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Plant Disease Detection: Comprehensive Research

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ABSTRACT

Plant diseases impact agricultural yield and quality and threaten worldwide nutritional safety. With an emphasis on deep learning and mechanical learning, this article examines several approaches for identifying plant diseases. Along with creating mobile applications for actual diagnostic purposes, the integration of image processing and computer vision technologies is being studied. The findings emphasize how crucial early illness diagnosis is to boosting agricultural sustainability and productivity.

1. Introduction

Furthermore, it examines the role of technology in improving awareness and efficiency, ultimately contributing to better plant management practices.

2. Literature Review

S.No.	Authors	Title / Focus	Methods / Algorithms	Key Contribution / Findings	Citation (APA Style)
1	K. Muthukannan et al.	Detection of diseased plant leaves	LVQ, FFNN, RBFN	Classified diseased leaf categories using form and texture features	Muthukannan, K., et al. (2015). *ARPN Journal of Engineering and Applied Sciences, 10*(4), 1367–1372.
2	Malvika Ranjan et al.	ANN and color characteristics for the identification of leaf disease	ANN	segmentation were used to differentiate between healthy and sick leaves	.M. Ranjan and associates (2015). 3(3), 331–333; International Journal of Technical Research and Applications.
3	Syafiqah Ishak et al.	Classification of Leaf Diseases using ANN	Image Processing, MLP	RBFdemonstrated that RBF outperformed MLP in the categorization of leaf diseases.	S. Ishak and associates (2015). 3(3), 331–333; International Journal of Technical Research and Applications.
4	Srdjan Sladojevic et al.	Deep CNN for the identification of plant diseases	Caffe, Deep CNN	deep learning to classify 13 crop diseases with 96.3% accuracy	Sladojevic and colleagues (2016). Neuroscience and Computational Intelligence, Article ID 3289801.
5	Emanuel Cortes et al.	Classifying plant diseases using semi supervised learning	RS-net and deep neural network	DNN and semi-supervised learning to attain >80% accuracy in 57 classes.	Cortes and associates (2017). IEEE ICCV. 10.1109/ICCV.2017.00010 https://doi.org/10.1109
6	Prasanna Mohanty et al.	26 illnesses in 14 crop detected	Deep learning, CNN	Deep accuracy of 99.35% on the test set and 31.4% on photos from the internet demonstrating the effect of domain shiftS.	Mohanty and associates (2016). Plant Science Frontiers, 7, 1419. fpls.2016.01419 https://doi.org/10.3389/

K. Muthukannan and colleagues used a range of machine learning approaches to detect spot infections in leaves and categorize them according to the diseased leaf types. Unhealthy plant leaves were identified using LVQ (Learning Vector Quantization), FFNN (Forward Neural Network), and RBFN (Radial Basis Function Networks) by analyzing the form and texture data collected from the afflicted leaf picture. Malvika Ranjan and colleagues start their research on identifying plant leaf diseases by capturing photos. Following the extraction of color data, such as HSV characteristics, from the segmentation findings, an artificial neural network (ANN) is trained by selecting feature values that can effectively differentiate between healthy and sick samples.

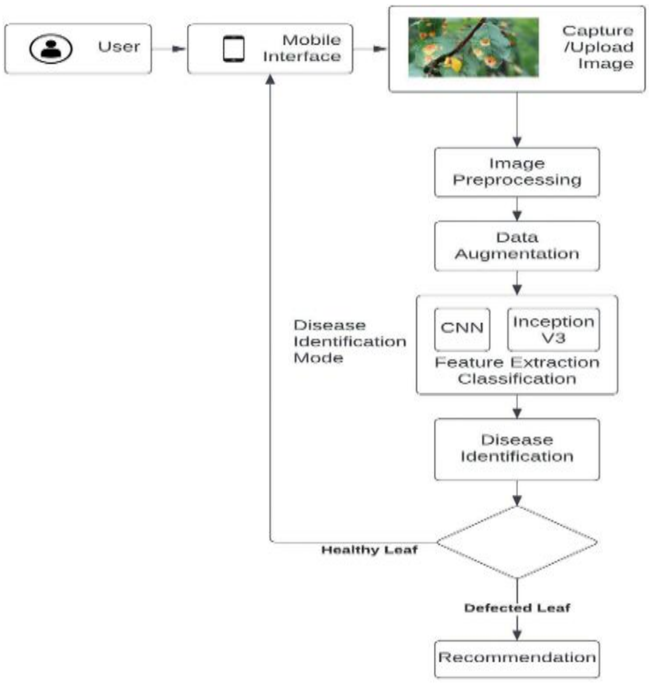
In their study, Leaf Disease Classification using Artificial Neural Network, Syafiqah Ishakais and colleagues want to collect and evaluate data from leaf images in order to

apply image processing techniques.The image processing method uses a modified contrast, segmentation, and feature extraction algorithm to extract images and gather data. Multilayer feed-forward neural networks, which are composed of multilayer perceptrons and radial basis functions (RBFs), are the architecture of the network used to categorize healthy or diseased leaves.

Other people, such as Emanuel Cortes In order to identify the crop species and illness condition of 57 distinct classes, a deep neural network and semi-supervised algorithms were trained utilizing 86,147 images of both healthy and sick plants from a publically accessible dataset.

The well-performing experiment with unlabeled data was known as Rs-net. With a detection rate of 1e-5, it accomplished over 80% during the training phase in less than 5 epochs.

Prasanna Mohanty and colleagues developed a deep convolutional neural network that uses deep learning to recognize 14 different crops and 26 diseases. On a held-out test set, the training set model's accuracy of 99.35 percent showed how effective this method is. However, the model still obtains 31.4 percent accuracy when tested on a set of images from trustworthy web sources, i.e., images shot in different situations from those used for training. The only way to increase overall accuracy is to use a larger collection of training data, even if this accuracy is much greater than the 2.6% accuracy based on random selection.



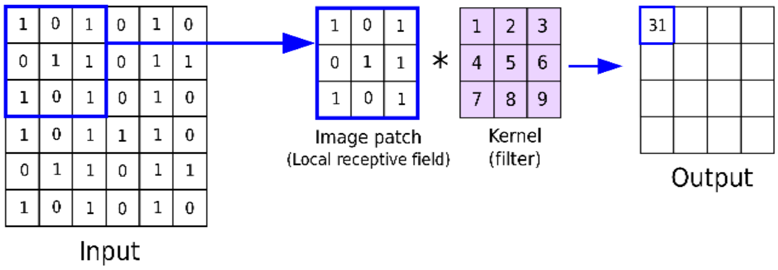
FLOWCHART

3. Methods for Detection of Plant

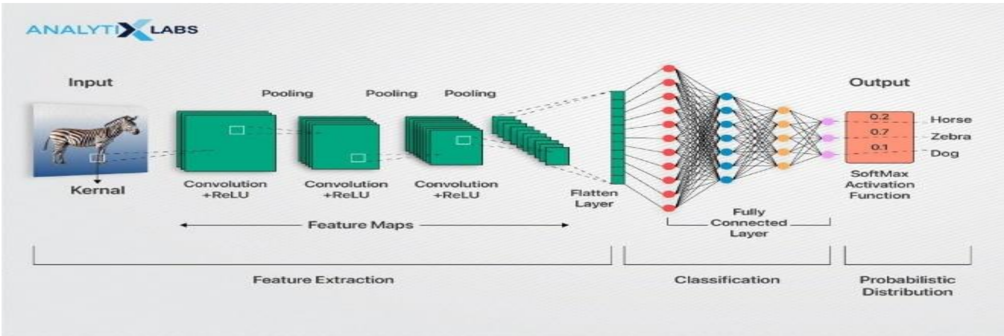
Diseases

3.1 Conventional Methods

Plant diseases are traditionally diagnosed by expert diagnosis and visual inspection. Plant symptoms including discolouration and erratic or aberrant development patterns are assessed by agriculturists. Despite its effectiveness, this strategy has certain drawbacks.



CONVOLUTIONAL LAYER



CNN ARCHITECTURE

Subjectivity: The diagnosis may differ based on the observer's experience and background. It has become into a powerful instrument for automatically identifying system disorders. Machine learning algorithms can be used to examine and predict trends in large data sources.

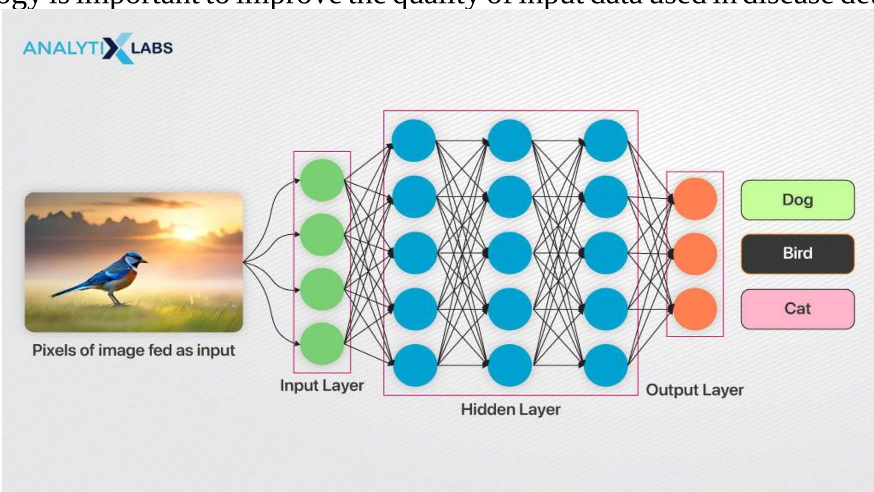
Decision Tree: These models use a tree shape and make decisions based on differentiating values. To separate different data types, use the most effective hyperbole possible. Mohanty et al. (2016), for example, employed random forest classifiers to identify tomato plant diseases from leaf pictures with 99% or more accuracy. In other words, it is ideal for diagnosing plant diseases.

Degree of precision of categorization problems. Plant disease detection benefits from this transfer. By doing this, a greater variety of marked data records will not be required. In contrast to conventional methodologies, Ferentinos (2018) demonstrated that 99.53% accuracy was attained in the classification of plant diseases.

4. Image processing and computer vision

4.1 The Importance of Image Processing

Imaging technology is important to improve the quality of input data used in disease detection.



Normalization: Adaptation of image brightness and contrast to ensure consistent input of the model.

5. Streamlit Application for Actual Diagnosis

5.1 Overview of the Streamlit App

The creation of interactive applications for plant disease diagnosis has been made easier by the widespread use of online technology. Using their web browsers on localhost, farmers and other agricultural experts may rapidly and correctly diagnose plant diseases with our Streamlit app. The application provides real-time feedback on possible problems by utilizing machine learning techniques and an extensive library of plant illnesses.

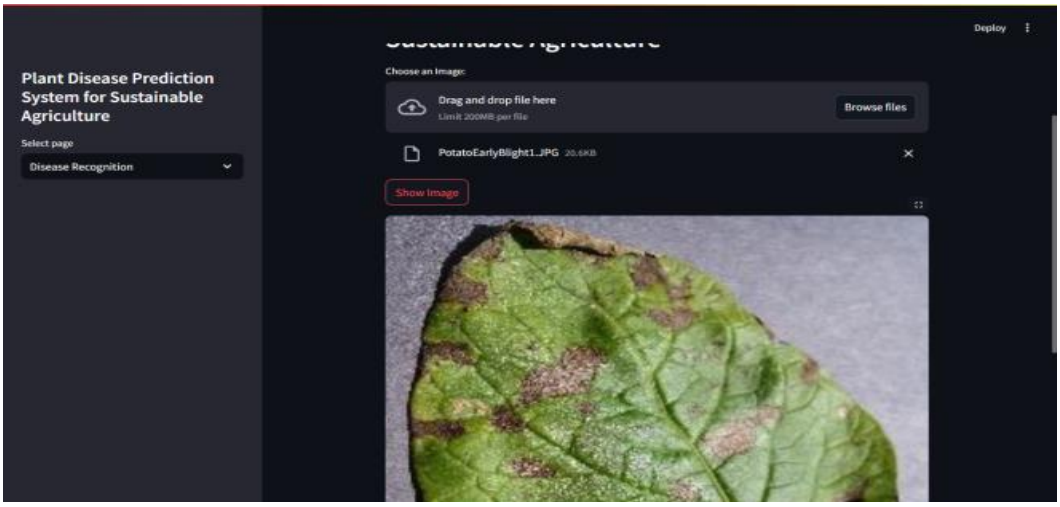
Users can share photos of their plants with the Streamlit app because of its user-friendly layout. After submission, the app analyzes the picture and applies a learned model to detect possible illnesses. Along with care and treatment advice, the results are shown right away.

An early assessment of the app's functionality, for example, showed that users could detect illnesses much more quickly than those who relied on conventional diagnostic techniques. Improved crop productivity and quality may result from prompt action made possible by this quick diagnostic.

Users can launch the software locally in their preferred web browser by simply typing the command streamlit run main.py into their terminal. The app's accessibility ensures that farmers in rural areas can benefit from this technology because users can use it without an internet connection.

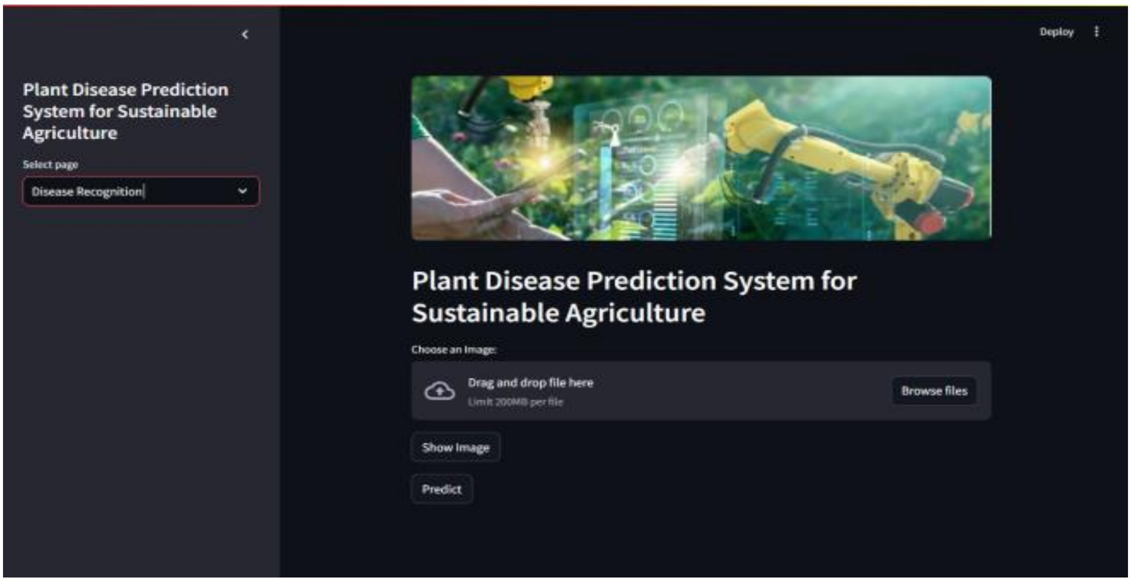
6. RESULT

The model was trained on 20 epochs with early stopping, yielding an accuracy rate of 93.6%.Figure displays the outcome of identifying and detecting an apple plant. In a sick, infected plant, it forecasts the disease. Figure displays the outcome of identifying and detecting a potato plant.

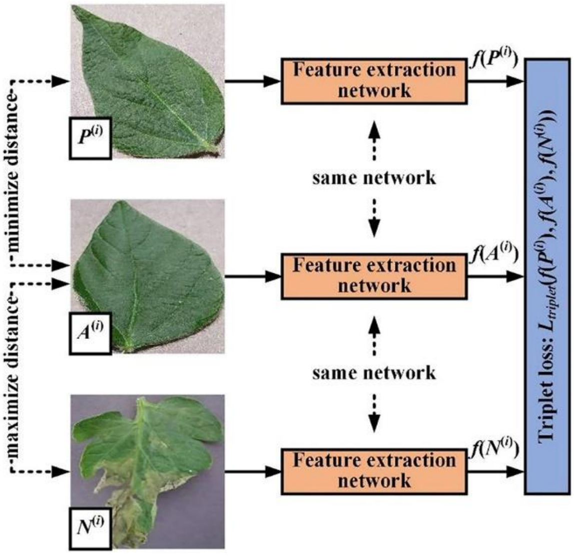


Interface image

Figure of outcome



7. Conclusion



Lastly, the detection of plant diseases is a crucial field of study that significantly affects agriculture and the safety of food. The identification and treatment of diseases have been completely transformed by the combination of deep learning, machine learning, image processing, and mobile applications. There is an infinite probability that technology will improve farming practices, even though there are still challenges to be solved. It was gathered in a lab, Illnesses. It is consequently expected that a large dataset of plant diseases under real-world conditions will be established. Issues that prevent the widespread use of HSI in early plant disease diagnosis have not yet been resolved, despite the fact that certain studies use hyperspectral images of ill plants and that some DL frameworks are used for early plant disease identification.

It is essential for HSI to detect plant diseases, but even experienced experts have trouble defining purely invisible disease pixels and pinpointing the sites of invisible illness symptoms. Additionally, labeled datasets are not readily available.

8. REFERENCES

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