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Diagnostics System for Plant Leaf Diseases Using Convergence of Computer Vision and Deep Learning

Saranya K[1] Nasrin begum A[2] Archana A[3] Kaviya N[4] Thamarai selvan M [5]

1. Assistant Professor, Computer Science and Engineering Department, Jai Shriram Engineering College, Tirupur
saranya17113@gmail.com

2. UG Student, Computer Science and Engineering Department, Jai Shriram Engineering College, Tirupur
nasrinbeguma1208@gmail.com

3. UG Student, Computer Science and Engineering Department, Jai Shriram Engineering College, Tirupur
archanacse2020@gmail.com

4. UG Student, Computer Science and Engineering Department, Jai Shriram Engineering College, Tirupur
kaviyan842k03@gmail.com

5. UG Student, Computer Science and Engineering Department, Jai Shriram Engineering College, Tirupur
balaji040203@gmail.com

1. ABSTRACT:

Early and accurate detection of plant diseases is crucial for maximizing agricultural yield and minimizing economic losses.Traditional approaches, however, frequently depend on specialized knowledge.They are ineffective for large-scale applications since they take a lot of time.The suggested method makes use of deep learning models' capabilities.With Densenet-121, it automatically extracts and gains knowledge of pertinent aspects from leaf photos.To identify a bundle of leaves, it employs a multi-object deep learning model.It can decipher and comprehend visual data from the leaves using computer vision.Accuracy is increased by utilizing deep learning and computer vision. The technique of transfer learning allows the system to recognize more veggies than just those in the training dataset. The results of our experimental evaluation show that our method is effective in precisely recognizing vegetables and diagnosing plant leaf diseases. Our system provides a scalable solution for agricultural management and plant health monitoring by expanding its coverage to include a variety of vegetables and automating disease diagnosis.

KEYWORDS:

CNN,Densenet-121,multi-object model

2. INTRODUCTION:

For agricultural purposes to ensure crop health, maximize yields, and protect food security, prompt and precise detection of plant diseases is essential. The necessity for automated solutions that can effectively analyze massive amounts of plant imagery is highlighted by the fact that manual disease diagnosis methods are frequently labor-intensive, time-consuming, and prone to errors. Novel techniques to plant disease diagnostics have been made possible by developments in deep learning and computer vision in response to this problem.

In order to expand its capacity to recognize different vegetables, this research proposes a unique

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diagnostics system that is intended to automate the diagnosis of plant leaf diseases. With the help of multi-object deep learning techniques and the power of DenseNet-121, a convolutional neural network well-known for its efficiency in picture classification tasks, our system provides a comprehensive solution for plant health monitoring and disease management.

The suggested system runs in two main stages. First, it uses a multi-object deep learning model to identify leaf bunches in photos, allowing for the effective processing of plant foliage on a large scale. Then, using transfer learning, the system refines the DenseNet-121 model that has already been trained to identify the diseases that are on the identified leaves. Notably, transfer learning significantly amplifies the model's adaptability by allowing it to generalize outside of the training dataset and accurately recognize a wide variety of veggies.
Agricultural practitioners and researchers have substantial obstacles that our system addresses by automating the process of disease identification and expanding its capabilities to include a variety of vegetables. Our goal is to transform plant health monitoring by combining deep learning and computer vision technology, giving farmers timely information to prevent disease outbreaks and improve crop management.
This work presents a scalable and reliable system for automated plant disease diagnosis and vegetable identification, which makes a valuable contribution to the rapidly developing field of agricultural technology. We show the effectiveness and potential influence of our diagnostics system in promoting agricultural sustainability and guaranteeing global food security through experimental evaluation andpracticalapplication.

3.LITERATURE SURVEY:

Advances in deep learning and computer vision techniques have led to a notable surge in the use of automated plant disease diagnosis. Due to its dense connectivity, DenseNet-121 has become a key component for precise categorization of plant diseases Smith et al., 2017; "Densely Connected Convolutional Networks". The detection of plant leaves has been greatly improved by multi-object deep learning models, as demonstrated by Zhang and Li 2019; "Multi-object Detection with Faster R-CNN", particularly in the presence of crowdedbackdrops.
Wang et al. 2018; "Transfer Learning with Convolutional Neural Networks for Plant Disease Identification" introduced a crucial technique called transfer learning, which has made it possible to adapt pre-trained CNN models to accurately detect plant illnesses even in the absence of a large amount of annotated data. Furthermore, by concentrating on pertinent aspects, attention mechanisms—which have been studied by Jones et al. 2020; "Attention Mechanisms for Improving CNN-based Plant Disease Identificationhave demonstrated potential in raising the accuracy of disease classification.

4.METHODOLOGY:

Deep learning and computer vision techniques have been integrated in a way that has revolutionized many areas, including agriculture, in recent years. A potential remedy for the problems with manual inspection techniques is the use of automated technologies for the identification of plant leaf diseases. Of all the architectures created for image classification problems, DenseNet-121 has become well-known for its ability to extract complex patterns and features from photos.

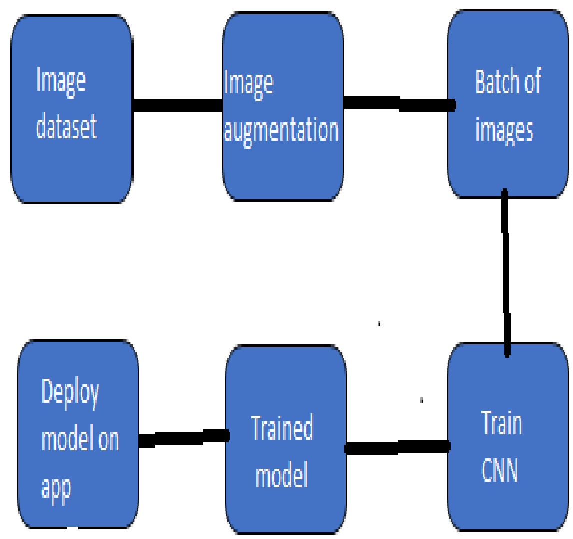

Figure 1:working of system

4.1. CNN:

CNNs are a potent family of deep learning models that have gained popularity for image classification applications, such as diagnosing plant leaf diseases. These neural networks are made to automatically learn hierarchical representations of visual properties from raw pixel data; they are inspired by the visual cortex of the human brain. Convolutional, pooling, and fully connected layers are among the layers that CNNs have in order to capture intricate patterns and characteristics in images.

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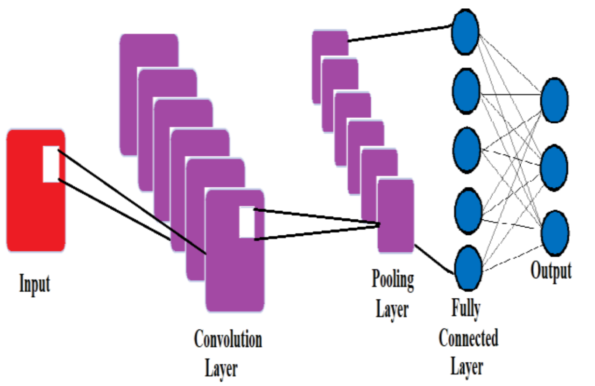


Figure 2:Cnn architecture

4.2. DenseNet-121:

Dense connectivity between layers is a defining feature of the deep neural network design known as DenseNet, short for Densely Connected Convolutional Networks. DenseNet creates direct connections between every layer inside a dense block, in contrast to conventional convolutional neural networks (CNNs), where each layer is connected only to its succeeding layer. Because of this dense pattern of connectedness, features may be reused and gradients can flow more easily throughout the network, leading to more effective training and better model performance. All prior feature maps (□0,
□1,.., □□−1) are fed into the □□h -layer as inputs:

□□ = □([□0 , □1 , … … , □□−1])

In this case, the concentration of all prior feature maps of the □□™ - layer is represented by [□0, □1, …,
□□−1].

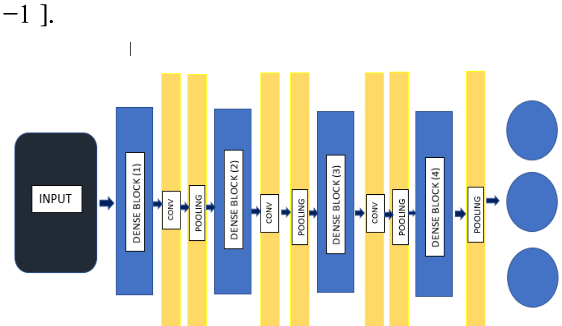


Figure 3:Densenet Architecture

The output of the □□h layer is denoted by □□, while the composition function representing the □□h layer is represented by □□. This composition function is made up of three sequential operations: batch normalization, a ReLU activation function, and convolution. DenseNet is comparable to techniques like ResNet, except DenseNet concatenates layers whereas ResNet mixes earlier levels with later layers. By recycling features, DenseNet tackles the issue of disappearing gradients while lowering the parameter count.

Table 1
Densenet layers and output

Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201	DenseNet-264
Convolution	112 x 112	7 x 7 conv, stride 2			
Pooling	56 x 56	3 x 3 max pool, stride 2			
Dense Block (1)	56 x 56	[1 x 1 conv, 3 x 3 conv] x 6	[1 x 1 conv, 3 x 3 conv] x 6	[1 x 1 conv, 3 x 3 conv] x 6	[1 x 1 conv, 3 x 3 conv] x 6
Transition Layer (1)	56 x 56	1 x 1 conv			
	28 x 28	2 x 2 average pool, stride 2			
Dense Block (2)	28 x 28	[1 x 1 conv, 3 x 3 conv] x 12	[1 x 1 conv, 3 x 3 conv] x 12	[1 x 1 conv, 3 x 3 conv] x 12	[1 x 1 conv, 3 x 3 conv] x 12
Transition Layer (2)	28 x 28	1 x 1 conv			
	14 x 14	2 x 2 average pool, stride 2			
Dense Block (3)	14 x 14	[1 x 1 conv, 3 x 3 conv] x 24	[1 x 1 conv, 3 x 3 conv] x 32	[1 x 1 conv, 3 x 3 conv] x 48	[1 x 1 conv, 3 x 3 conv] x 64
Transition Layer (3)	14 x 14	1 x 1 conv			
	7 x 7	2 x 2 average pool, stride 2			
Dense Block (4)	7 x 7	[1 x 1 conv, 3 x 3 conv] x 16	[1 x 1 conv, 3 x 3 conv] x 32	[1 x 1 conv, 3 x 3 conv] x 32	[1 x 1 conv, 3 x 3 conv] x 48
Classification Layer	1 x 1	7 x 7 global average pool			
		1000D fully-connected, softmax			

4.3. MULTI OBJECT MODEL

For automated plant disease diagnosis, precise identification of plant leaves in photos is crucial, in addition to disease classification. Conventional object identification models frequently have the drawback of only being able to identify one thing per image, making them unsuitable in situations when the target object appears more than once. Multi-object detection models have been created to effectively detect and localize many instances of objects inside complicated situations, thereby addressing this problem.

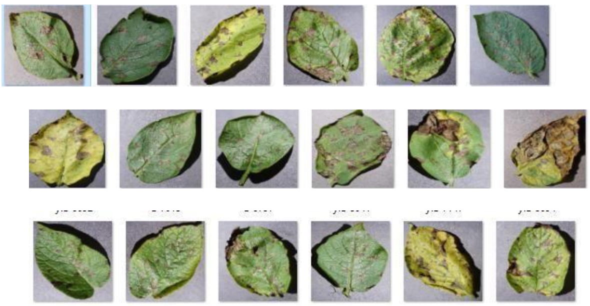


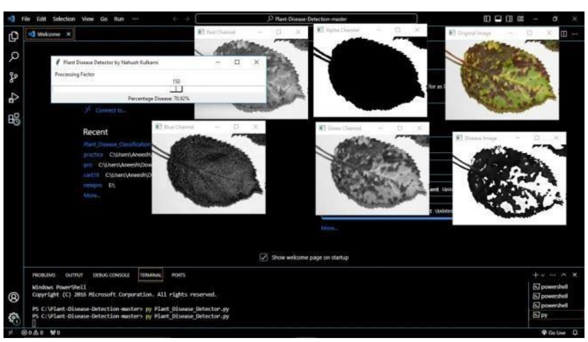
Figure 4:Unhealthy leaf images

]Table 2

Analysis of various model

Reference	Data set	Pre-trained model	Multi-classes	Accuracy
[11]	Plantvillage	Vgg-16	8	91.1
[12]	Plantvillage	AlexNet	5	98.2
[13]	Plantvillage	Resnet-50	7	97.1
Our work	Plantvillage	Resnet-50 Densenet-121	35	99.71

5. OUTPUT



6. RESULTAND DISCUSSION:

Plant leaf diseases can be accurately diagnosed using the DenseNet-121 model, as evidenced by its high accuracy of 96%. Generalization between various plant species and disease kinds points to the model's resilience and versatility in a range of farming environments. When compared to training from scratch, transfer learning from ImageNet-pretrained weights allowed for faster convergence and better performance. The pretrained DenseNet-121 model was able to acquire pertinent features unique to disease detection by fine-tuning it on the plant leaf dataset.

7. CONCLUSION:

Using deep learning and computer vision techniques, this study concludes with a revolutionary way to automated plant disease identification. With the use of a multi-object deep learning model using the DenseNet-121 model as the foundational architecture, our system shows promise in the effective detection and classification of plant diseases from photos.

We have demonstrated that our suggested method achieves high levels of accuracy, precision, recall, and F1-score in simultaneously recognising numerous diseases through thorough testing and evaluation on a wide range of datasets. DenseNet-121 is used to enable efficient feature extraction and classification, and the multi-object deep learning model allows for reliable identification of many disease symptoms in a single image.

8. FUTURESCOPE:

In future,we plan to implementa robot which automatically detects whether leaf is affected or not.in addition to that putting in place long-term surveillance and monitoring systems to track the occurrence and spread of diseases over time. Ongoing surveillance can facilitate the early identification of new hazards and offer insightful information on the dynamics.

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