [36]

Step 4: Classifier

The final step is to classify the images. Classifiers are used to classify images. The next section of this article will discuss the most commonly used classification models, as illustrated in Figure 2, including support vector machines (SVM), K-nearest neighbor (KNN), random forests (RF), and convolutional neural networks (CN) [37].

- K-Nearest Neighbor (KNN) Algorithms: In statistics and data mining, the nearest neighbor (KNN) approach is a widely used technique. By calculating the distance between all of the training points and the test data, an algorithm known as KNN can predict the correct class for the test data. Next, the number of training points (k) that are highly similar to the test data is displayed. The result obtained is the average of the selected training points, k, as shown in Figure 6.
- Support Vector Machine: This supervised machine learning technique can be applied to problems related to classification and regression. However, text classification and other classification tasks make up the majority of its applications. The SVM algorithm treats each data point as a point in n-dimensional space, where n is the number of features you have. A distinct coordinate represents the value of each feature. Figure 7 displays the support vector machine. The next step is classification, where we identify the best hyperplane to effectively separate the two classes.

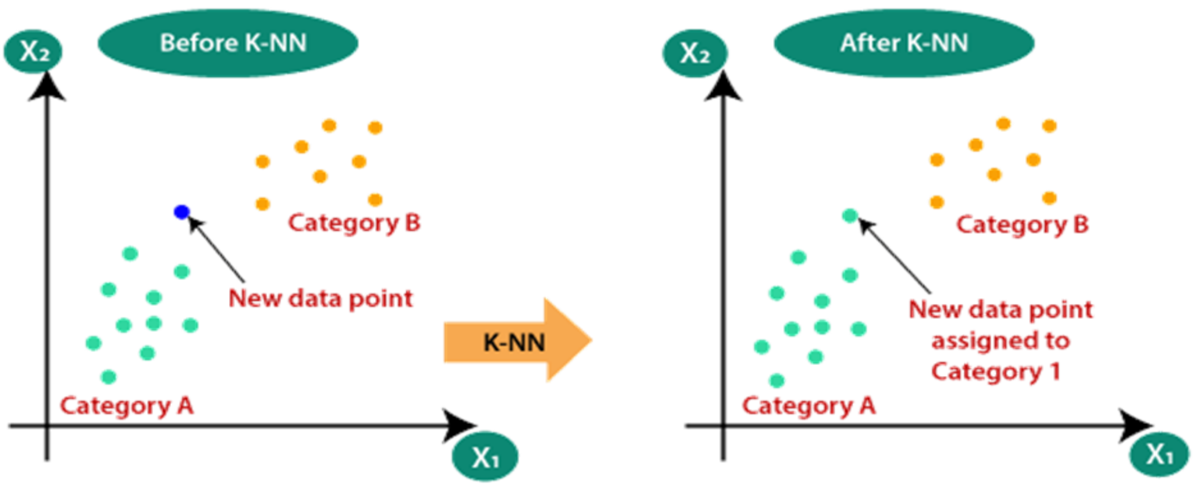

Figure 6: K-nearest neighbor (kNN) [38]

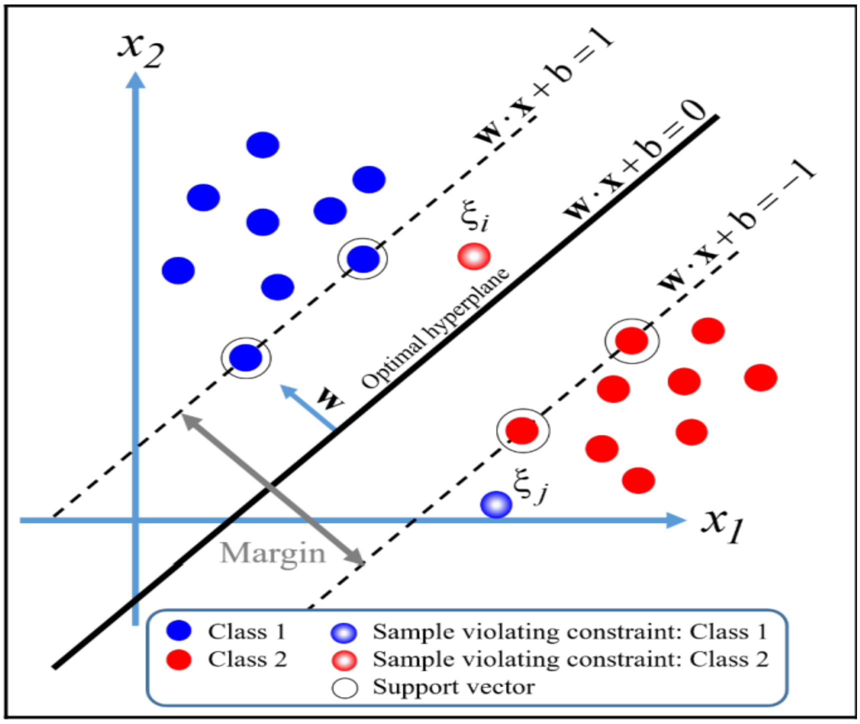

Figure 7: Support Vector Machine [39]

- Random Forest (RF): It is a combined model of stochastic Decision Tree (DT) classifiers. During training, the system generates multiple decision trees (DT). This classifier selects the class labels of the test dataset through a vote among all classification trees. While building each tree individually, this model uses bagging and randomization features. This model enables the creation of a forest of unrelated trees. Predicting a tree forest's performance will be more accurate than predicting an individual tree [32].
- Convolutional Neural Networks: These particular deep learning models are frequently employed for the classification of images [40] and [41]. To accomplish this goal, we will categorize plant diseases using CNN. Convolutional, pooling, and fully linked layers are the three types of layers found in CNN. The input image is processed by filters, or kernels, in the convolutional layer to produce various feature maps [35]. To maintain a low number of weights, each feature map's size is shrunk in the pooling layer. This procedure is also known as a reduction. There are various kinds of clustering techniques, including mean, max, and global clustering. The completely linked layer is utilized to transform the 2D feature maps after these aforementioned layers. Figure 8 shows the CNN architecture for image classification.

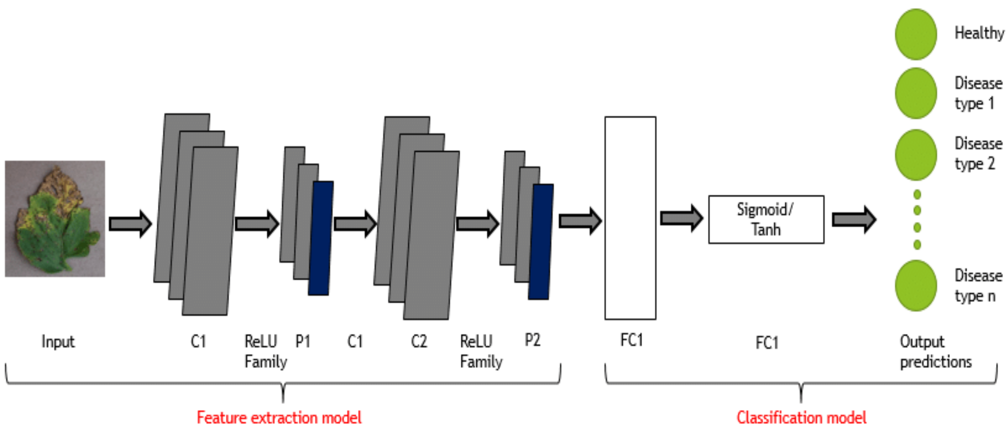

Figure 8: CNN architecture for image classification [42]

• EfficientNet: A family of CNN models called EfficientNet is incredibly effective and scalable. It was created to deliver cutting-edge results in image classification. EfficientNet is more accurate than traditional models while using fewer computer resources. This can be achieved by improving the basic model using neural architecture search and compound scaling, as shown in Figure 9. Due to its efficiency and performance, the EfficientNet family, ranging from EfficientNet-B0 to EfficientNet-B7, is extensively utilized in various computer vision applications. Moreover, it provides flexibility in scaling [43].

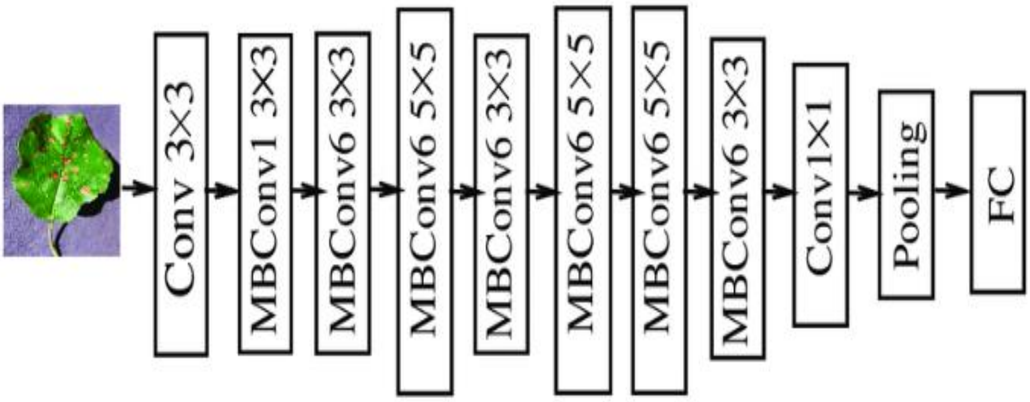

Figure 9: EfficientNet architecture [44]

• DenseNet: DenseNet is a convolutional neural network architecture that utilizes dense connectivity to pass input from one layer to the next, thereby enabling effective gradient flow and feature reuse. DenseNet, composed of dense blocks, mitigates the vanishing gradient problem and achieves parameter efficiency, resulting in compact models with high performance. Variants of DenseNet with reduced parameters and computational demands, such as DenseNet-121 and DenseNet-169, demonstrate competitive accuracy on standard datasets. This architecture is a reliable choice for deep learning applications due to its widespread adoption in various computer vision tasks [10].

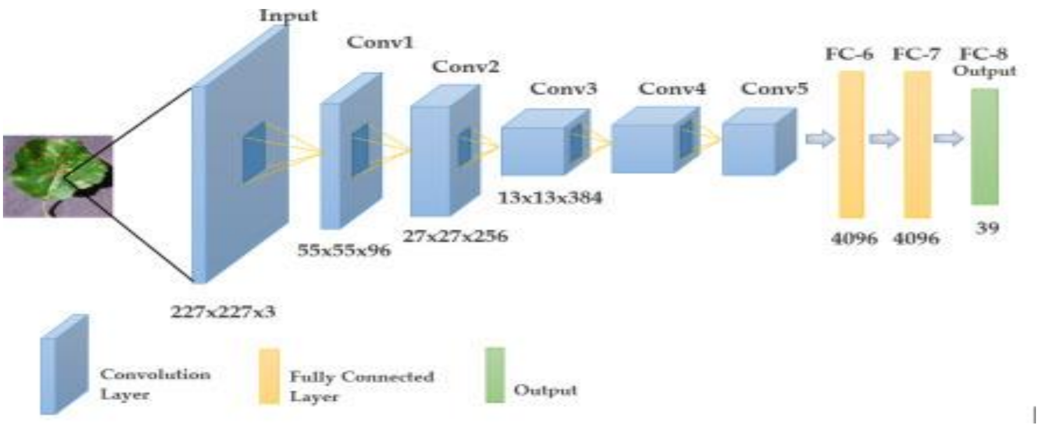

Figure -10 DenseNet architecture [10]

• ResNet: is a groundbreaking deep learning architecture designed to address the degradation issue in very deep networks by introducing residual learning. ResNet facilitates the efficient training of networks with hundreds of layers by utilizing residual blocks with shortcut connections, leading to significant performance improvements in image recognition tasks. Key ResNet variations, such as ResNet-50, ResNet-101, and ResNet-152, have been extensively employed in computer vision applications and have set new records in various

competitions. ResNet serves as a fundamental architecture in the realm of deep learning, inspiring numerous subsequent models due to its innovative residual block design.
We have provided a general explanation of the algorithms available for plant disease classification and concluded that CNN yields the highest accuracy. Table 2 shows the best models based on CNN, which are GoogLe Net [45], VGG Net [46], and Alex Net [47]. ResNet [48], EfficientNet [10], and DenseNet.

Table 2: Comparison of DL techniques

No	DL algorithm	Number of Layers	Parameters in millions	Classification accuracy
1	AlexNet	5	61	95 %
2	VGGNet	36	143	99 %
3	GoogLe Net	22	11.6	99 %
4	ResNet	50	25	96 %
5	EfficientNet B7	230	66	97.5 %
6	DenseNet	100	10	98 %

Conclusion

This paper conducts a comprehensive survey of recent advancements in the field of plant leaf disease recognition, focusing on the integration of deep learning. One of the key points emphasized in the paper is the pivotal role that large and diverse data sets play in effectively training deep learning models. Furthermore, the paper showcases deep learning models to enhance the model's performance, concluding that the EfficientNet B4 model achieved 99% accuracy and stands out as the top model in comparison to other deep learning models.

References

[1] M. Agarwal, A. Singh, S. Arjaria, A. Sinha, and S. Gupta, "ToLeD: Tomato leaf disease detection using convolution neural network," *Procedia Computer Science*, vol. 167, pp. 293-301, 2020.

[2] M. G. Akbari, S. Khorashadizadeh, and M.-H. Majidi, "Support vector machine classification using semi-parametric model," *Soft Computing*, vol. 26, no. 19, pp. 10049-10062, 2022.

[3] P. Revathi and M. Hemalatha, "Classification of cotton leaf spot diseases using image processing edge detection techniques," in *2012 International conference on emerging trends in science, engineering and technology (INCOSET)*, 2012: IEEE, pp. 169-173.

[4] M. A. Rajab, F. A. Abdullatif, and T. Sutikno, "Classification of grapevine leaves images using VGG-16 and VGG-19 deep learning nets," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 22, no. 2, pp. 445-453, 2024.

[5] R. Thapa, K. Zhang, N. Snavely, S. Belongie, and A. Khan, "The Plant Pathology Challenge 2020 data set to classify foliar disease of apples," *Applications in plant sciences*, vol. 8, no. 9, p. e11390, 2020.

[6] S. Saha *et al.*, "Deep Learning-Based Approach for Plant Disease Classification," in *International Conference on Data Science and Applications*, 2023: Springer, pp. 227-242.

[7] J. G. Thanikkal, A. K. Dubey, and M. Thomas, "Advanced plant leaf classification through image enhancement and canny edge detection," in *2018 7th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO)*, 2018: IEEE, pp. 1-5.

[8] R. M. Al-Amri, A. A. Hadi, A. H. Mousa, H. F. Hasan, and M. S. Kadhim, "The Development of a Deep Learning Model for Predicting Stock Prices," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 31, no. 3, pp. 208-219, 2023.

[9] B. Richey, S. Majumder, M. Shirvaikar, and N. Kehtarnavaz, "Real-time detection of maize crop disease via a deep learning-based smartphone app," in *Real-Time Image Processing and Deep Learning 2020*, 2020, vol. 11401: SPIE, pp. 23-29.

[10] Ü. Atila, M. Uçar, K. Akyol, and E. Uçar, "Plant leaf disease classification using EfficientNet deep learning model," *Ecological Informatics*, vol. 61, p. 101182, 2021.

[11] M. Sardogan, A. Tuncer, and Y. Ozen, "Plant leaf disease detection and classification based on CNN with LVQ algorithm," in *2018 3rd international conference on computer science and engineering (UBMK)*, Sarajevo, 2018.
[12] M. A. Rahman, M. M. Islam, G. S. Mahdee, and M. W. U. Kabir, "Improved segmentation approach for plant disease detection," in *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*, Dhaka, 2019, pp. 1-5.
[13] M. A. Jasim and J. M. Al-Tuwaijari, "Plant leaf diseases detection and classification using image processing and deep learning techniques," in *2020 International Conference on Computer Science and Software Engineering (CSASE)*, Duhok, 2020, pp. 259-265.
[14] S. Uğuz and N. Uysal, "Classification of olive leaf diseases using deep convolutional neural networks," *Neural computing and applications*, vol. 33, no. 9, pp. 4133-4149, 2021.
[15] D. Tiwari, M. Ashish, N. Gangwar, A. Sharma, S. Patel, and S. Bhardwaj, "Potato leaf diseases detection using deep learning," in *2020 4th international conference on intelligent computing and control systems (ICICCS)*, Madurai, 2020, pp. 461-466.
[16] M. Chohan, A. Khan, R. Chohan, S. H. Katpar, and M. S. Mahar, "Plant disease detection using deep learning," *International Journal of Recent Technology and Engineering*, vol. 9, no. 1, pp. 909-914, 2020.
[17] D. Jiang, F. Li, Y. Yang, and S. Yu, "A tomato leaf diseases classification method based on deep learning," in *2020 Chinese control and decision conference (CCDC)*, Hefei, 2020, pp. 1446-1450.
[18] F. Marzougui, M. Elleuch, and M. Kherallah, "A deep CNN approach for plant disease detection," in *2020 21st international Arab conference on information technology (ACIT)*, Giza, 2020, pp. 1-6.
[19] Y. Guo *et al.*, "Plant disease identification based on deep learning algorithm in smart farming," *Discrete Dynamics in Nature and Society*, vol. 2020, pp. 1-11, 2020.
[20] K. Akshai and J. Anitha, "Plant disease classification using deep learning," in *2021 3rd International Conference on Signal Processing and Communication (ICPSC)*, Coimbatore, 2021, pp. 407-411.
[21] R. Sharma, A. Singh, N. Jhanjhi, M. Masud, E. S. Jaha, and S. Verma, "Plant Disease Diagnosis and Image Classification Using Deep Learning," *Computers, Materials & Continua*, vol. 71, no. 2, pp. 2126-2140, 2022.
[22] A. Ksibi, M. Ayadi, B. O. Soufiene, M. M. Jamjoom, and Z. Ullah, "MobiRes-net: a hybrid deep learning model for detecting and classifying olive leaf diseases," *Applied Sciences*, vol. 12, no. 20, p. 10278, 2022.
[23] R. M. J. Al-Akkam and M. S. M. Altaei, "Plants Leaf Diseases Detection Using Deep Learning," *Iraqi Journal of Science*, vol. 63, no. 2, pp. 801-816, 2022.
[24] L. S. P. Annabel, T. Annapoorani, and P. Deepalakshmi, "Machine learning for plant leaf disease detection and classification–a review," presented at the 2019 International conference on communication and signal processing (ICCSP), Chennai, 2019.
[25] J. Kufel *et al.*, "What is machine learning, artificial neural networks and deep learning?—Examples of practical applications in medicine," *Diagnostics*, vol. 13, no. 15, p. 2582, 2023.
[26] V. Nasteski, "An overview of the supervised machine learning methods," *Horizons. b*, vol. 4, no. 51-62, p. 56, 2017.
[27] S. Tufail, H. Riggs, M. Tariq, and A. I. Sarwat, "Advancements and Challenges in Machine Learning: A Comprehensive Review of Models, Libraries, Applications, and Algorithms," *Electronics*, vol. 12, no. 8, p. 1789, 2023.
[28] P. Dayan, M. Sahani, and G. Deback, "Unsupervised learning," *The MIT encyclopedia of the cognitive sciences*, pp. 857-859, 1999.
[29] K. R. Gavhale and U. Gawande, "An overview of the research on plant leaves disease detection using image processing techniques," *Iosr journal of computer engineering (iosr-jce)*, vol. 16, no. 1, pp. 10-16, 2014.
[30] G. Kaur, S. Kaur, and A. Kaur, "Plant disease detection: a review of current trends," *International Journal of Engineering & Technology*, vol. 7, no. 34, pp. 874-881, 2018.
[31] C. G. Dhaware and K. Wanjale, "A modern approach for plant leaf disease classification which depends on leaf image processing," in *2017 International Conference on Computer Communication and Informatics (ICCCI)*, Coimbatore, 2017, pp. 1-4.

[32] K. P. Panigrahi, H. Das, A. K. Sahoo, and S. C. Moharana, "Maize leaf disease detection and classification using machine learning algorithms," in *Progress in Computing, Analytics and Networking: Proceedings of ICCAN 2019*, Bhubaneswar, 2020, pp. 659-669.

[33] Z. Iqbal, M. A. Khan, M. Sharif, J. H. Shah, M. H. Ur Rehman, and K. Javed, "An automated detection and classification of citrus plant diseases using image processing techniques: A review," *Computers and electronics in agriculture,* vol. 153, pp. 12-32, 2018.

[34] J. D. Pujari, R. Yakkundimath, and A. S. Byadgi, "Classification of fungal disease symptoms affected on cereals using color texture features," *International Journal of Signal Processing, Image Processing and Pattern Recognition,* vol. 6, no. 6, pp. 321-330, 2013.

[35] V. Ramya and M. A. Lydia, "Leaf disease detection and classification using neural networks," *Int. J. Adv. Res. Comput. Commun. Eng,* vol. 5, no. 11, pp. 207-210, 2016.

[36] K. Khairnar and N. Goje, "Image processing based approach for diseases detection and diagnosis on cotton plant leaf," in *Techno-Societal 2018: Proceedings of the 2nd International Conference on Advanced Technologies for Societal Applications-Volume 1*, Maharashtra, 2020, pp. 55-65.

[37] T. Gayathri Devi and P. Neelamegam, "Image processing based rice plant leaves diseases in Thanjavur, Tamilnadu," *Cluster Computing,* vol. 22, pp. 13415-13428, 2019.

[38] M. A. R. Khan, A. R. Paul, F. Rahman, J. Akter, Z. Sultana, and M. Rahman, "Appropriate Job Selection Using Machine Learning Techniques," vol. 63, no. 2, pp. 1-35, 2023.

[39] K. Kittidachanan, W. Minsan, D. Pornnopparath, and P. Taninpong, "Anomaly detection based on GS-OCSVM classification," in *2020 12th international conference on knowledge and smart technology (KST)*, Pattaya, 2020, pp. 64-69.

[40] S. Lawrence, C. L. Giles, A. C. Tsoi, and A. D. Back, "Face recognition: A convolutional neural-network approach," *IEEE transactions on neural networks,* vol. 8, no. 1, pp. 98-113, 1997.

[41] S. Chen, H. Xu, D. Liu, B. Hu, and H. Wang, "A vision of IoT: Applications, challenges, and opportunities with China perspective," *IEEE Internet of Things journal,* vol. 1, no. 4, pp. 349-359, 2014.

[42] M. LACHGAR, H. HRIMECH, and A. KARTIT, "Transfer learning for plants' disease classification with Siamese networks in low data regime," *International Journal of Computer Engineering and Data Science (IJCEDS),* vol. 1, no. 1, pp. 8-13, 2021.

[43] P. Sardar, R. R. Ema, S. Kabir, M. Adnan, and S. Galib, "Severity stage identification and pest detection of tomato disease using deep learning," *Int. J. Comput,* pp. 191-201, 2023.

[44] S. M. Hassan, A. K. Maji, M. Jasiński, Z. Leonowicz, and E. Jasińska, "Identification of plant-leaf diseases using CNN and transfer-learning approach," *Electronics*, vol. 10, no. 12, p. 1388, 2021.

[45] C. Szegedy *et al.*, "Going deeper with convolutions," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, Boston, 2015, pp. 1-9.

[46] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," presented at the 3rd International Conference on Learning Representations (ICLR 2015), San Diego, 2015.

[47] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Communications of the ACM,* vol. 60, no. 6, pp. 84-90, 2017.

[48] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, Las Vegas, 2016, pp. 770-778.