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Crop Disease Detection Using Deep Learning Techniques on Images

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Abstract: Agriculture plays a crucial role in the economic development of many countries and sustains the global population despite facing various challenges like climate change, pollinator decline, and plant diseases. These threats to food security highlight the need for innovative solutions to prevent crop loss. Leveraging smartphone technology for automated image recognition-based disease diagnosis has emerged as a promising approach, thanks to their computing power and high-resolution cameras. To address this issue, we have focused on deep learning-based image detection techniques to identify plant diseases using the "PlantVillage" dataset. Several deep learning architectures, including AlexNet, GoogleNet, ResNet50, and InceptionV3, were employed and trained using two approaches: 'Training from scratch' and 'transfer learning’. The results of the analysis reveal GoogLeNet architecture achieved the highest accuracy of 0.999 for color images and 0.996 for segmented images, whereas InceptionV3 trained from scratch gave the highest accuracy of 0.994 for grayscale images with a train-test ratio of 90:10. All the models trained from scratch achieved the maximum F1-score of 1.0 for color and segmented images whereas for grayscale images, GoogleNet and InceptionV3 achieved the highest F1-score of 0.999 with train-test ratio 90:10. These findings indicate the potential of deep learning methods in detecting and diagnosing plant diseases, which can significantly enhance the efficiency and accuracy of disease diagnosis processes in agriculture. Further research and improvements in image recognition techniques can lead to more robust and effective solutions for securing global food production.

Keywords: Machine Learning, Deep Learning, Crop Disease, Agriculture, Image Detection

Introduction

Agriculture is crucial in developing countries where food security is becoming a major problem. Panchal *et al.* (2023), stated that as a result of transportation issues, plant diseases, and a lack of storage facilities, the crops were lost. Crop disease is a big problem that needs to be handled because it causes more than 15% of the world's crops to be lost. And timely detection is challenging in different parts of the infrastructure, crop diseases are also a significant component of food security. The farmers relied on a variety of age-old methods, but not all of them were equally successful in identifying plant illnesses with their unaided eyes. Plant or leaf disease costs money and jeopardizes the development of numerous agricultural goods globally as detailed by Saleem *et al.* (2020). The inappropriate use of pesticides and fungicides is due to the failure to recognize illnesses, bacteria, and viruses in plants. Since the biological characteristics of diseases are of particular interest to scientists, they have become quite interested in plant diseases. The use of modern technology in precision farming results in improved decisions. Expert visual inspections and biological investigations are frequently used in plant diagnosis. This tactic often costs money and time. Identification of plant diseases using complex and robust methods is essential to resolving these problems. To improve the effectiveness of disease identification, conventional Machine Learning (ML) approaches have been implemented in agricultural operations. Recent examples of Deep Learning (DL), a type of machine learning, have shown its outstanding capacity to find,

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identify, and categorize things in the real world. Conversely, this shift in agricultural research has resulted in DL-based fixes, suggested by Andújar *et al.* (2016). State-of-the-art outcomes employing DL techniques have been reached for agricultural tasks like harvesting fruit, identifying plants, and differentiating between crops and weeds. The present research emphasis has been on identifying crop diseases, which is a major agricultural concern.

The objectives of this research are to:

1) Analyze the Image-based detection techniques for plant diseases
2) Describe the feature extraction for disease identification using deep learning
3) Analyze the types of crop diseases and relevant areas of sensors used during crop disease detection
4) Identify the challenges that occur during crop disease detection
5) Recommend advanced image detection techniques for improving crop disease detection

The study by LeCun *et al*. (2015); Schmidhuber (2015). Aim to elucidate the utilization of deep learning models for the detection of crop diseases through image analysis. The motivation stems from the remarkable progress in applying deep learning techniques to image-based plant disease detection. To train the deep learning models, the publicly available PlantVillage dataset was employed and performance evaluation metrics were utilized. Leveraging deep learning for plant disease detection holds the potential to enable early treatment interventions, mitigating the adverse effects of plant diseases on agricultural productivity.

Literature Review

Image-Based Plant Disease Detection

The image-based plant disease detection technology is recently represented in various areas. Crop waste is representing enhanced disease, which becomes a critical identification method of disease stated by Panchal *et al.* (2023). Currently in developing countries, most of the population is based on agriculture in the form of direct and indirect energy. It represents the significant usage of application-based plant disease detection that helps the farmers to understand the reason behind the disease based on the plant's size, the color of the leaf, the size of the leaf, and the growth pattern. In the present era, the widespread adoption of smartphones enables individuals worldwide to effortlessly capture images of plants. As a result, over 300 million people currently possess internet access, utilizing a multitude of applications for their convenience and diverse needs. Similarly (Jain *et al*., 2022) have described the role of AI-based models for weed and pest detection. Although the government has access to a variety of tools, including a 24 h helpline number for farmers to place orders and obtain answers to their queries, it can be difficult to effectively assist those who live in rural areas when they are having issues finding solutions to their problems. Self-paced image-based disease identification is a simple answer to this issue.

The study described that the modified version of algorithms helps to enhance the performance of classification in diseases of various plant species. Additionally, Saleem *et al.* (2020), the utilization of Convolutional Neural Networks (CNNs) and Deep Learning (DL) optimizers leads to superior outcomes in the classification of plant diseases. The CNN model is utilized to categorize the results of the enhanced plant disease categorization. For categorizing various plant diseases, MobileNet models are used. Similar to this, other research has mostly concentrated on advanced training strategies that analyze ways that aid in assessing the effectiveness of AlexNet and GoogleNet. The value of the fine-tuning method can be seen by contrasting the most complex DL structures for plant disease categorization. As a result, it is discovered that deep learning is the most precise and accurate paradigm for the identification of plant diseases.

Relevant Areas of Image Sensors Used in Plant Disease Detection

A huge size of current development in path systems using various kinds of sensitive sensors and multiple data analysis pipelines helps to provide the various kinds of sensor systems. It is classified as an optical sensor along with RGB, multi and hyperspectral reflectance, thermal, and fluorescence imaging sensors by Javaid *et al.* (2016). In the realm of plant pathology, digital photographic images play a pivotal role as they enable the assessment of plant health. With the ability to capture RGB Red, Green, and Blue) images effortlessly, digital cameras facilitate the identification, quantification, and detection of diseases in a straightforward manner. The technological requirements of simple-handled devices include a photo sensor with light sensitivity, spatial resolution, and digital and optical focus, all of which contribute to the improvement that is seen every year. The latest and most powerful digital camera-based sensors that are available in mobile phones and tablets are being used by farmers and psychopathologists in the current age. Using this technique, the fruits and crops are also screened to avoid storage disease. The thermal sensors show the infrared thermography excess plant temperature, which is connected to the plant water status mentioned by Dargan *et al.* (2020).

Issues/Challenges in the Image-Based Plant Disease Detection

Various techniques are used to identify the diagnosis of the disease that has been developed and are proven in the molecular biology delivery that aids in the accurate identification of the pathogenic factors. These techniques are used to analyze plant disease and significant damage and the development of new techniques for the accurate identification of pathogenic factors (Jain *et al*., 2016). However, many farmers are not able to use the numerous methodologies used during analysis because they are expensive and require a lot of resources to be implemented. Additionally, the classification of issues involved the use of several technologies, such as decision trees, random forests, linear regression, K-nearest neighbors, logistic regression, Support Vector Machines (SVM), Naive Bayesian, and clustering as detailed by Panigrahi *et al*. (2020). Because of the Deep Learning (DL) approaches' ground-breaking results, artificial intelligence and computer vision have advanced. These techniques, as opposed to the conventional approach, result in more accurate predictions, promoting better decision-making. The issue with data visualization in tables and other exhibits originates from the fact that the bulk of datasets will have variable and inconsistent material. The use of image-based plant disease detection may result in low-quality images of plant leaves, which are considered by all the different research publications. The inception of the PlantVillage project was motivated by the objective of developing precise image classifiers capable of accurately identifying plant diseases Katafuchi and Tokunaga (2021).

Feature Extraction for Disease Identification

The automatic plant disease detection system receives the images of the diseased leaves as input and diagnoses the illness correctly. According to Panchal *et al*. (2023), this system's effectiveness will depend on the feature extraction techniques used. Images of infected leaves that are input into the system are processed using image processing algorithms to extract features from the pictures. According to Sapkal and Kulkarni (2018), there are two primary types of feature extraction methods employed. The first method involves utilizing image processing techniques to extract features from the input of infected leaf images. Various properties, such as color, shape, texture, Histogram of Oriented Gradients (HOG), Speeded-Up Robust Features (SURF), and more, can be extracted using image processing methodologies. The second method makes use of Alexnet's pre-trained deep learning model, which will automatically detect features from the input image. Both methods apply the Backpropagation Neural Network (BPNN) algorithm to the gathered features. Further, the BPNN is especially used for the deep neural network that is working on error-prone projects that include images and other speech recognition tasks. Xie *et al*. (2020) described that CNN has developed into a complete deep-learning approach in recent years. They fully exploit image big data and find the discriminative features from the original photographs themselves to do away with memory-intensive and time-consuming image processing. Due to CNNs' ability in pattern recognition, early plant leaf disease detection has become a new area of focus for smart agriculture.

Materials

Data and Processing

To develop a computer vision algorithm for crop disease detection, we used the PlantVillage Dataset as a starting point for learning from scratch as described by Hughes and Salathé (2015). The PlantVillage dataset is a large and comprehensive dataset of plant images that was created to aid in the development of computer vision algorithms for crop disease diagnosis. The development of the dataset was undertaken by the PlantVillage team at Penn State University, led by Dr. David Hughes and received funding from both the National Science Foundation and the Bill and Melinda gates foundation. PlantVillage project provides the dataset available openly and freely. The dataset contains over 54,000 high-quality images of 26 different crop diseases and 14 plant species along with images of healthy plants, which have a diverse range of 38 class labels.

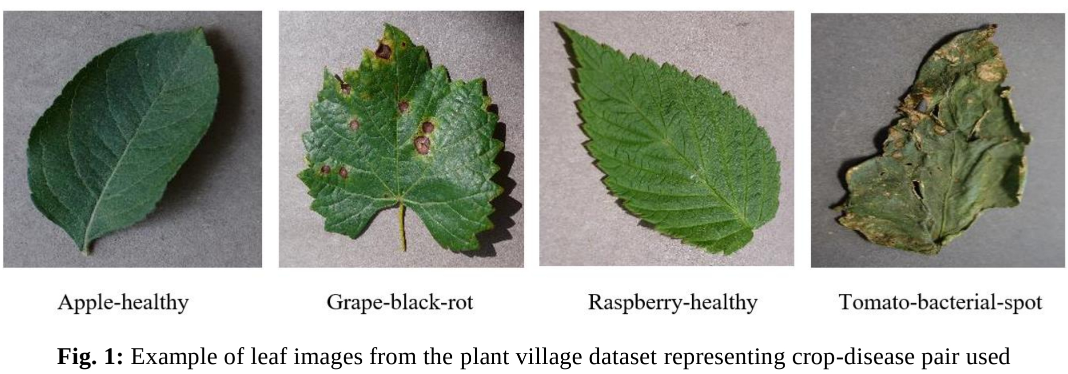

Fig. 1: Example of leaf images from the plant village dataset representing crop-disease pair used

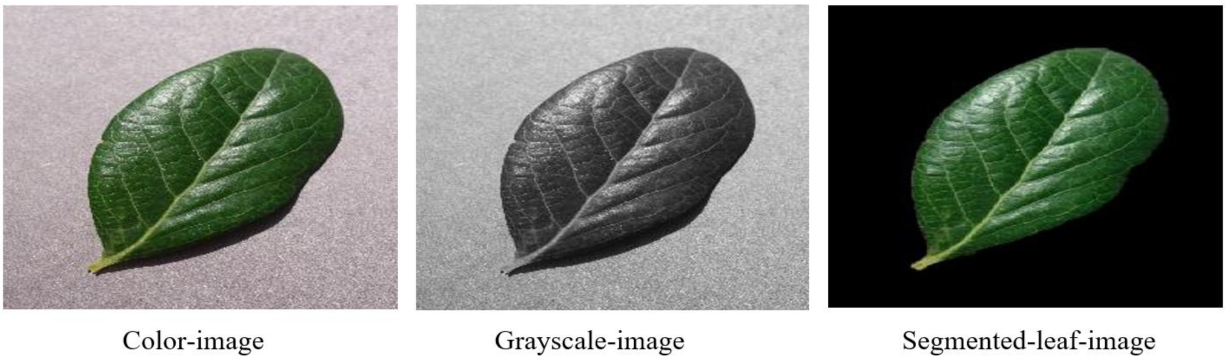

Fig. 2: Displays sample images extracted from the three distinct versions of the PlantVillage dataset

The images were collected from multiple sources, including professional photographers, citizen scientists, and farmers. Figure 1 exhibits a sample of leaf images derived from the PlantVillage dataset, which represents the crop-disease pairs employed in the dataset. The dataset includes images of both leaves and fruits from the various plant species. The dataset comprises the following plant species: Apple, orange, blueberry, corn, grape, peach, cherry, pepper, potato, soybean, squash, strawberry, raspberry and tomato. The diseases included in the dataset are Apple scab, cedar apple rust, bacterial spot, common rust, late blight, early blight, leaf curl, mosaic virus, powdery mildew, septoria leaf spot, target spot, tomato yellow leaf curl virus, spider mites, and two-spotted spider mites. The complete PlantVillage dataset encompasses three distinct versions, each offering unique variations and additions. (1) Color-54,305 images, (2) Gray scale-54,305 images, (3) Leaf Segmented-54,306 images. Figure 2 illustrates a selection of sample images derived from the three versions of the PlantVillage dataset.

The ImageNet dataset has several advantages in this research, used in pre-trained DL architecture as detailed by Deng *et al*. (2009). It is one of the largest datasets currently available, which makes it a perfect source of data for certain machine-learning models. By classifying the photos using the WorldNet hierarchy, the models created for identifying objects are accurate and efficient. This research's ideal data source contains more than 50,000 color photos of crop leaves, including both healthy and damaged plants. According to the WorldNet hierarchy, the ImageNet dataset comprises a staggering collection of 14,197,122 annotated images. It has 1000 different object categories, with an average of 1000 images per category.

Data analysis is a crucial step in cleaning and modelling the data once it has been acquired. Extraction of pertinent data from data sources is a step in the data analysis process. To ensure that the information is correct and dependable, this procedure also aids in cleaning and deleting extraneous data from the obtained data Mukherjee (2019). To deliver precise findings for the completion of the work, Tensor Flow a system for managing information and analysis was used.

Several libraries built on the Python programming language were used to examine the data in the PlantVillage datasets. Tensor Flow, Numpy and Keras for building Neural Network Architecture, as well as MatplotLib for plotting libraries were utilized for the analysis. These libraries all serve various purposes and are essential to the study. A crucial library for developing and deploying machine learning models is TensorFlow (Ragab and Arisha, 2018). It offers a thorough and adaptable environment for creating and developing neural networks. It also makes computing effective and scalable, which makes it a perfect library for the study of massive datasets.

Methods

In crop disease detection for image classification problems, we focus on some popular deep learning architectures namely AlexNet, GooLeNet, ResNet50, and InceptionV3. These architectures are used to determine healthy and diseased crops with their names.

GoogLeNet

In 2014, Google introduced GoogleNet, also referred to as Inception-v1, as a convolutional neural network architecture developed by developed by Szegedy *et al*. (2014). It was developed by researchers at Google with the aim of advancing deep learning methodologies. It was designed to be a deeper and more efficient neural network for image classification tasks, with fewer parameters and lower computational complexity compared to AlexNet architectures. GoogleNet consists of 22 layers, including several inception modules that perform parallel convolutions at multiple scales. These inception modules

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are designed to capture a wide range of features at different levels of abstraction, allowing the network to effectively learn complex patterns in the input images. A notable innovation in GoogleNet is the integration of 1×1 convolutional layer, which serve to decrease the dimensionality of feature maps before executing computationally intensive convolutions. By employing factorized convolutional layers, the network's parameter count is reduced, leading to enhanced computational efficiency. To teach the network the features that are important for image classification, a sizable dataset of images is used for training. The picture data is fed into the network in the instance of crop disease detection and the characteristics are retrieved from the images. The next step is to train a classifier with these attributes so that it can recognize the presence of a particular crop disease in fresh photos. The complete model of GoogleNet is shown in Fig. 3. In our implementation, we used the Keras API to build the GoogleNet model. We trained the GoogLeNet model from scratch using the Keras library.

AlexNet

AlexNet, devised by Alake (2020), is a deep convolutional neural network architecture. Comprised of a total of eight layers, including five convolutional layers and three fully connected layers, AlexNet boasts an impressive parameter count of 60 million. Its groundbreaking performance in the ImageNet Large Scale Visual Recognition Challenge of 2012 positioned AlexNet as the winner, establishing new benchmarks in object recognition and image classification. It was one of the first deep learning models to demonstrate the power of convolutional neural networks for computer vision tasks and has since inspired many other architectures in the field. Figure 4 shows the AlexNet model architecture.

ResNet50

ResNet50, introduced by Lenyk (2021) researchers at Microsoft research Asia is a convolutional neural network-based architecture widely recognized in the field of deep learning. The name "ResNet" comes from "residual network," which refers to the use of residual connections to overcome the degradation problem that can occur in deep neural networks. ResNet50 has found utility across diverse computer vision tasks, including object detection, image classification, and image segmentation. Its architecture includes residual blocks, which allow for more efficient training and deeper network architectures. We trained ResNet50 in two-way, first Learning from scratch and second Transfer learning. We used two functions in ResNet50, 'residual_block' and 'ResNet50'. Figure 5 shows the ResNet50 model architecture. In the context of ResNet50 transfer learning, ResNet50 is a deep neural network consisting of 50 layers. Prior to the transfer learning process, ResNet50 has undergone pre-training on the ImageNet dataset. This pre-training enables ResNet50 to recognize a wide range of objects and features in images.

InceptionV3

InceptionV3 is a popular deep-learning model frequently employed for image classification tasks. It incorporates inception modules that leverage convolutional layers with diverse kernel sizes to capture information across various scales and resolutions. With a total of 48 layers, InceptionV3 employs factorized convolutional layers to decrease the number of parameters, leading to enhanced computational efficiency. Figure 6 shows an implementation of the InceptionV3 model using TensorFlow and Keras. The model consists of a stem, several inception blocks, and a classifier.

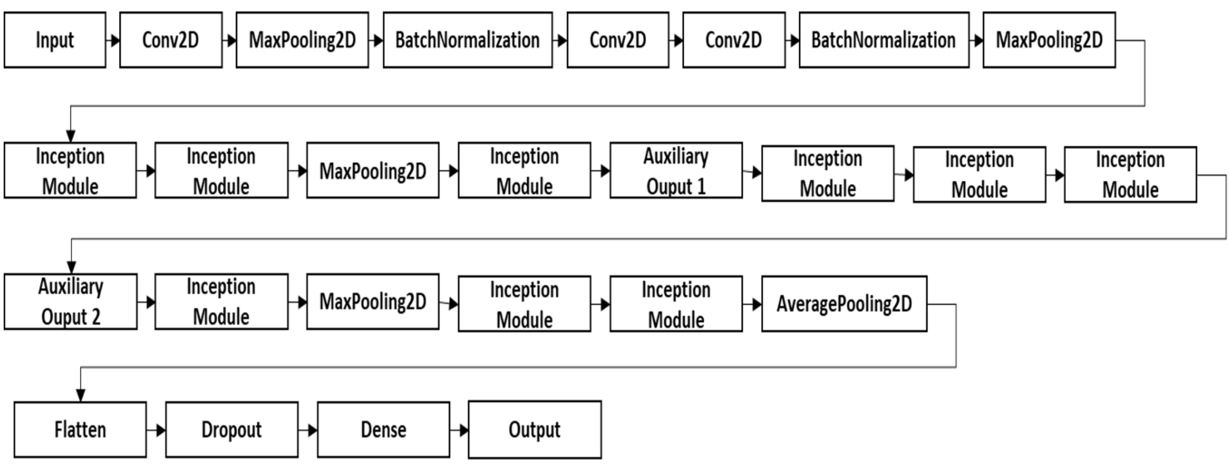

Fig. 3: GoogLeNet model

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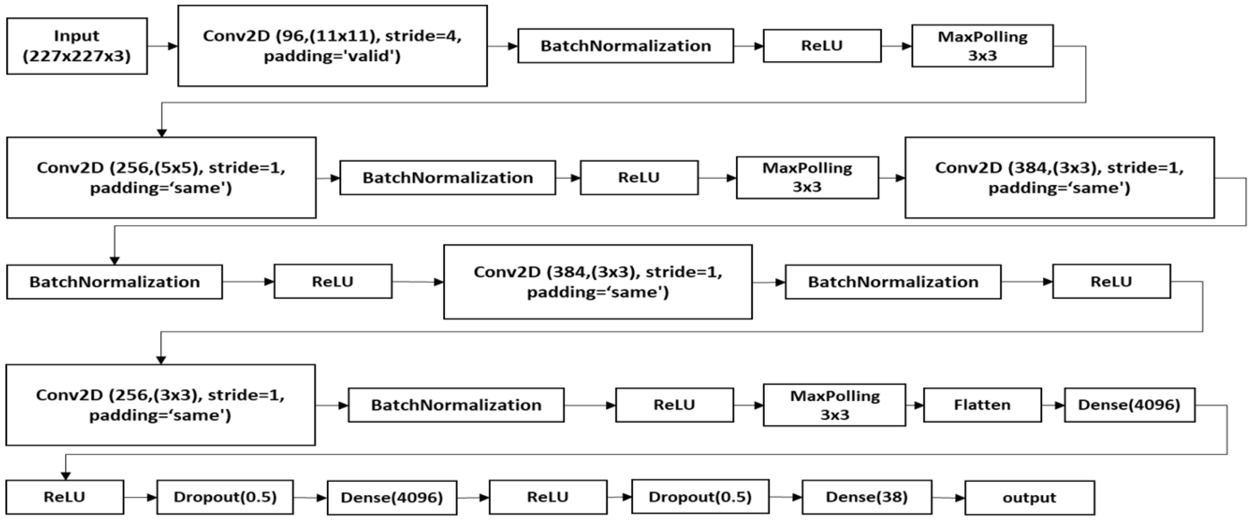

Fig. 4: AlexNet model

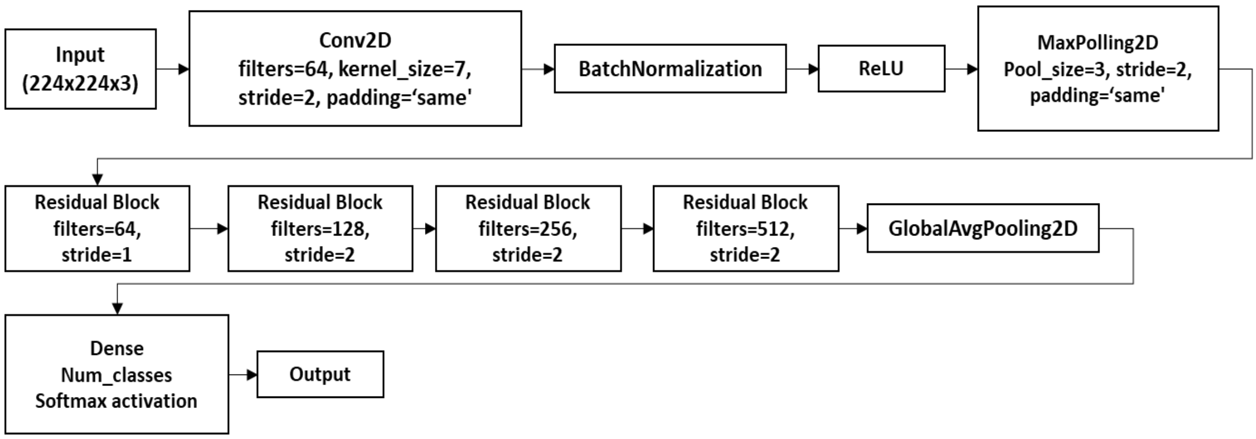

Fig. 5: ResNet50 model

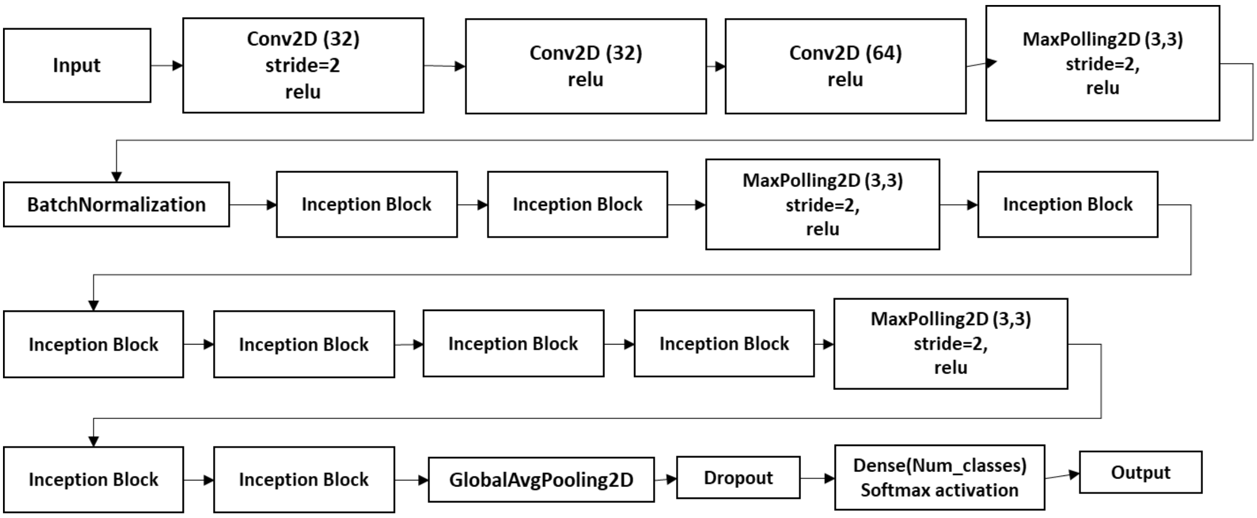

Fig. 6: InceptionV3 model

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To reduce the spatial dimensions of the input image, the stem of the InceptionV3 architecture comprises several convolutional layers and a max pooling layer. In addition, the inception blocks utilize convolutional layers with varying kernel sizes to effectively capture information at multiple scales and resolutions. Each block includes four parallel convolutional branches that are concatenated along the channel dimension. The classifier includes a global average pooling layer, a dropout layer for regularization, and a fully connected layer with softmax activation for classification. The 'inception-block' function is used to define the structure of each inception block. We trained the InceptionV3 model from scratch. In the case of InceptionV3 Transfer Learning, the InceptionV3 architecture has undergone pre-training on the ImageNet dataset.

Results

The study's aim is to predict crop-disease pairs using deep learning. Two learning approaches were used to train the models, training from scratch and using transfer learning. The results suggest that AlexNet, GoogLeNet, ResNet50, and InceptionV3 did well in the task. The evaluation of deep learning models was conducted using two metrics: Accuracy and F1-score. Table 1 displays the number of samples in the training, validation, and test datasets for different train-test ratios. Table 2 compares the performance of four different Convolutional Neural Network (CNN) models, namely AlexNet, GoogLeNet, ResNet50, and InceptionV3, on various train-test splits and different types of image color, grayscale, and segmented.

From Table 2 it can be observed that GoogLeNet architecture achieved the highest accuracy of 0.999 for color images and 0.996 for segmented images, whereas InceptionV3 trained from scratch gave the highest accuracy of 0.994 for grayscale images with a train-test ratio 90:10. All the models trained from scratch achieved the maximum F1-score of 1.0 for color and segmented images whereas, for grayscale images, GoogleNet and InceptionV3 achieved the highest F1-score of 0.999 with train-test ratio 90:10.

Table 3 compares the performance of two different Convolutional Neural Network (CNN) models, namely AlexNet and GoogLeNet on various train-test splits and different types of image color, grayscale, and segmented in the paper by Mohanty *et al*. (2016). Mohanty *et al*. (2016) achieved the highest accuracy of 0.9934 for color images and 0.9925 for segmented images in GoogleNet. In comparison to the results obtained by Mohanty *et al*. (2016), our findings demonstrate a significant improvement. Specifically, we achieved the F1-score of 1.0 with both AlexNet and GoogleNet for color images by training from scratch with an 80:20 train-test ratio, whereas for grayscale and segmented images, both models performed better than that given in Mohanty *et al*. (2016).

Figures 7-9 show the bar graphs for the F1 score of all the models trained from scratch on the three datasets of color, grayscale, and segmented leaf respectively, for all the training-testing ratios.

Table 1: Comparison of DL Train-test ratios and total instances in training, validation, and testing sets

Train-test ratio	Total instances in the training set	Total instances in test set	Total instances in the validation set
90-10	48,880	2,740	2,700
80-20	43,440	5,420	5,460
70-30	38,020	8,160	8,140
60-40	32,600	10,860	10,880

Table 2: Performance comparison of different CNN models on various train-test splits

		AlexNet		GoogLeNet		ResNet50				InceptionV3			
		Learning from scratch		Learning from scratch		Learning from scratch		Transfer learning		Learning from scratch		Transfer learning	
Train-test split %		F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy
90-10	Color	1.000	0.998	1.000	0.999	1.000	0.980	0.999	0.994	1.000	0.997	0.977	0.955
	Grayscale	0.988	0.983	0.999	0.989	0.977	0.958	0.988	0.988	0.999	0.994	0.966	0.958
	segmented	1.000	0.986	1.000	0.996	1.000	0.993	0.988	0.985	1.000	0.996	1.000	0.987
80-20	Color	1.000	0.991	1.000	0.997	1.000	0.994	0.988	0.992	1.000	0.995	0.966	0.957
	Grayscale	0.988	0.983	0.977	0.977	0.966	0.941	0.977	0.982	0.988	0.980	0.944	0.924
	segmented	0.988	0.985	1.000	0.994	1.000	0.985	0.988	0.983	1.000	0.994	0.966	0.943

Table 2: Continue

70-30	Color	0.988	0.989	1.000	0.996	0.966	0.981	0.977	0.990	1.000	0.989	0.955	0.937
	Grayscale	0.988	0.980	0.977	0.977	0.933	0.912	0.977	0.988	0.955	0.978	0.911	0.912
	segmented	0.977	0.975	0.999	0.990	0.977	0.988	0.988	0.979	0.977	0.993	0.944	0.921
60-40	Color	0.969	0.982	0.966	0.975	0.966	0.988	0.977	0.989	1.000	0.985	0.933	0.901
	Grayscale	0.955	0.926	0.966	0.975	0.900	0.894	0.977	0.975	0.944	0.961	0.922	0.905
	segmented	0.966	0.970	0.988	0.988	0.966	0.960	0.988	0.978	0.966	0.981	0.877	0.893

Table 3: Performance comparison of AlexNet learning from scratch and GoogLeNet learning from scratch models on various train-test splits

Learning from scratch		AlexNet		GoogLeNet	
Train-test split %		Based on [16] research paper F1-score	Based on our implementation F1-score	Based on [16] research paper F1-score	Based on our implementation F1-score
80-20	Color	0.9782	1.0000	0.9836	1.0000
	Grayscale	0.9449	0.9888	0.9621	0.9777
	segmented	0.9722	0.9888	0.9824	1.0000
60-40	Color	0.9724	0.9699	0.9824	0.9666
	Grayscale	0.9388	0.9555	0.9547	0.9666
	segmented	0.9595	0.9666	0.9740	0.9888
50-50	Color	0.9644	0.9666	0.9772	1.0000
	Grayscale	0.9312	0.9111	0.9507	0.9444
	segmented	0.9551	0.9666	0.9720	0.9777
40-60	Color	0.9555	0.9000	0.9729	0.9888
	Grayscale	0.9088	0.9444	0.9361	0.9555
	segmented	0.9404	0.9666	0.9643	0.9666
20-80	Color	0.9118	0.8888	0.9430	0.9555
	Grayscale	0.8524	0.8666	0.8828	0.8666
	segmented	0.8945	0.8666	0.9377	0.9777

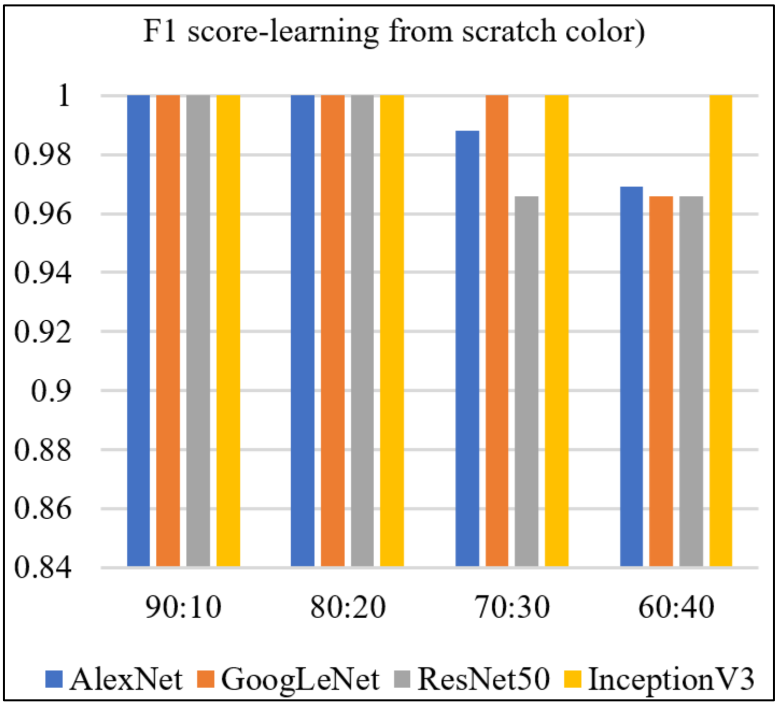

Fig. 7: F1-score of all the models trained from scratch for color images

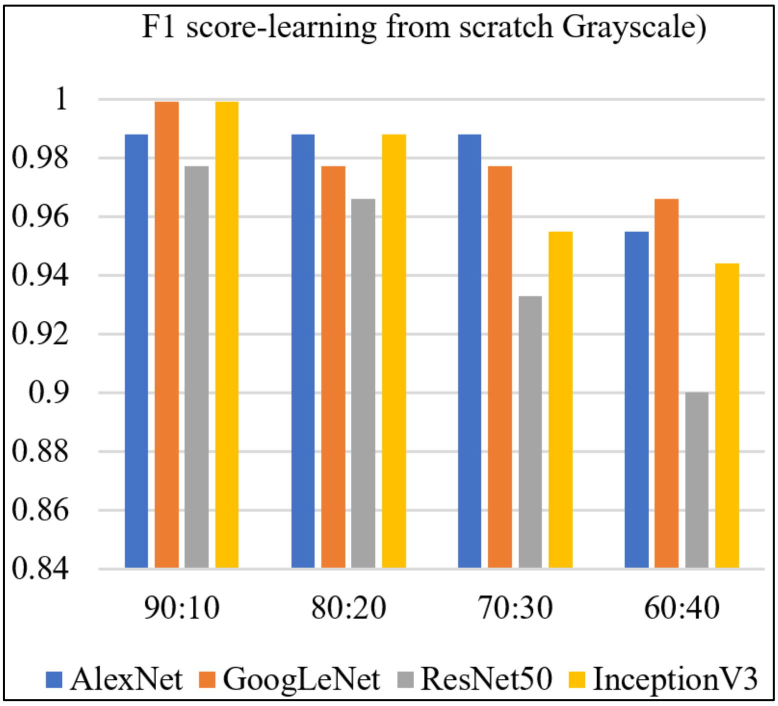

Fig. 8: F1-score of all the models trained from scratch for grayscale images

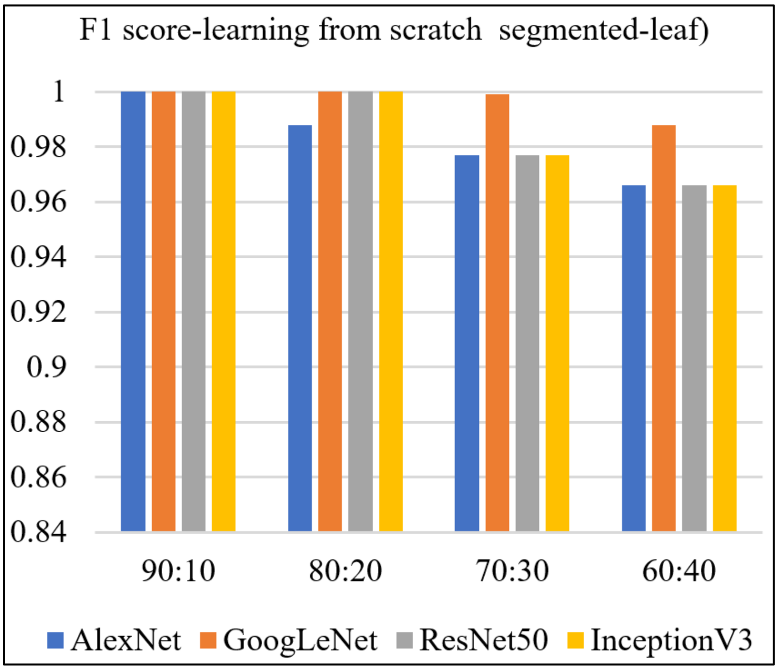

Fig. 9: F1-score of all the models trained from scratch for segmented images

Discussion

Three datasets of color, grayscale and segmented leaves were trained on four different deep learning models AlexNet, GoogleNet, ResNet50 and InceptionV3. ResNet50 and InceptionV3 models were available on pretrained dataset of ImageNet by applying transfer learning to the PlantVillage dataset. Transfer learning was not available for AlexNet and GoogleNet models. All the models were executed from scratch, whereas ResNet50 and InceptionV3 were also implemented using transfer learning. The models were evaluated for accuracy and F1-score. The models were trained using Holdout method by splitting the dataset into training and test sets in different ratios, namely, 90:10, 80:20, 70:30 and 60:40. The test scores were validated for accuracy to ensure overfitting does not occur. The best results were obtained using the 90:10 training-test ratio. The highest F1-score of 1.0 was achieved by all the models by implementing from scratch for color and segmented images of leaves, whereas the highest F1-score of 0.999 was achieved by GoogleNet and InceptionV3 for grayscale images. All models achieved high accuracy for the three categories of images, however, GoogleNet and InceptionV3 gave the highest accuracy. In the case of ResNet50 transfer learning improved the F1-score and accuracy for grayscale images. However, training the models from scratch gave the best performance as compared to transfer learning. This could can be attributed to the very focused images available in PlantVillage dataset for leaves as compared to ImageNet which is a very large image dataset.

Conclusion

Agriculture holds a pivotal role in economic development and addressing food scarcity. Implementing advanced technologies and artificial intelligence is essential for improving agricultural practices and combating crop diseases, which significantly impact agricultural productivity. The research aims to explore Image-based crop disease detection, analyzing various crop diseases, and detection areas and identifying challenges while recommending advanced image detection techniques. In comparison to other research studies, our work offers several notable contributions. Firstly, we trained and evaluated four distinct Deep Learning (DL) models using both learning from scratch and transfer learning approaches. By fine-tuning our trained models on different datasets, we can leverage the knowledge gained from our initial training and adapt it to new domains or specific tasks. This capability opens up possibilities for improving accuracy, robustness, and generalizability across various applications. Deep convolutional neural network architectures AlexNet, GoogLeNet, ResNet50, and InceptionV3 were trained on plant leaf images for crop-disease prediction. The PlantVillage dataset, comprising 54,306 images of 38 classes representing 14 crop species and 26 diseases, demonstrated an impressive top F1-score of 1.0 by integrating location and time information into image classification tasks. The deep learning models achieved remarkable performance in learning from scratch, with GoogleNet emerging as the best performer among the architectures. In transfer learning, ResNet50 outperformed InceptionV3. The study showcases the potential of these deep learning techniques for accurately detecting crop diseases through crop images, offering high accuracy and F1 scores. These findings pave the way for implementing effective crop disease detection systems to enhance agricultural sustainability.

Limitations

The research encountered certain limitations stemming from constraints in hardware resources and data availability, as well as the need for more advanced Deep Learning (DL) models. Firstly, the limited hardware resources posed a challenge in terms of computational power and processing capabilities. The absence of high-performance computing infrastructure restricted the complexity and scale of the DL models that could be implemented. Consequently, the potential for exploring larger and more intricate models was constrained. Secondly, the availability and quality of the dataset proved to be a limiting factor. The research relied on a specific dataset, which might have had limitations in terms of size, diversity, or representativeness. The restricted dataset might have constrained the overall performance and generalizability of the DL models employed. Additionally, the rapid advancements in DL techniques and architectures necessitated further exploration of more advanced models. Understanding these limitations helps in interpreting the findings appropriately and provides valuable insights for future research endeavors.

Future Work

For future research, it is recommended to use larger datasets with more images to further evaluate the performance of CNN models. Additionally, more computationally powerful deep learning architectures could be explored to potentially improve classification accuracy. These improvements can contribute to the development of more accurate and efficient crop disease detection. With ongoing technological advancements, it is conceivable that future image classification tasks could incorporate location and time data alongside the image data obtained from smartphones. By incorporating this additional information, it may be possible to further enhance the accuracy and reliability of crop disease detection. Based on the findings of such research, a smartphone-assisted crop disease diagnosis system could be developed. Such a system has the potential to significantly benefit the agricultural industry by providing a cost-effective and easily accessible solution for crop disease detection and prevention. It is suggested that the information, which is taken for the experimental setup, can be improved and large data sets can be analyzed for the improvement of the result accuracy.

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Author's Contributions

Kinjal Vijaybhai Deputy: Conceptualization, methodology, validation, software, formal analysis, investigation, resources, data curation, written originally drafted preparation and visualization.

Kalpdrum Passi: Conceptualization, methodology, validation written reviewed, and edited supervision project administration and funding acquisition.

Chakresh Kumar Jain: Conceptualization, methodology, validation written reviewed, and edited supervision project administration and funding acquisition.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and that no ethical issues are involved.

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