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A Comprehensive Survey on the Revolution of Plant Disease Detection and Diagnosis through Automated Image Processing Techniques with CNN and RNN.

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Abstract

Plant disease detection and diagnosis is a critical task in agriculture, as it enables early identification of plant diseases and helps in minimizing crop damage. In recent years, automated image processing techniques with convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have revolutionized plant disease detection and diagnosis. This comprehensive survey aims to provide an overview of the recent advancements in the field of automated plant disease detection and diagnosis through image processing techniques with CNNs and RNNs. Firstly, the survey discusses the key challenges faced in plant disease detection and diagnosis, such as the complex nature of plant diseases and the lack of availability of expert knowledge in certain areas. It then explores the role of automated image processing techniques in overcoming these challenges, by enabling accurate and efficient detection and diagnosis of plant diseases. The survey then delves into the various stages involved in the process of automated plant disease detection and diagnosis, including image acquisition, pre-processing, feature extraction, and classification. It discusses the various types of CNN architectures used for plant disease detection, such as AlexNet, VGGNet, ResNet, InceptionNet, and DenseNet, and their respective advantages and limitations. The survey also covers the role of RNNs in plant disease detection, particularly in the area of time-series data analysis, where RNNs have proven to be effective in predicting the spread of plant diseases over time. In addition, the survey provides an overview of the various publicly available datasets for plant disease detection, such as Plant Village, PhytoPath, and Tomato-Plant-Disease. Furthermore, the survey explores the various applications of automated plant disease detection and diagnosis, such as in precision agriculture, plant breeding, and disease management. It also discusses the future directions in the field, such as the integration of multiple modalities of data, such as hyper spectral and thermal data, and the development of more robust and interpretable models

***Keywords*:** Supervised learning, convolutional neural networks (CNN), recurrent neural networks (RNN), deep

Learning methods

1. Introduction

Anyone who has ever planted a garden knows not only the rewards of beautiful flowers, fruit, and/or vegetables, but also the disappointment when plants become diseased or damaged. Many factors cause plants to exhibit poor Vigor, changes in appearance, or even death. Both biotic (non-living) and biotic (living) factors can negatively impact plant health. Disorders that result from non-living factors (such as nutrient deficiencies, over/under watering, temperature stress, and chemical damage) are discussed in subsequent chapters [6][7][8]. This chapter focuses on those living organisms that cause disease: fungi, water Molds, bacteria, viruses, nematodes, phytoplasmas, and parasitic plants.

Despite the great success of this approach for document retrieval, the textual annotation of images has shown its inability to satisfy the need for information on the actual content of images, so itis a long, cumbersome, expensive, and repetitive task for the human, especially with the bases ofimages which become today bigger and bigger. In addition, the keyword indexing technique haslimitations and enormous disadvantages; the images do not carry semantics directly accessible tothe machine as the case of textual documents. It is always necessary to insert keywords manually to index images. Moreover, it is often impossible to make a description of a rich and subjectivecontent conveyed by the images because the results of the queries depend on the set of availablekeywords, human subjectivity, and of linguistic, cultural, and religious constraints. In Thus, faced with huge and dynamic image databases like those presented on the World Wide Web, this annotation approachis clearly impossible.

Deep learning (DL) techniques have revolutionized various fields, including plant disease detection and diagnosis. ML and DL models have been successfully applied to identify and classify plant diseases, providing farmers and researchers with valuable tools for timely and accurate disease deduction. Plant diseases pose a significant threat to agricultural productivity and food security. Traditional methods of disease diagnosis relied on visual inspection by experts, which could be time-consuming, subjective, and prone to errors. ML and DL algorithms have overcome these limitations by enabling automated and efficient disease deduction.

- The approach used.
- The problem presented.
- The datasets used.
- The performance achieved.
- Limitations of the study, if any.

2. RELATED WORKS

In the context of convolutional neural networks (CNNs), "related work" refers to the existing research and literature that has been conducted on the topic of CNNs. This includes academic papers, articles, and projects that explore various aspects of CNNs, their applications, and improvements. Related work is crucial in the research process as it helps researchers to build upon existing knowledge, identify gaps in the current understanding, and contribute new insights to the field. Here are some common areas of related work in CNN research:

Table 1: Comparative Analysis

Author & year	Dataset	Algorithm Used	Result and Accuracy
Ji M,Zhang L, Wu Q, 2020[18]	Automatic Grape Leaf Diseases From Open Access Repository	United Model (CNN)	99.17%

Jana, S,A. Rijuvana Begum, and S. Selvaganesan, 2020[19]	Design And Analysis Of Pepper Leaf	ANN	91.95%
Negi A, Kumar K, Chauhan P, 2021[21]	Healthy And Diseased Plant Leaves Classification	Disease Detection in Plants Using CNN Mode	96.02%
Reddy TV,Rekha KS, 2021[22]	Deep leaf disease prediction framework (DLDPF)	Cascade Inception based Deep CNN with Transfer Learning (CIDCNN-TL)	97.62%
Memon , **Kumar, P. and Iqbal, R,** 2022[23]	Cotton Leaf Disease	floating point operations (FLOPs) of each model	98.53%
Krishnan VG,DeepaJR,Rao PV, Divya V, Kaviarasan S, 2022 [24]	Photographs of Bananas in CIAT's Image Library	CNN method achieved	93.45%
MoussafirM,Chaibi H, Saadane R, Chehri A, Rharras AE, JeonG, 2022[25]	Tomato Disease	Genetic algorithm	98.1 %

Plant disease detection is the process of identifying and diagnosing plant diseases. Plant disease detection methods include visual inspection, laboratory testing, and the use of technology such as sensors and artificial intelligence. Collecting samples from the afflicted plant and analyzing them in a controlled environment is what laboratory testing entails [25]. Techniques such as pathogen culture, DNA analysis, and microscopic investigation can assist in identifying the specific disease-causing agent. Plant disease detection methods based on technology are becoming more popular. Sensors can be put in the field to monitor and detect environmental variables.

3. RESEARCH METHODOLOGY

Our research is carried out in the following sections. Each step is implemented precisely with the visualization of its state. In this section; we analyze the effect of each model hyperparameter in the convolutional part of a CNN and propose a method to build efficient architectures. Using the visualization techniques presented above, we can understand how each hyperparameter impacts the efficiency of the CNN and how it should be tweaked in the presence of desynchronization.

3.1 Supervised learning

Supervised learning refers to the problem space wherein the target to be predicted is clearly labelled within the data that is used for training. In this section, we introduce at a high-level two of the most popular supervised learning architectures, CNN and RNN as well as some of their variants [9].

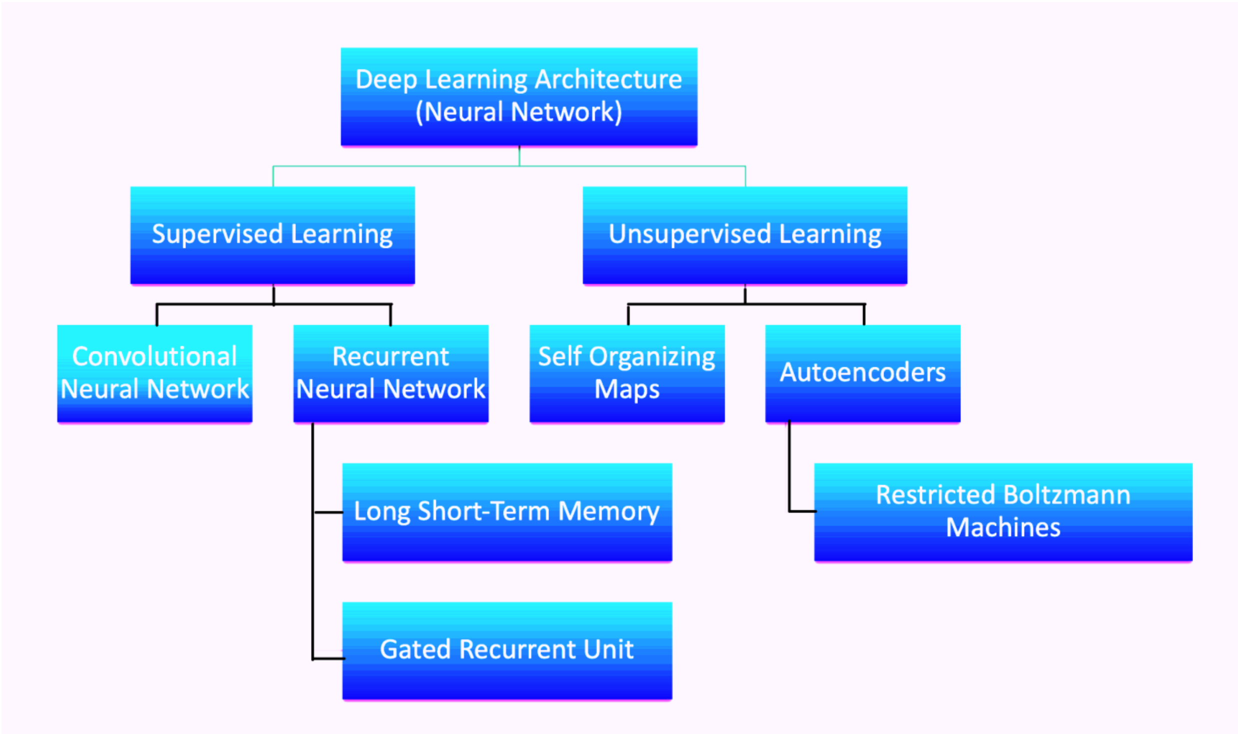

Figure 1: Deep Learning Architecture

3.1.1 Convolutional Neural Networks (CNN):

Convolutional Neural Networks (CNNs) are a type of deep learning model designed for processing structured grid-like data, such as images or time series. They are widely used in various computer vision tasks, including image classification, object detection, and image segmentation. The key idea behind CNNs is to exploit the spatial structure of the input data by using convolutional layers. A convolutional layer consists of a set of learnable filters, also known as kernels, that slide across the input data and perform element-wise multiplications and summations to produce feature maps. These feature maps capture local patterns or features present in the input.

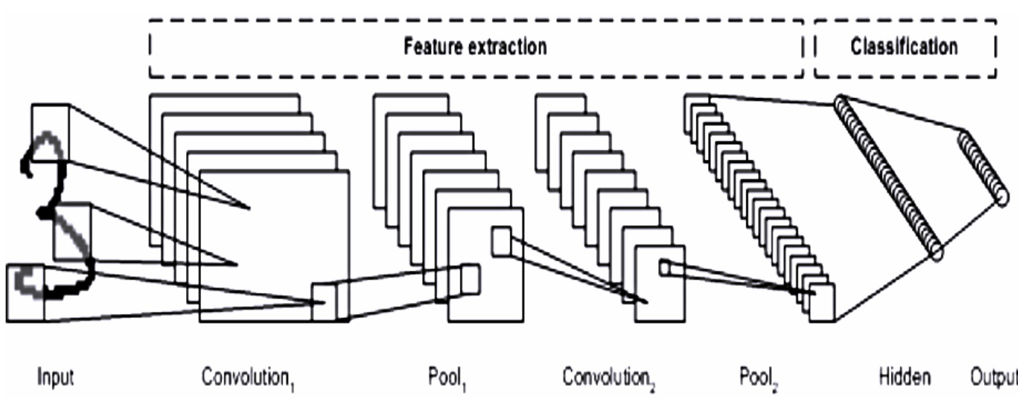

Figure 2:Convolution Neural Networks

The final layers of a CNN are usually fully connected layers, which take the output of the convolutional layers, flatten it, and feed it into traditional neural network architecture for classification or regression. The fully connected layers capture global relationships and make predictions based on the extracted features. Training a CNN involves forward propagation, where the input data passes through the layers to generate predictions, and backward propagation, where the model's parameters are adjusted using an optimization algorithm (e.g., gradient descent) to minimize a loss function (e.g., cross-entropy) based on the training data. This process is repeated iteratively until the model converges to optimal weights.

3.1.2 Recurrent Neural Networks (RNN):

The RNN is one of the foundational network architectures from which other deep learning architectures are built [17]. The primary difference between a typical multilayer network and a recurrent network is that rather than completely feed-forward connections, a recurrent network might have connections that feed back into prior layers (or into the same layer). This feedback allows RNNs to maintain memory of past inputs and model problems in time [4].RNNs consist of a rich set of architectures (we'll look at one popular topology called LSTM next). The key differentiator is feedback within the network, which could manifest itself from a hidden layer, the output layer, or some combination thereof [3].

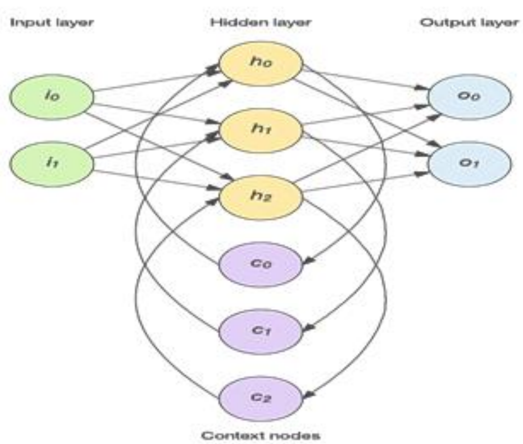

Figure 3: Long Short-Term Memory

Long short-term memory (LSTM)is a type of artificial neural network that are designed to handle sequential data by incorporating feedback connections. They are particularly well-suited for tasks that involve processing sequences, such as natural language processing, speech recognition, machine translation, and time series analysis.

Examining how CNN performs is an essential aspect of this study. As a result, we reviewed and analyzed several relevant studies [21][22]. We also compared CNN to other current technologies and summarized the most important advantages and disadvantages that affect CNN's performance [12]. It should be noted that the current paper focuses on comparing techniques used for the same data and on the same scale. We also investigated and discussed the most significant problems and limitations identified by previous research. Agriculture is a major industry and foundation of the economy in several countries [25]. However, multiple factors such as population growth, climate change, and food safety concerns have propelled researchers to seek more innovative techniques for the protection and improvement of crops [10][11].It's important to note that the choice of dataset and the specific architecture and configuration of the CNN or RNN models can vary depending on the task at hand.

4. Discussion

From the Table1given above the values of the correct result are given as follows accuracy, the performance of GoogLeNet, VGGNet, DenseNet and ResNet is similar and all inferior to United Model accuracy obtained High.

- The overall United Model (CNN) accuracy obtained is 99.17% in Error of 0.83%. Hence Automatic Grape Leaf Diseases fromOpen Access Repository can be recognized easily with higher precision and accuracy.

- The overallCNN method achieved accuracy obtained is Low 1accuracy 93.45% in Error of 7.55%. Hence Photographs of Bananas in CIAT's Image Library from Open Access Repository can be recognized easily with higher precision and accuracy.

Table 2: Model and Accuracy

Model	Accuracy
United Model (CNN)	99.17%
Floating point operations (FLOPs) of each model	98.53%
Genetic algorithm	98.1 %
Cascade Inception based Deep CNN withTransfer Learning (CIDCNN-TL)	97.62%
Disease Detection in Plants Using CNN Mode	96.02%
CNN method achieved	93.45%

The combination of United Model (CNN)algorithms has resulted in more robust and powerful illness detection and diagnostic systems. This study has focused more on United Model (CNN)methods in Deep learning. Future researchers can perform a content analysis of specific areas of Deep learning such as supervised learning, video analytics, text analytics, classification, and prediction.

5. Conclusion

Finally, this comprehensive analysis provides a thorough summary of recent advances in automated plant disease identification and diagnosis using image-processing approaches based on CNNs and RNNs. It outlines the field's significant difficulties and prospects, as well as a road map for future study in this area. This comprehensive assessment seeks to give academics, practitioners, and stakeholders in the field of plant pathology a clear grasp of how automated image processing techniques such as CNN and RNN have revolutionized plant disease detection and diagnosis. It examines the current state-of-the-art, problems, and future development potential, paving the way for enhanced agricultural practices and sustainable crop management. We investigated the revolution in plant disease identification and diagnosis by automated image analysis in this comprehensive assessment.

Traditional plant disease detection methods depended mainly on manual examination and visual assessment, which are time-consuming, subjective, and frequently error-prone. The incorporation of automated image processing techniques, particularly CNN and RNN, has overcome these constraints and transformed the discipline. CNN models have excelled in analysing plant photos, capturing subtle patterns, and distinguishing healthy plants from unhealthy plants. The use of transfer learning and pre-trained models has sped up the creation of robust and accurate disease detection systems. RNN models, on the other hand, have demonstrated their effectiveness in analysing sequential data, such as time-series images, for illness progression monitoring and prediction. The combination of United Model (CNN)algorithms has resulted in more robust and powerful illness detection and diagnostic systems.

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