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(059)

Monitoring Virtual Classroom In E-learning Environment Using Artificial Intelligence

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Content:

1. Introduction:

Plant diseases represent a significant threat to global food security, with annual agricultural yield losses reaching up to 40% due to infestations[1]. Effective plant health management and early disease detection are crucial for minimizing these losses and promoting sustainable agricultural practices[2]. Successful disease infection relies on three key factors: a suitable host, a favorable environment, and the presence of pathogens such as fungi, bacteria, or viruses[3]. Despite significant advances in plant disease detection through deep learning techniques, most research has predominantly focused on identifying diseases specific to individual plant species. This leaves a gap in addressing common diseases that affect multiple species. To fill this gap, our project aims to develop a comprehensive system capable of detecting some of common diseases impacting two or more plant species, thereby providing a broader and more disease-focused solution to enhance crop protection and improve agricultural productivity.

2. Literature review:

Literature review:	plant detect disease			
Project name	Automatic and Reliable Leaf Disease Detection Using Deep Learning Techniques(SOA)[4]	A novel deep learning method for detection and classification of plant diseases[5]	Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern[6]	Barley disease recognition using deep neural networks.[7]
Aim of the project	DETECT THE TOMETO LEAF DISEASES	DETECT THE Pepper leaf, Potato leaf,Tomato leaf .DISEASES	DETECT THE TOMETO LEAF,Apple leaf,Grape leaf DISEASE	DETECT THE BERLEY Diseases
Dataset	Plant Village tomato leaf images	PlantVillage dataset	Plant Village Dataset	Barley DISEASES datasets
models	EfficientNet	DenseNet-77	deep features + LBP(Local Binary Pattern)	MobileNet
Performance	Accuracy:99.89 /F1-score:99.4	Accuracy:99.98 2	Accuracy:96.50 -98.80	Accuurcy:8 6.95/f-score:86.9 7
Year	20/5/2021	28/9/2021	23/6/2023	2024

After reviewing previous studies, we decided to build a project aimed at detecting common diseases that affect multiple plant species, addressing the gap in current research that often f54ocuses on specific plants and diseases unique to those plants. By targeting diseases that impact two or more plant species, our approach expands the scope of plant disease detection, offering a broader and more disease-focused solution compared to previous research.

3.0 Status of the Art (SOA) in Deep Learning Implementation Relevant Models:

3.1. Relevant Models:

3.1.1. Describe the models in detail, including their architecture and methodologies:

EfficientNet is a convolutional neural network built upon a concept called "compound scaling." This concept addresses the longstanding trade-off between model size, accuracy, and computational efficiency.

EfficientNet uses Mobile Inverted Bottleneck (MBConv) layers, which are a combination of depth-wise separable convolutions and inverted residual blocks. Additionally, the model architecture uses the Squeeze-and-Excitation (SE) optimization to further enhance the model's performance.

EfficientNet Architecture. Source

The MBConv layer is a fundamental building block of the EfficientNet architecture. It is inspired by the inverted residual blocks from MobileNetV2 but with some modifications.

The MBConv layer starts with a depth-wise convolution, followed by a point-wise convolution (1x1 convolution) that expands the number of channels, and finally, another 1x1 convolution that reduces the channels back to the original number. This bottleneck design allows the model to learn efficiently while maintaining a high degree of representational power [8].

Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels $\hat{C}_i$	#Layers $\hat{L}_i$
1	Conv3x3	224×224	32	1
2	MBConv1, k3x3	112×112	16	1
3	MBConv6, k3x3	112×112	24	2
4	MBConv6, k5x5	56×56	40	2
5	MBConv6, k3x3	28×28	80	3
6	MBConv6, k5x5	14×14	112	3
7	MBConv6, k5x5	14×14	192	4
8	MBConv6, k3x3	7×7	320	1
9	Conv1x1 & Pooling & FC	7×7	1280	1

Figure3

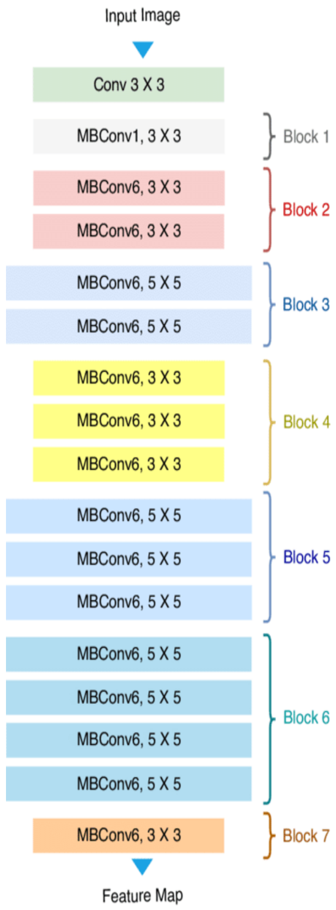

*Figure3.**2***

3.1.2. Highlight their strengths and limitation:

3.1.2.1. Strengths:

it has demonstrated state-of-the-art performance across a wide range of computer vision tasks, including image classification, object detection, and semantic segmentation.
EfficientNet has the potential to significantly reduce the computational resources required for training and running machine learning models. By creating a more efficient model architecture, EfficientNet could make developing and deploying machine learning models easier and more cost-effective.
Flexibility The model. becuse the EfficientNet family offers different versions (EfficientNet-B0 to EfficientNet-B7), allowing users to choose models based on the trade-off between performance and computational resources.

3.1.2.2. Limitations:

One of the main limitations of EfficientNet is that it requires many computational resources to train. While the computational requirements are much lower than previous state-of-the-art models, they are still significant, EfficientNet is also limited to computer vision tasks and may not apply to other domains. while the Neural Architecture Search technique used to develop EfficientNet is highly effective, it can be time-consuming and computationally expensive to achieve state-of-the-art performance on a wide range of benchmarks while reducing computational requirements.

3.2. Applicability to Your Project:

3.2.1. Explain how the models reviewed in the literature relate to your project:

We can adopt the EfficientNet model, especially the EfficientNet-B0 version, because the advanced versions of the EfficientNet model need more space and are expensive. In this research, they used the EfficientNet-B0 version to build the rest of the versions on it to reduce the cost and effort.

4. Dataset

4.1. Dataset Description:

We are using an Images dataset that contain images of different plants disease, and we labeled it with in the following classes:

- Downy Mildew
- Powdery Mildew
- Blight
- Rust
- Healthy

We collect the data from multiple datasets (New Plant Diseases Dataset, Wheat Leaf dataset, cotton leaf disease dataset, Sunflower Fruits and Leaves Dataset, Lettuce Diseases, Coffee plant disease, Watermelon Disease Recognition Dataset, Pumpkin Leaf Diseases Dataset, Mango Leaf Disease Dataset)the links in the reference[9].

	Down Mildew		Powdery_Mildew		blight		rust		healthy		
	train	valid	train	valid	train	valid	train	valid	train	valid	total image of plant
lettuce	24	6							1848	437	2315
watermelon	304	76							164	41	585
sunflower	96	26							107	27	256
pumpkin	320	80							320	80	800
cherry			1683	421					1826	456	4386
pampkin			320	80					320	80	800
lettuce			14	4					1848	437	2303
mango			400	100					400	100	1000
tomato			1004	252					3051	481	4788
corn					915	231			1162	465	2773
coton					358	90			340	86	874
grape					1722	430			1692	423	4267
potato E					1939	485			1824	456	4704
potato L					1939	485			1824	456	4704
tomato E					1920	480			3051	481	5932
tomato L					1851	463			3051	481	5846
apple							1760	440	2008	502	4710
wheat							166	42	81	21	310
corn							1907	477	1162	465	4011
coffee							325	82	428	107	942
total image disease	744	188	3421	857	10644	2664	4158	1041	26507	6082	56306

Common dataset plant disease table *Figure3.**2***

4.2. Dataset Relevance

4.2.1. Explain why this dataset is suitable for your problem.

We believe this data is highly suitable for our project because we collected it ourselves following a specific standard, focusing on commonly occurring diseases that affect two or more plant species. Additionally, we ensured the quality of the images selected from other data sources.

4.2.2. **Highlight any challenges in collecting, curating, or accessing the dataset**

we had a challenge in data imbalance because when we collect from New Plant Diseases Dataset the average image is between 3051 to 1722 and other data are les then five hundred.

5. Baseline Model

5.1. Proposal of Baseline Model Selection:

We will use the EfficientNet-B0 model, because it can recognize images with better accuracy and lower costs compared to other models. If we want to expand in the future to newer versions of EfficientNet, we can use EfficientNet-B0 as they did in the SOA.

6. Conclusion

6.1. Accomplishments:

Choosing the idea and presenting it.
Choosing research and extracting benefits from it.
Collecting data from different data sources.
Choosing the model and models that we will compare it wit.

6.2. Major challenges or issues:

Our devices cannot handle training data.
When comparing with other models, there is a possibility of a better. model than the one we chose.
Overfitting, due to data bias.
Lack of time to implement the project.

6.3. Overview of next steps:

Improving the model if the accuracy is weak.
Comparison with other models.
Preparing and submitting the final report.

7. Reverence

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Wheat Leaf dataset(https://www.kaggle.com/datasets/olyadgetch/wheat-leaf-dataset),

cotton leaf disease dataset(https://www.kaggle.com/datasets/seroshkarim/cotton-leaf-disease-dataset),

Sunflower Fruits and Leaves Dataset (https://www.kaggle.com/datasets/noamaanabdulazeem/sunflower-fruits-and-leaves-dataset),

Lettuce Diseases (https://www.kaggle.com/datasets/ashishjstar/lettuce-diseases),

Coffee plant disease (https://www.kaggle.com/datasets/coffeedisease/coffee-plant-disease),

Watermelon Disease Recognition Dataset

(https://www.kaggle.com/datasets/sujaykapadnis/watermelon-disease-recognition-dataset),
Pumpkin Leaf Diseases Dataset
(https://www.kaggle.com/datasets/tahmidmir/pumpkin-leaf-diseases-dataset-from-bangladesh),
Mango Leaf Disease Dataset
(https://www.kaggle.com/datasets/aryashah2k/mango-leaf-disease-dataset))