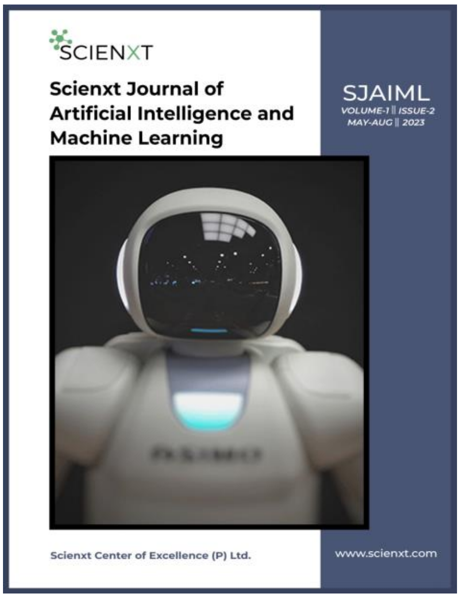

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Smart agriculture: Plant disease detection using deep learning survey

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Abstract:

Deep Learning Models (DLMs) may now be effectively used to produce smart agriculture by pinpointing the disease affected leaf on farms. Convolutional neural networks (CNNs) have consistently outperformed previous technologies in a variety of fields, including agriculture. The primary challenge in computer vision is thought to be semantic picture segmentation. Despite significant advancements in practical, nearly all meaningful picture enhancement algorithms are unable to produce adequate solution due to a lack of details sensitivity, issues determining the same matching, or a combination of the two. The majority of post-processing enhancement techniques rely on Conditional Random Fields, which are a superb vital tool for addressing the fundamental issues with the methods listed above. Identification of plant diseases is therefore important a crucial way in the early detection and illness to lessen its impacts forecast for diseases research objectives in the context. In order to assign disease sections in leaf crops, this study provides an effective approach for identifying plant diseases utilizing meaningful segmentation techniques assessing this network and contrasting it. The findings of the experiment and their comparisons declare regarding disease.

Keywords:

Processing, Random Fields, Detection, Identification, Forecasting.

1. Introduction:

Crops are constantly at risk from a wide range of biotic variables, including dryness, salinity, heat, and other biotic factors. The Third Green Revolution, often known as "Smart Farming," is the process of integrating contemporary Technologies of information and communication (ICT) [3]. This Revolution, which follows transforming agriculture, relying on the combined application solutions. [1] To aid in early disease discovery and increase productivity, numerous standard approaches are performed. [2] These practises seriously damage human health by causing environmental pollution and crop contamination.[5] Artificial intelligence has been used in various attempts to peoples accurately identify affected area and the advent of modern technologies. In order for self-driving cars to function, deep learning algorithms must be able to recognise and learn from the images that are provided to them as raw input. Earlier applications required the identification of fundamental features. Even yet, it wasn't until the invention of meaningful that it became possible to grasp an image at the pixel level [5]. It brings together visual elements that are related to the same subject. The computer vision problem of semantic segmentation entails pictures and converting it into a mask with a highlighted area of interest [9]. Many people refer to this process as semantic segmentation of the entire pixel in which every pixel in a picture has a specific a categorization based on the object of interest to which It's appropriate there. Semantic segmentation, which groups images combined that relate to the same object of interest, overcomes this challenge by identifying what is present in the image and where (by finding all pixels that correspond to it[6]). Prior to now, computer vision issues could only identify features like edges (lines and curves) or gradients; they never really offered a comprehension of images at the pixel level [7]. The researcher uses post-processing techniques such to some extent in the putting the semantic image fragmentation algorithm (CRF) into practise. It combines the structured modelling capabilities the CRF together with the strength of CNN component extraction to improve retail outcomes and produce masks that are more pleasing to the eye [8]. In order to effectively show how to identify and recover leaf boundaries. Illnesses in plants, the suggested work studies disease diagnosis using deep learning, CRF, and semantic segmentation.

With the aid of a portable mobile phone, image processing, and CNN-based Transfer Learning Models, a recognition system that can aid in the creation of a new low-cost smart system for use in smart agriculture applications in the context of global smart cities is being developed [8].

CNN (Conventional Neural Network): Artificial neural networks (ANNs) of the convolutional form are frequently employed to evaluate visual images. CNNs, often referred to as Shift Invariant or Space Invariant Artificial Neural Networks, are constructed using shared-weight convolution kernels or filters that slide along input features to produce feature maps (SIANN), which are translation-equivariant outputs[7]. They could be used for video and image recognition, recommender systems, image classification, segmentation, and image analysis for medical uses. The classification of images, financial time series, brain-computer interfaces, natural language processing, and financial time series are further applications that can be made use of using them. By altering multilayer perceptron's, CNNs are produced [7]. Multilayer perceptron's, another name for fully connected networks, are constructed by connecting every neuron in one layer to every other neuron in the network.

These networks are susceptible to data overfitting because of their "full connectivity."

Semantic segmentation method:

The practise of grouping together parts of an image that are typical of the same item class is known as semantic segmentation, also known as picture segmentation. Due to the categorization of every pixel in a picture, it is a type of pixel- level prediction [3]. For this task, benchmarks including Cityscapes, PASCAL VOC, and ADE20K are used. The Mean Intersection-Over-Union (Mean IoU) and Pixel Accuracy measures are frequently used to assess mod [2].

1.1. SegNet:

SegNet is a semantic segmentation model that employs a pixel-by-pixel classification layer and an encoder- decoder architecture [2]. It consists of a matching decoder network that up samples the low-resolution encoder feature maps for pixel-wise classification to full input resolution feature maps, and 13 convolutional layers in the encoder network that have the same structure as the VGG16 network. The way Seg Net handles up sampling in the decoder network is one of its distinctive characteristics [1]. Seg Net achieves non-linear up sampling by max-pooling indices from the respective encoder feature maps, as opposed to straightforward interpolation techniques or learnable up sampling layers [2]. In order to achieve effective semantic segmentation, it is essential to preserve the spatial information.

2. Related Work:

Table.1: Research articles referred

Reference	Title	Year	Finding	Author
(2)	Using deep learning to recognize plant leaves locally	2018	Method for localizing leaves using wide-angle photos taken on-site with a performance of 78.0%.	Erika Fujita, Katsumasa Suwa, and Huu Quan Cap
(3)	Leaf Classificationfor Plant Recognition with Deep Transfer Learning	2018	Traditional feature-based methods to deep learning accuracy of 99.6% and 90.54%	M onu Bhagat & Dilip Kumar
(6)	Deep Learning for Disease Recognition and Plant Leaf Detection	2019	Plant varieties of the apple, corn, grapes, potatoes, sugarcane and tomatoes in particular. 96.5 percent accuracy.	Bobby D. Gerardo, Nanette V. Dionisio, and Sammy V. Militante
(8)	Exploratory Data Analysis and Machine Learning-Based Soil Sensors-Based	2020	Fungal diseases. Average accuracy hasbeen found more than 98%.	Vinay S. Palaparthy, Manish Kumar, and Ahlad Kumar

	Plant Disease Prediction System			
(4)	An Index for Efficiently Detecting Wheat Fusarium Using Sentinel-2 Multispectral Imagery	2020	Best in monitoring FHB severity. Accuracy was up to 78.6%.	Wenjiang Huang, Xiaoping Du, Linyi Liu, and Yingying Dong.
(1)	Deep LearningUsing GANs to Augment Data for Citrus Disease Severity Detection	2020	Huanglongbing (HLB)-infected leaf images accuracy of 92.60%.	Xinhui Ma, Baoping Cheng, Qingmao Zeng, Erxun Zhou, and Wei Pang
(12)	A Framework for Phenotypic Feature Extraction from Multiview Stereo Plant Point Clouds and Leaf Segmentation	2020	For each individual leaf, phenotypic features such leaf area, length, width, and inclination angle are calculated and compared with ground truth accuracy of 96.8% and 97.8%.	Guoliang Shi, Sifan Wang, Weijian Kong, Dawei Li, and Yang Chen
(9)	Utilising a Deep Neural Network Model, Automatic	2021	The system proposedfor only citrus fruit and lead disease and its	Muhammad Usama Asghar, Ulfat Batool, Muhammad Zubair

	Disease Detection of Citrus Fruit and Leaves		average accuracy percent is 94.55%.	Asghar, Asad Khattak;
(5)	With Stepwise Transfer Learning, Efficient Convolutional Neural Networks Detect Plant in Unbalanced Datasets	2021	Stem, leaf, pulp but ontransfer learning and ithas achieved the accuracy of 99%	Dongil Han, Mobeen Ahmad, Muhammad Abdullah, Hyeonjoon Moon,
(11)	Cardamom PlantDisease DetectionApproach Using EfficientNetV2	2021	Plant infections have a terrible accuracy of 98.26% and might result in extremely high loss or no harvest.	Jaidhar C. D., Nagamma Patil, and Sunil C. K.
(6)	Classification of Corn Leaf Disease Using an End-to-End Deep Learning Model	2022	ResNet152 and InceptionV3, which have accuracy rates of 98.37% and 96.26%, respectively, are used in the model.	Hassan Amin, Mona Soliman, Aboul Ella Hassanien, and Ashraf Darwish
(10)	A Deep Learning-Based	2022	Only kiwifruit, apple, pear,	Khalid Mahmood Arif, Johan

	Plant Disease Detection Approach for Horticultural Crops with Performance Optimization		avocado, and grapevine are likely to be successful with it. Discovered to be 93.80%.	Potgieter, and Muhammad Hammad Saleem

3. Significance of Methods:

3.1. CNN Advantages:

- Exceptionally high accuracy for picture recognition issues.
- Detects key traits automatically, without human intervention.

3.2. CRF Advantages:

- Numerous studies demonstrate that CRF performs the NER task better than MEMM and HMM. Because of this, Stanford NER is built using CRF.
- If you select the appropriate characteristics, you can achieve high-quality labelling (for NER tasks, for example).
- In terms of feature selection, CRF is sufficiently flexible. Furthermore, conditional independence of characteristics is not required.

3.3. SegNet Advantages:

- Improved boundary delineation
- Less number of parameters
- Each encoder in SegNet contains a subsampling stage, typically achieved through max-pooling. This reduces the feature map size and increases the receptive field of each pixel, allowing it to capture a larger context from the input image.
- Subsampling is also useful for achieving translation invariance, which means the model can recognize the same object regardless of its position in the image.

3.4. Discussion and Challenges:

The accuracy is usually the largest issue since the symptoms of the majority of the illnesses are quite similar to one another. There are many researchers and universities working on this plant diseases detection.

4. Conclusion:

This study uses semantic segmentation techniques, such as SegNet, to propose an effective method for locating plant diseases. The medicinal use of such plants and potential treatments for those diseases are future research topics. Overall findings point to the potential application of semantic segmentation of leaf disease using deep learning identify particular diseased leaf crop portions and prevent a loss in food output. In the long-term strategy, we want to create the suggested system.

5. References:

(1) Hassan Amin, Ashraf Darwish, Aboul Ella Hassanien, Mona Soliman End-to-End Deep Learning Model for Corn Leaf Disease Classification, pp.31103-31115, 2022. https://ieeexplore.ieee.org/document/9734016

(2) Zhiyan Liu, Rab Nawaz Bashir, Salman Iqbal, Malik Muhammad Ali Shahid, Muhammad Tausif, Internet of Things (IoT) and Machine Learning Model of Plant Disease Prediction, Blister Blight for Tea Plant, pp.44934-44944, 2022. https://ieeexplore.ieee.org/document/9761267

(3) Muhammad Hammad Saleem, Johan Potgieter, Khalid Mahmood Arif. A Performance-Optimized Deep Learning-Based Plant Disease Detection Approach for Horticultural Crops of New Zealand, pp. 89798- 89822, 2022. https://ieeexplore.ieee.org/document/9864587.

(4) Asad Khattak, Muhammad Usama Asghar, Ulfat Batool, Muhammad Zubair Asghar, Automatic Detection of Citrus Fruit and Leaves Diseases Using Deep Neural Network Model, 2021. https://ieeexplore.ieee.org/document/9481921.

(5) Sunil C. K., Jaidhar C. D., Nagamma Patil, Cardamom Plant Disease Detection Approach Using EfficientNetV2, 2021. https://ieeexplore.ieee.org/document/9663367

(6) Mobeen Ahmad, Muhammad Abdullah, Hyeonjoon Moon, Dongil Han, Plant Disease Detection in Imbalanced Datasets Using Efficient Convolutional Neural

Networks with Stepwise Transfer Learning (2021) https://ieeexplore.ieee.org/document/9568965

(7) Qingmao Zeng, Xinhui Ma, Baoping Cheng, Erxun Zhou, Wei Pang, GANs-Based Data Augmentation for Citrus Disease Severity Detection Using Deep Learning, pp.172882-172891, 2020. https://ieeexplore.ieee.org/document/9200543.

(8) Manish Kumar, Ahlad Kumar, Vinay S., Palaparthy, Soil Sensors-Based Prediction System for Plant Diseases Using Exploratory Data Analysis and Machine Learning, 2020. https://ieeexplore.ieee.org/document/9301331.

(9) Dawei Li, Guoliang Shi, Weijian Kong, Sifan Wang, Yang Chen A Leaf Segmentation and Phenotypic Feature Extraction Framework for Multiview StereoPlant Point Clouds (2020 https://ieeexplore.ieee.org/document/9079597/metrics#metrics.

(10) Linyi Liu, Yingying Dong, Wenjiang Huang, Xiaoping Du, A Disease Index for Efficiently Detecting Wheat Fusarium Head Blight Using Sentinel-2 Multispectral Imagery, 2020, https://ieeexplore.ieee.org/document/9034180.

(11) Sammy, V., Militante, Bobby, D., Gerardo, Nanette, V., Dionisio Plant Leaf Detection and Disease Recognition using Deep Learning, 2019. https://ieeexplore.ieee.org/abstract/document/8942686.

(12) Huu Quan Cap, Katsumasa Suwa, Erika Fujita, A Deep Learning Approach for On-Site Plant Leaf Detection, 2018.