Review

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Transfer Learning Models Used in the Classification of Plant Leaves Disease: A Review

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نماذج التعلم الانتقالي المستخدمة في تصنيف أمراض أوراق النبات: مراجعة

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ABSTRACT

In many countries around the world, agriculture plays a crucial role due to rapid population growth and the resulting increasing demand for food. Therefore, there is an urgent need to improve crop quality, which has a clear impact on increasing the economic and financial growth of farmers. Important factors contributing to the decline in crop quality are diseases caused by bacteria, viruses, fungi and other agricultural pests. The impact of these diseases can be mitigated using plant disease detection techniques based on artificial intelligence techniques. Transfer learning models in such cases are particularly useful for early identification and detection of these diseases, as they are specifically data-centric and prioritize specific outcomes related to the task at hand. This study provides a comprehensive overview of the different stages of the general plant disease detection system and a comparative analysis of the temporal model used to classify plant diseases. This analysis aims to enhance agricultural economic growth and provide tangible benefits to farmers and agricultural businesses, which have a direct impact on the financial and economic income of countries.

Key words: Classification, Convolutional Neural Networks; Image Processing, Plant Leaves Disease and Transfer Learning.

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INTRODUCTION

The agriculture sector has become a key component of economic development, prompting farmers to select appropriate crops based on climatic conditions, soil quality, and economic value[1]. In the face of increasing challenges such as climate change, population growth, and political instability, the agriculture industry has begun to look for new ways to increase food production. This has prompted researchers to explore advanced and precise technologies aimed at achieving higher levels of productivity [1].

Farmers can benefit from precision agriculture and information technology to collect data and make decisions aimed at enhancing agricultural production. Precision agriculture is a modern technology that provides advanced means to increase farm productivity. By relying on these technologies, economic growth can be achieved in the agricultural sector [2]. It includes multiple applications such as pest detection, weed management, crop estimation, and diagnosis of plant diseases. Farmers use pesticides to control pests, reduce diseases, and raise crop yields [3].

Plant diseases are a major challenge, as they reduce production and cause economic losses to farmers. Therefore, identifying plant diseases is vital to the success of the farming system. Farmers rely on visual observation to detect disease symptoms, which requires continuous monitoring . As farms grow in size, traditional methods of plant disease detection become costly and less accurate[4].

Farmers may have to send samples to experts, which raises costs and is time-consuming. So, techniques such as transfer learning are needed to detect plant diseases more quickly and accurately. Transfer learning allows models to be trained efficiently using limited data, reducing the need for large amounts of samples [5]. The following sections of this article will cover the basic steps in developing an effective and more accurate disease detection system, as well as the models used to identify and classify these diseases.

This review is organized as follows: In Section (2), the basic stages of a plant disease classification system will be reviewed, where it will discuss each stage in detail and explain its role in the classification process. Section (3), will provide a comprehensive overview of transfer learning models, focusing on how they improve the accuracy of disease classification and reduce the need for large amounts of data. Section (4), will provide a brief introduction to the tools and techniques used in developing transfer learning models, highlighting their features and ways to effectively apply them in this field. Section (5) compares studies based on transfer learning models. Finally, Section (6) summarizes the conclusions from this review.

GENERAL PLANT DISEASE DETECTION SYSTEM

Plant diseases can be diagnosed by examining the parts of the plant (leaf, stem, and root). Digital image processing techniques can also be employed to discover disease in stems, leaves, flowers, and fruits, as well as to analyze the shape and color of affected areas. Image processing technology consists of five basic phases, as illustrated in the data flow diagram in Figure 1 below.

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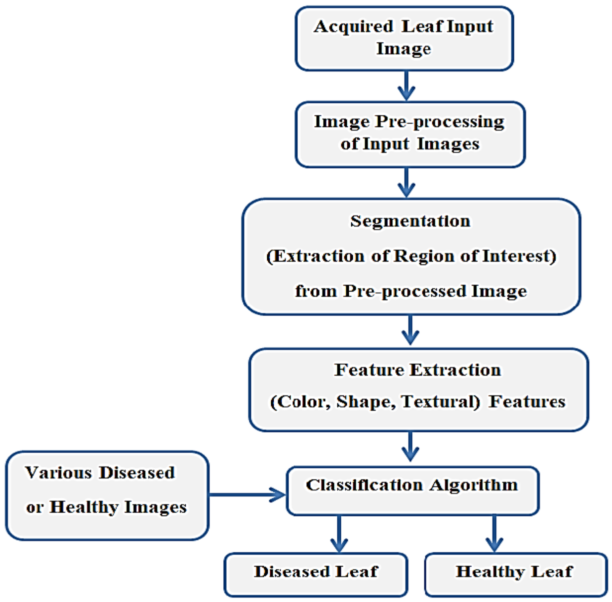

Figure. 1 Plant disease detection system [7]

- **Image Acquisition:** The initial stages of plant disease detection systems involve capturing images. High-quality images of plants be able to gain by using scanners, digital cameras, or drones.
- **Annoted Dataset**: A knowledge-based dataset of the captured images is generated and classified into various categories.
- **Image processing:** The captured images are pre-processed to enhance the main features that will help in the subsequent analysis. The segmentation technique is used to divide the plant image into several parts, which facilitates the process of extracting the affected area of leaves, stems, or roots from the background.
- **Feature extraction:** The features such as shape, color, and texture of diseased parts of plants are obtained using techniques such as gray-level co-occurrence matrix (GLM), hybrid vision, artificial intelligence, and other methods.
- **Classification:** ultimately, any machine-learning Technologies can be employed to classify different types of plant diseases [7].

TRANSFER LEARNING

In the field of deep learning, transfer learning refers to the reuse of previously trained networks to perform new tasks. This method is popular because of the ability to train the network with a limited amount of data while achieving a high level of accuracy[8]. Transfer learning relies on leveraging the knowledge gained from previous tasks to improve the performance of new tasks. During this process, the last layer of the previously trained network (FG16, PresNet50, ConceptNet, GoogleNet, MobileNet, and XNet, etc.) is substituted by a new layer

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that includes a convolutional layer, a fully connected layer, and a Softmax classification layer specially designed to fit a certain number of classes [9]. The following sections briefly explains some of the common transfer learning models used in the agricultural field.

- **VGG16**

The VGG16 model contains of (16) layers known for its robustness and precision in weights, as well as its exceptional classification ability. This model is ordinarily used in transfer learning due to its relative ease of use. Instead of depending on a large number of hyperparameters, it focuses on using convolutional layers with (3x3) filters, with a stride of (1) and the same type of padding [10]. The MaxPooling layer also uses a (2x2) filter with a stride of (2). Both types of layers are designed consistently across the model architecture. Ultimately, the output consists of two fully connected (FC) layers followed by a SoftMax layer. FC layers are used in extracting features for image classification [11].

- **AlexNet**

The development of AlexNet has rekindled researchers' interest in convolutional neural networks (CNNs). AlexNet is a pretrained CNN comprising eight weight layers: five convolutional layers and three fully connected layers. Additionally, there are three max-pooling layers following the 1st, 3rd, and 5th layers, computing approximately sixty million parameters. The architecture also includes activation layers, and each fully connected layer contains 4,096 neurons. The second fully connected layer is linked to a SoftMax classifier, which provides output across 1,000 classes [12].

- **GoogLeNet**

GoogLeNet is a seven-level convolutional network, named after LeNet, and was the winning network in 2014. This network, consisting of 144 layers, requires an input size of 224×224×3. The input data is augmented and resized to fit this format for training the model. The transfer learning steps for this network differ from those used in AlexNet and VGG16. GoogLeNet was designed for computational efficiency, enabling it to run on devices with limited resources. The trained model classifies the testing data, and performance parameters are then evaluated [13].

- **MobileNet**

MobileNet [14] was developed by a research team at Google. This model is designed for efficient mobile and embedded vision applications. It features depth wise separable convolution layers, which reduce computation by approximately eight to nine times [14]. Despite having 154 layers, MobileNet is smaller and faster than GoogLeNet due to the use of a width multiplier and adjustments to resolution, resulting in shorter training times. The model requires an input size of 224×224×3. The input data is expanded and resized to fit this training format. The trained model is then employed to classify the test data and the performance indicators are evaluated [15].

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- **InceptionNet**

InceptionNet is a deep CNN architecture developed by researchers of Google in 2014. This architecture achieved a top(5) accuracy of (93.3)% in the ILSVRC competition. InceptionNet, which consists of 22 layers, provides a complex and innovative CNN model. Unlike traditional sequential architectures, it includes a network layer within the network, a pooling layer, and small and large convolutional layers that operate in parallel. As well, the dimensionality is reduced by a (1×1) convolution operation. The parallel processing and dimensionality reduction strategy used in this architecture significantly reduces the number of operations and parameters, resulting in efficient memory and computational savings [16].

- **ResNet50**

ResNet50 is a CNN architecture within the ResNet family, designed to address the difficulty of training deep neural networks. Its developed by Microsoft Research Asia, is well-regarded for its efficiency in image classification. It features 50 layers, balancing depth and computational cost, while the ResNet family also includes shallower models like ResNet-18 and ResNet-32 [17].

AN OVERVIEW OF TOOLS FOR TRANSFER LEARNING

The tools discussed in the following sections offer a versatile platform for developing transfer learning models, which can be applied for disease detection and diagnosis in plant leaves.

- **Colab**: Google's Jupyter Notebook service gives you free access to computing resources, including GPUs, without any prior setup required. Colab is particularly well-suited to data analysis, machine learning, data science, and education. It combines executable Python code with text, images,charts, LaTeX ,HTML, and other elements into one document stored on Google Drive [18]. Colab tool's logo and main interface are shown in Figure (2) and Figure (3), respectively. It is particularly suitable for data science and machine learning. It differs from other tools in that it allows the user to connect to the development environment online and does not require installing additional components.

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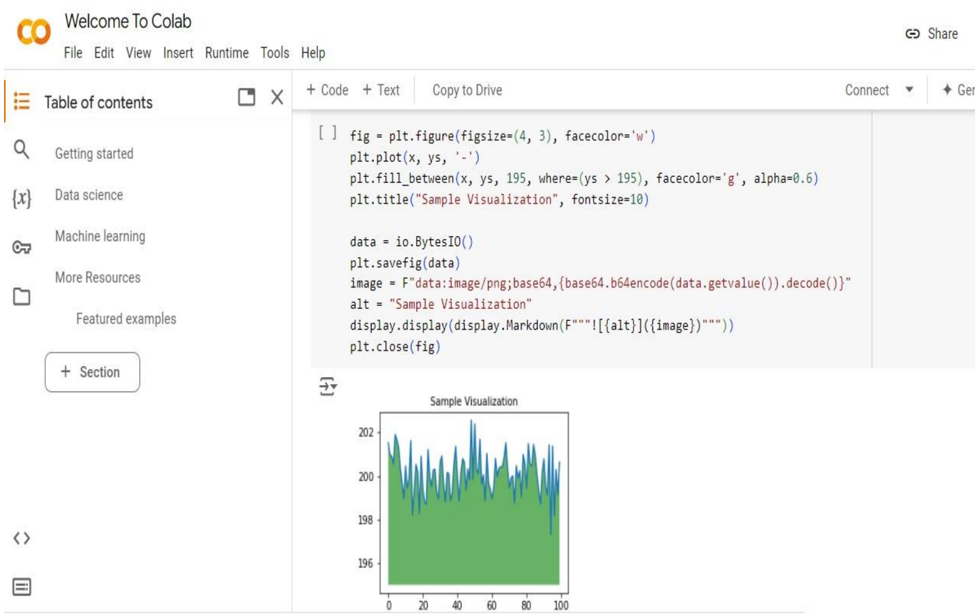
Finger. 2 The Google Colab Logo [18]



Finger 3 : The Google Colab Main Interface [18]

- **Matlab:** Matlab, developed by MathWorks, is a proprietary programming language and numerical computing environment that supports multiple paradigms. MATLAB enables matrix manipulations, function and data plotting, algorithm implementation, user interface creation, and integration with software developed in other programming languages [15]. The MATLAB tool's logo and primary interface are shown in Figure (4) and Figure (5), respectively.

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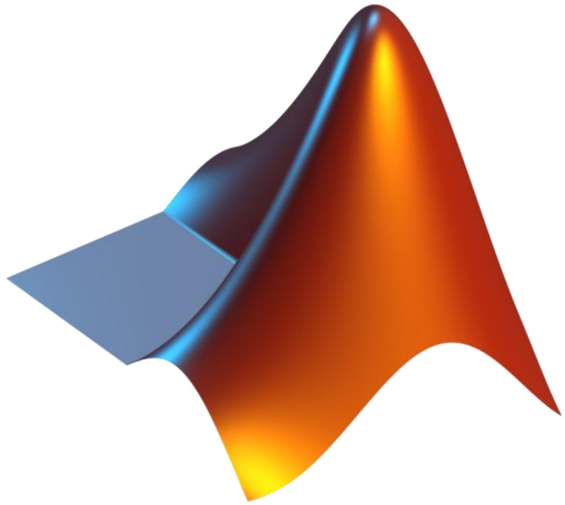
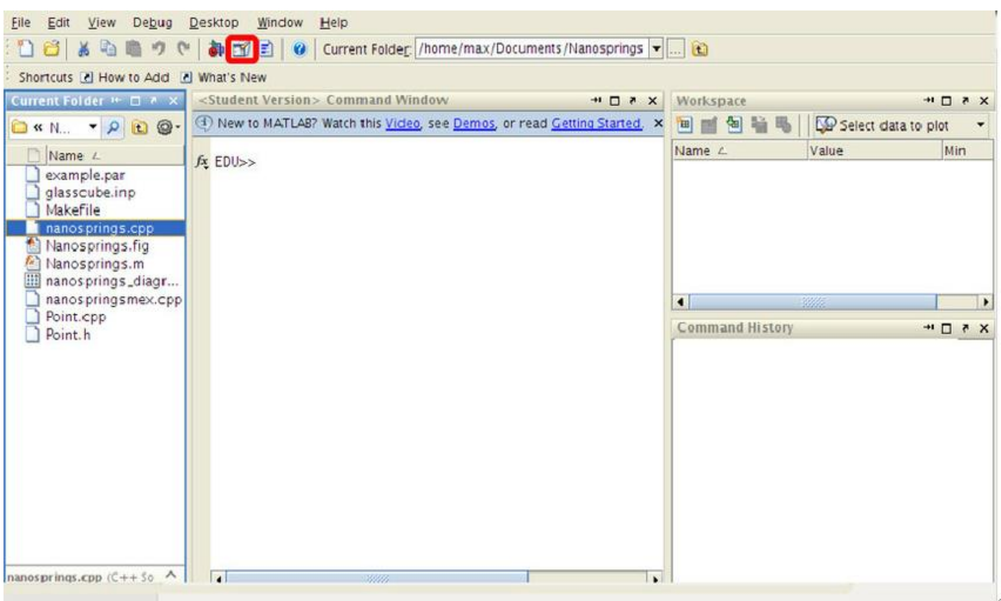


Finger. 4 : The Matlab Logo [15]



Finger. 5: The Matlab Main Interface [15]

- **Amazon SageMaker (AWS):** AWS SageMaker is a cloud-based platform for machine learning that enables developers to create, train, and deploy machine learning models on the cloud. It can also be used to deploy ML models on embedded systems and edge devices. The platform was launched in November 2017 [19]. The AWS SageMaker tool logo and primary interface are shown in Figure (6) and Figure (7), respectively.

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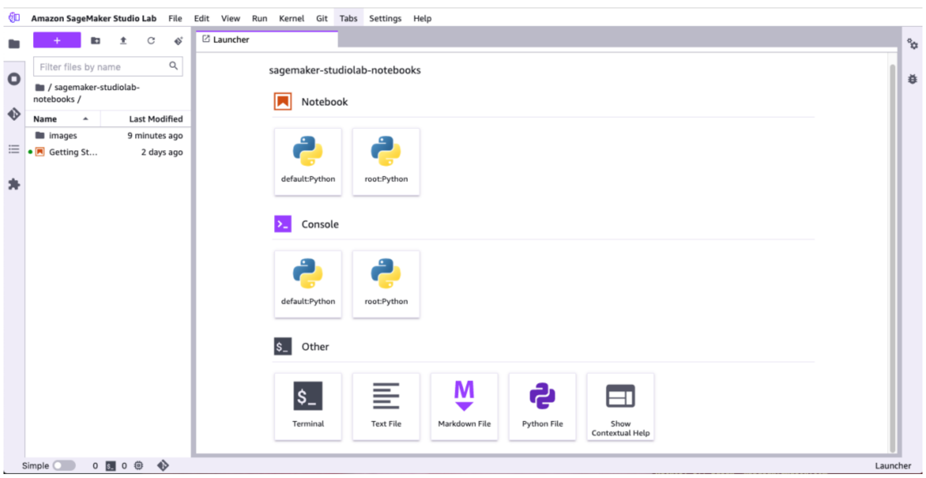
Finger. 6 : The AWS SageMaker Logo [20]



Finger. 7 : The AWS SageMaker Main Interface [20]

COMPARATIVE ANALYSIS

To provide a comprehensive overview of Transfer Learning models employed for diagnosing plant diseases, 23 relevant studies were selected for this review. These studies involved classifying plant leaves using various Transfer Learning models and datasets comprising multiple diseases. It is worth noting that all the studies included in the current review adopted the accuracy scale as a performance measure. The analysis aimed to enhance agricultural production and contribute to the country's economic growth based on the predicted outcomes. Such predictions enable farmers and agricultural enterprises to detect disease vulnerabilities early and take corrective action, improving overall performance. The studies reviewed were published between 2020 and 2024. A summary of the comparison of various Transfer Learning classifiers and datasets utilized for plant disease detection is presented in Table 1.

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Table I : Comparison of Transfer Learning Models.

NO.	Reference	Disease Type	Dataset Used	Transfer Learning Models	Tools Used	Results
1.	Ganatra et al. (2020) [21]	Crops Leaf Disease	Crops Dataset	VGG 16 , Inception and ResNet 50	Google Colab	ResNet 50 achieved the highest accuracy of 99.70%.
2.	Lauguico et al. (2020) [22]	Grape Leaf Disease	Grape Dataset	ResNet50 , GoogLeNet and AlexNet,	Matlab	AlexNet achieved an accuracy of 95.65%.
3.	Arshad et al. (2021) [23]	Tomato and Corn Leaf Disease	Tomato dataset and Corn Dataset	ResNet50 and VGG16	Google Colab	ResNet50 attained the highest accuracy of 98.7%.
4.	Wagle et al. (2021) [24]	Tomato Leaf Disease	PlantVillage Dataset	GoogLeNet, MobileNet, AlexNet and VGG16	Matlab	VGG16 attained an accuracy of 99.17%.
5.	Kibriya et al. (2021) [25]	Tomato Leaf Disease	PlantVillage Dataset	VGG16 and GoogLeNet	Matlab	GoogLeNet achieved an accuracy of 99.23%.
6.	Zainorzuli et al. (2021) [26]	Paddy Leaf Disease	Paddy Dataset	GoogleNet, AlexNet, and ResNet-50.	Matlab	The highest accuracy reached was 89.82%.
7.	Akther et al. (2021) [27]	Potato Leaf Disease	Potato Dataset	VGG16	Google Colab	VGG16 attained an accuracy of 96.88%.
8.	Pal et al. (2021) [28]	Paddy Leaf Diseases	Paddy Dataset	Inspection,VGG16, GoogleNet and ResNet-50	Matlab	ResNet-50 achieved an accuracy of 96.27%.
9.	Rao et al. (2021) [29]	Mango and Grapes Leaf Diseases	PlantVillage Dataset	AlexNet	Matlab	AlexNet achieved an accuracy of 99% for grapes and 89% for mangoes.
10.	Tockova et al. (2022) [30]	Grape Leaf Disease	PlantVillage Dataset	ResNet50	AWS SageMaker	ResNet50 attained an accuracy of 97%.
11.	Nguyen et al. (2022) [31]	Tomato Leaf Disease	PlantVillage Dataset	GoogLeNet,VGG, Resnet50 and AlexNet	Google Colab	VGG achieved the highest accuracy of 99.72%.

12.	Wadadare et al. (2022) [32]	Tomato Leaves Disease	Tomato Dataset	Inception	Google Colab	The Inception model achieved an accuracy of 93.03%.
13.	Elfatimi et al. (2022) [33]	Beans Leaf Diseases	Beans Dataset	MobileNet	Google Colab	The MobileNet model achieved an accuracy of 92%.
14.	Dahiya et al. (2022) [34]	Plant Leaves Disease	PlantVillage Dataset	GoogleNet, ResNet50, MobileNet, and AlexNet	Matlab	The ResNet50 model achieved the highest accuracy.
15.	Mousavi et al. (2022) [35]	Grapevine Leaves Disease	Grapevine Dataset	AlexNet, VGG16, ResNet50 and GoogLeNet	Matlab	VGG16 model gained accurucy of 99.6%
16.	Tahir et al. (2022) [36]	Tomato Leaf Disease	Tomato Dataset	VGG16	Google Colab	The VGG16 model attained an accuracy of 99.6%.
17.	Shah et al. (2023) [37]	Rice Blast Disease	Rice Dataset	VGG16,ResNet50 and Inception	Google Colab	The ResNet 50 model achieved the highest accuracy of 99.75%.
18.	Simhadri et al. (2023) [38]	Rice Leaf Disease	Rice Dataset	AlexNet and Inception	Matlab	The Inception model achieved an outstanding accuracy of 99.64%.
19.	Bouacida et al. (2024) [39]	Crop Plant Disease	PlantVillage Dataset	Inception	AWS SageMaker	The Inception model achieved an accuracy of 94.04%.
20.	Stephen et al. (2024) [40]	Cotton Plant Disease	Cotton Dataset	GoogleNet, Resnet50 Inception and MobileNet	AW SageMaker	MobileNet achieved the highest accuracy of 93.9%.
21.	Mannepalli et al. (2024) [41]	Rice leaf Disease	Rice Dataset	VGG16	Google Colab	The model achieved an accuracy of 97.77%.
22.	Sofiane et al. (2024) [42]	Tomato Leaf Disease	PlantVillage Dataset	VGG16	Google Colab	The model achieved an accuracy of approximately 97.77%.
23.	Kaur et al. (2024) [43]	Mango Leaf Disease	Mango Dataset	VGG16	Google Colab	The model attained an impressive accuracy of approximately 94%.

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Based on the comparison presented in Table (1), Figure (8) below illustrates the transfer learning models according to their frequency of employ in diagnosing plant diseases.

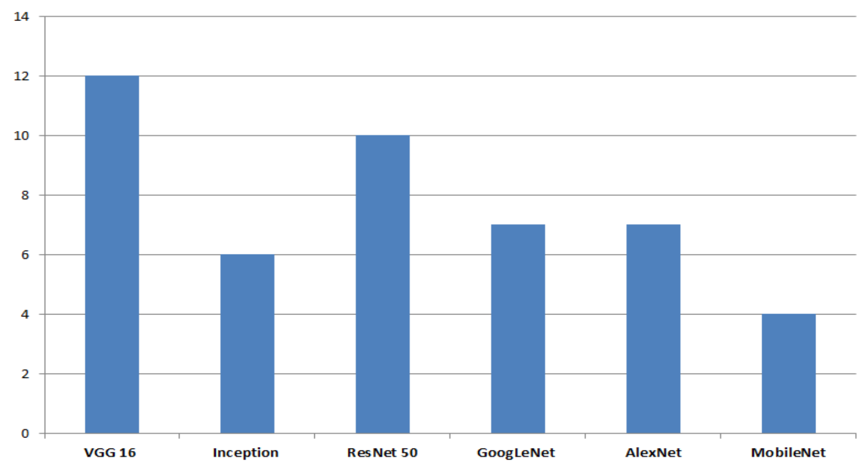

Figure.8 Transfer Learning Models in the current study

Examining the figure above, it is evident that most studies have employed the VGG16 and ResNet50 networks as effective tools for classifying plant leaf diseases. Therefore, this paper suggests that researchers consider adopting these models to achieve optimal classification accuracy. Additionally, Figure (9) demonstrates that most researchers working on plant leaf disease detection have utilized tools such as Google Colab and Matlab, while AWS SageMaker has been rarely used in the reviewed studies.

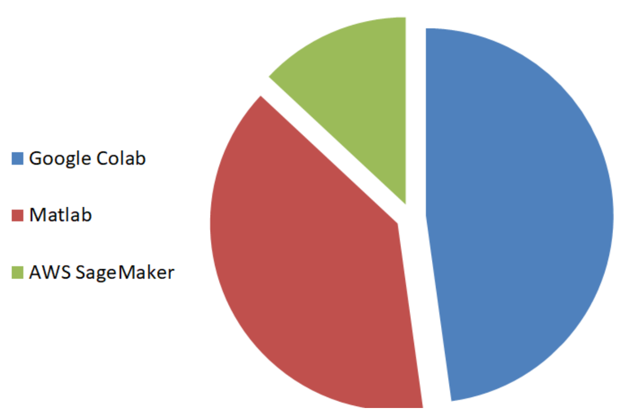

Figure. 9 Tools used in plant leave diseases in the current study

Based on Table 1, Figure 10 below illustrates that one-third of the researchers utilized the PlantVillage dataset in their studies, as opposed to the others who employed datasets for various diseases. The PlantVillage dataset consists of over 54,300 images of unhealthy and healthy

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leaves of various plants, divided into diseases and species with 38 categories. The rest of the datasets have a limited number of images that are specific to the same disease.Therefore, the review suggests that researchers should use this dataset, as it contains a substantial number of images for different crops, enhancing the training process.

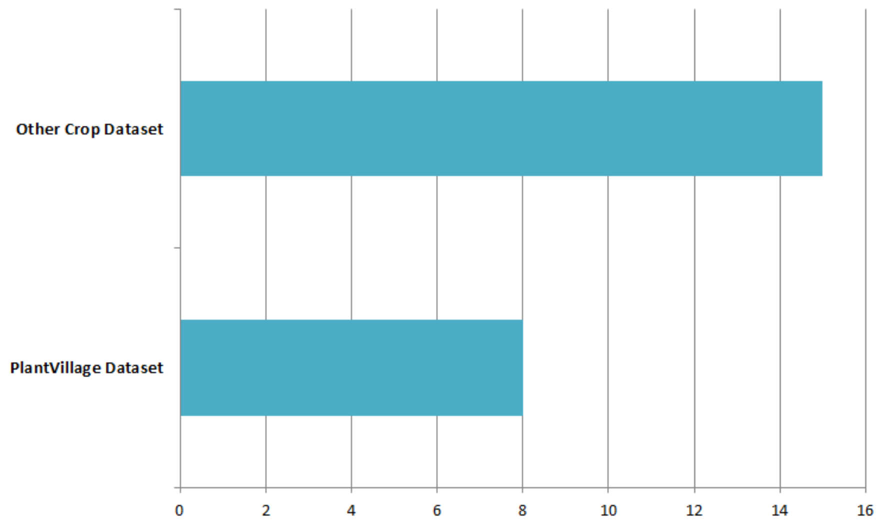

Figure. 10 Dataset used in plant leave diseases in the current study

CONCLUSIONS

A comparative study of six Transfer Learning model architectures for the classification of plant leaf diseases is conducted in this review. Many authors have favored VGG16 and ResNet50 classifiers for disease classification over other classifiers. Additionally, it was noted that numerous researchers utilize Google Colab as a development environment for constructing and evaluating transfer learning models, and the PlantVillage dataset as a benchmark dataset. Through a comprehensive survey of the research in this paper, it concluded that Google Colab is an effective tool and has been widely used by researchers because it is easy to use and not complicated. In addition, the PlantVillage dataset because it contains a large set of images, which contributes to increasing model learning and thus improving accuracy. In the future, more advanced hybrid architectures of transfer learning classifiers could be evaluated for plant leaf disease detection. Ultimately, this review intends to assist farmers in the automatic detection of diseases in crops.

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Conflict of interests.

There are non-conflicts of interest.

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Review

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مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية

الخلاصة:

في العديد من البلدان حول العالم، تلعب الزراعة دورًا حاسمًا بسبب النمو السكاني السريع والطلب المتزايد على الغذاء الناتج عن ذلك. وبالتالي، هناك حاجة ماسة إلى تعزيز جودة المحاصيل التي لها تأثير واضح على زيادة النمو الاقتصادي والمادي لدى المزارعين. ومن العوامل المهمة التي تساهم في انخفاض جودة المحاصيل هي الأمراض التي تسببها البكتيريا والفيروسات والفطريات وغيرها من الآفات الزراعية. ويمكن التخفيف من تأثير هذه الأمراض باستخدام تقنيات الكشف عن أمراض النبات المعتمدة على تقنيات الذكاء الاصطناعي. تعد نماذج التعلم الانتقالي في مثل هذه الحالات مفيدة بشكل خاص لتحديد والكشف المبكر لهذه الأمراض، لأنها تركز بشكل خاص على البيانات وتعطي الأولوية لنتائج محددة تتعلق بالمهمة المطروحة. تقدم هذه الدراسة نظرة عامة شاملة للمراحل المختلفة لنظام الكشف عن أمراض النبات العام وتحليلًا مقارنًا للنموذج الزمني المستخدم لتصنيف أمراض النبات. يهدف هذا التحليل إلى تعزيز النمو الاقتصادي الزراعي وتوفير فوائد ملموسة للمزارعين والشركات الزراعية والتي لها تاثير مباشر الدخل المادي والاقتصادي للبلدان.

الكلمات المفتاحية:

التصنيف، الشبكات العصبية التلافيفية، معالجة الصور ، أمراض أوراق النبات والتعلم الانتقالي.