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Review Article

The Use of Artificial Neural Networks in Agricultural Plants

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A B S T R A C T

Artificial Neural Networks use high-performance computing and big data technology, opportunities for science to create new opportunities in agriculture. The purpose of writing this article is to analyze the use of artificial neural networks on (a) plant diseases based on plant leaf diseases, (b) plant pests, (c) growth or quality, and (d) agricultural products. The writing method used is a literature study of the research that has been done. The keywords used in the search for references include ANN, plant, diseases, pests, growth or quality, and agricultural products. Publishers for the reference in this article are ScienceDirect and IEEE. The years of publication of the references are restricted from 2015 to 2022. Based on the literature study results, it was concluded that Artificial Neural Networks' deep learning models are accurate for detecting and classifying leaf diseases and pests, detecting growth, and application to agricultural plant products.

INTRODUCTION

Machine learning (ML) technology is a learning technology that is developing yearly, especially in scientific fields, for example, biochemistry [1], [2], meteorology [3], [4], economics [5], [6], Hakuakultur [7], [8], bioinformatics [9], robotics [10], [11], and food security [12], [13].

Machine learning (ML) technology is a learning technology that is developing yearly, especially in scientific fields, for example, biochemistry [14], [15]. Artificial neural networks, through learning with data sets that contain input and produce output, have neurons connected through weighted links [16]. The human brain is the most complex object in the universe, having 100 billion neurons and connected by 100 trillion interconnections. ANN has replaced the principle of calculations performed by biological nerves of brain tissue. Artificial Neural Networks have many disciplines because of their ability to map, model, and classify non-linear processes. It includes image processing, system identification and control, pattern recognition, etc. [17].

Various real complex problems in everyday life can be solved using artificial neural network methods, such as problems in communication networks [18], [19], electricity [20], [21], fuel [22], genetics and environment and as well as plants.

ML has been used to increase agricultural production by analyzing the application of yield prediction, disease detection, crop quality weed detection, and how the farm will benefit from machine learning technologies [23]. Real and complex agricultural problems in everyday life are garden diseases caused by pathogens, which are infectious diseases, and this causes agricultural yields to decrease or disappear [24]. Research has been carried out using artificial neural networks to overcome this problem, such as identifying plant diseases using ANN [25], identification of Barracuda mango plants using an expert team [26], and using DoubleGAN (double generative adversarial network) to identify images of unhealthy plant leaves [27]. Other studies that have also been conducted to address crop problems are regarding cropping or the quality of crops and type of plant [28], and in agriculture, artificial neural networks have been used for farm products such as tomato cooling machines, where ANN is used to regulate the air temperature inside the device so that the quality of the tomatoes remains good [29].

This article aims to analyze the use of artificial neural networks in plants based on plant leaf diseases, plant pests, growth or quality, and agricultural products.

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Table 1. Journal Search Results

Keywords	Results	
	ScienceDirect	IEEE
Artificial neural networks	80	56
Use of artificial neural networks in diseases of plant leaves	23	30
Use of artificial neural networks in plant pests	7	11
Use of artificial neural networks in plant growth or quality	19	16
The use of artificial neural networks in agricultural products		10
	129	123

METHOD

The topic of this paper is about the benefits of artificial neural networks in plants. Where the references used are in accordance with the criteria needed through the media in the network. Data from references is filtered for processing and analysis.

1. Research Journal Search
   Journal searches in this study used data for literature studies from the results of research publications in international Journal. Publisher for the reference in this article is ScienceDirect and IEEE. The year of publication of the references is restricted from 2015 to 2022. The keywords used are artificial neural networks, diseases of plant leaves, plant pests, and growth or quality.

2. Journal Search Results
   Table 1 results of searches that have been carried out, namely 252 articles in journals and proceedings. By applying a filter based on the year of publication, the detailed results of the journal results are found using the publisher's keywords. Reference sources that have been searched for as many as 252 are re-elected, namely based on titles and abstracts to get appropriate references. The title or abstract of the journal having the words "ANN" Plant and "diseases"/"pests"/" growth or quality" is required for the journal to be used as a reference. These requirements leave 118 journals that can be analyzed. Then the remaining journals are selected based on their contents. Appropriate discussion these journals with the aim of this review journal being the next screening requirement. The total journals that will be used as references are 65 journals.

3. Data Processing
   After the data is collected from reference sources, it is then processed. The processed data is about ANN that has been used in agricultural crops. The data is processed by comparing each reference and making a comparison table, by making a comparison table for each reference used. Comparisons are made to distinguish the differences and similarities of the journals used.

4. Data Analysis
   Literature study in data analysis using a combination method (Mix Method). Data analysis was carried out using qualitative data, the qualitative data used is about the use of ANN in agricultural crops. Qualitative data from each reference source used to draw conclusions.

RESULTS AND DISCUSSION

The Use of Artificial Neural Networks in Agricultural Plant Diseases

Deep convolutional neural networks (DCNN) is one of the intelligent systems used to identify and classify biotic (bacterial and fungal diseases) and abiotic (herbicide injuries and nutrient deficiencies) in plants. The results of this model training provide a fast response and accuracy [30], [31]. Convolutional Neural Networks have been used to predict plant diseases by analyzing changes in leaf physiognomy and comparing them with color, shape, structure, etc. The results of this model training provide a fast response and accuracy [32]. Identification of diseases on plant leaves was also carried out using a deep learning model training process [33]. Images of plant leaves are used as input for predictors of plant leaf disease [34], [35]. And input images are stored in the form of a database [36]. Plant disease research using leaf images as ANN input, namely research on disease detection in apple plants, where a training accuracy of 99% has been obtained [37].

Research on detection and classification of plant diseases that also uses leaf images as ANN input is research on tomato plants. Where the results of learning by using 7176 images of tomato leaves obtained 10 diseases on tomato leaves [38]. Images of tomato leaves are also used as input for the Convolutional Neural Network with Learning Vector Quantization algorithm, namely 500 samples, where four diseases have been found on tomato leaves [39], and 3663 images of tomato and apple leaves were also used as input for training using ANN to detect diseases in tomato plants and get an accuracy of 87% [40].

Plant diseases such as cotton plants were detected using a back-propagation type of artificial neural network method. The design of the artificial neural network with 3 layers and 10 neurons 2 outputs is to see if there is disease and no disease in cotton leaves. Samples from cotton leaves are in the form of leaf images where from 18 images obtained 6 types of leaf diseases with different types based on digital image assessment and feature extraction of cotton leaf samples types based on digital image assessment and feature extraction of cotton leaf samples [41]. Research on the detection of maize plant diseases has also used leaf images as Convolutional Neural Network (CNN) input which are processed using the stacking method. Where to use 500 samples of corn leaf images sourced from the Google website and Plant Village as well as the Google website. Disease types found were northern blight, brown spot, round spot, rust, southern leaf blight, dwarf mosaic and gray leaf spot. The results of the CNN model training are processed using the stacking method with an accuracy rate of 98,8% [42].

Table 2. Search Results using Keyword "Artificial Neural Networks" and "Agricultural Plant Diseases"

Crop	Observed	Models	Algorithms Result
Plant	Biotic (bacterial and fungal diseases) and abiotic (herbicide injuries and nutrient deficiencies) in plants	DCNN	A fast response and accuracy
Plant	In leaf physiognomy and comparing them with color, shape, structure	ANN	A fast response and accuracy
Apple	Leaf disease	ANN	99% has been obtained
Tomato	Leaf disease	ANN	7176 images of tomato leaves obtained 10 diseases on tomato leaves
Tomato	Leaf disease	Convolutional Neural Network with Learning Vector Quantization	500 images of tomato leaves obtained 4 diseases on tomato leaves
Tomato	Leaf disease	ANN	99% has been obtained
Cotton	Leaf disease	ANN	From 18 images obtained 6 types of leaf diseases
Maize	Leaf disease	CNN	Accuracy rate of 98,8% is obtained
Coffee	Leaf disease	CNN	obtain high precision

This research was conducted to detect disease on coffee leaves using leaf images as CNN input. Where 150 images of coffee leaves used are provided by experts. The results of training using the CNN Convolutional Neural Network model to identify rust on coffee leaves obtain high precision [43]. Based on the results of journal searches using the keywords artificial neural networks and agricultural plant diseases, the conclusions obtained can be seen in table 2.

The Use of Artificial Neural Networks in Agricultural Plant Pests

DetectNet is one of the most suitable CNN models for digital image-based remote sensing. It has been used for weed detection in strawberry plants. Carolina Geranium (Geranium carolinianum) is a broadleaf weed that is widespread in Florida strawberries. the results of the training data are from 705 sample images, 88 positive images and 109 negative images are obtained [44]. Goosegrass is a weed species that grows on tomato and strawberry plants. To detect goosegrass, CNN has been used with RGB input (YOLOv3-tiny) or multispectral/hyperspectral imagery which was evaluated as a potential detector. This training uses two annotation evaluation techniques, namely leaf blade and whole plant annotations. The results of the training where the leaf blade annotation method showed superior results [45]. CNN is also used to detect pests on strawberry, cherry potato and pepper plants. The CNN architecture uses ResNet-50, VGG-16, ResNet-50, Inception V3 and Alexnet training. The training results provide higher accuracy, the results obtained on grapes are 95.99%, peppers 99%, and potatoes 34%. Inception V3 also with good training results with accuracy between 99.75% for cherry and 99% for strawberry [46].

CNN data collection is done using open source, where the data consists of various types of plant leaves and pests from plants. The training was carried out with 14,810 input images taken and 400 images for testing. Due to different lighting conditions, low accuracy is obtained [47], [48]. . CNN can be used to detect the location of weeds growing on cereal plants, namely the parts covered with leaves. The CNN model used is the grouping and full convolutional neural network model. Full convolutional neural network training evaluates errors to predict pest locations. This system uses ImageNet to initialize the weights, and the training success rate is 86%, out of 876 samples 406 weeds are detected. [49]. CNN data collection is done using open source, where the data consists of various types of plant leaves and pests from plants. The training was carried out with 14,810 input images taken and 400 images for testing. Due to different lighting conditions, low accuracy is obtained.

DCNN has been used for detection of surfgrass plants, which are grassy plants. The samples used for each weed species are 500 negative images (images without weeds) and 500 positive images (images of weeds). The learning results obtained reached an average accuracy of > 99 [50].

Deep Learning is used to identify pests (Aphid, Flea Beetle Cicadellidae, Flax Budworm Red Spider Mite) attached to plants. To classify and identify plant pests using the Faster R-CNN model training and the Cloud system. The number of inputs from the faster R-CNN training was 75,000 images, and 500 images were selected for each iteration to produce 5 classes of insect pests [51]. Deep Learning has also been used to detect pests on strawberry plants. In experiments showing multivariate nonlinear models achieving an identification accuracy rate of more than 94% [52], [53]. Deep Learning is also used to classify tomato plant pests with digital images as input. The purpose of the training is to characterize and analyze the content in tomatoes, because each tomato has a different morphology [54]. Deep Learning is also used to classify tomato plant pests with digital images as input. The purpose of the training is to characterize and analyze the content in tomatoes, because each tomato has a different morphology [54].

Based on the results of journal searches using the keywords artificial neural networks and agricultural plant pests., the conclusions can be seen in table 3.

Table 3. Search Results using Keyword “Artificial Neural Networks” and “Agricultural Plant Pests”

Crop	Observed	Models	Algorithms Result
Tomato and strawberry	Goosegrass	CNN	The results of the training where the leaf blade annotation method
Cherry, Strawberry, Pepper, Potato, Grape.	Pests	CNN	Fast
Leaf	Pests	CNN	Superior
Cereal plants	Pests	CNN	86% of 876 sample weeds were detected automatically 406.
Strawberry	Carolina Geranium	DetectNet	Seven hundred-five sample images, 88 positive images, and 109 negative images are obtained.
Surfgrass	Pests	DCNN	The average accuracy of > 99
Plant	Insect	Deep Learn	Superior
Strawberry	Pest	Deep Learn	94%
Tomato	Pest	Deep Learn	Classificatio

Table 4. Search Results using Keyword “Artificial Neural Networks” and “Agricultural Plant Growth” or “Quality of Plants”

Crop	Observed	Models	Algorithms Result
Chili	Chili root	ANN	The growth of chili plants which was affected by the temperature of the root zone, was measured for 60 days of cultivation in the growth chamber.
Chinese cabbage	Leaf	ANN	Superior
Water	Water quality	AI	Optimal
Vegetable	Disease control	AI dan ML	Reliable
Corn	Leaf	3D Models	Accurate

The Use of Artificial Neural Networks in Agricultural Plant Growth or Quality

Research on plant growth using ANN has been carried out on hydroponic chili plants to detect root growth. Regulation of root growth by controlling the temperature of the root zone is called Root Zone Temperature (RST). Where RST as ANN input can increase the growth of hydroponic chilies. The modeling used is to assist ANN-based systems in input-single-output (SISO) systems [55]. Research on nitrogen uptake in chicory plants has also been carried out using ANN. They use chlorophyll fluorescence images to distinguish various methods of nitrogen processing from RGB images. The simulated image feature values are used as input to build the BPNN model to assess population quality. The ANN used as a transfer function between the input layer and the hidden layer is set to the sigmoid tangent function. The above vegetation extraction method successfully extracted samples of various growth stages from agricultural fields [56]. Study the use of artificial intelligence, namely optimizing water consumption related to fruit and vegetable processing type and structure. They use 634 data to analyze the results of optimizing fruit and vegetable processing technology. The results obtained that the lowest water consumption will be achieved when the concentrate production is at a ratio of 2 to 1 for juices and beverages [57]. Computational and data processing capabilities using ML have also been used to increase vegetable yields [58].

Research using 3D models to estimate AI in maize plants has obtained good results for introducing new interpretations of the classical biomass index definition. The proposed methodology relies heavily on the quality of the 3D reconstruction for the segmentation of each leaf. The 3D reconstruction partially influences SKF's segmentation step, which utilizes a 3D framework to separate independent leaves. When the leaf surface has large holes due to a lack of texture in the processing process, the framework is forced to create unnecessary branches, which may result in excessive leaf segmentation. This problem is partially overcome by the flexibility of the SOM but introduces inaccuracies in the finishing area [59].

Based on the results of journal searches using the keywords artificial neural networks and agricultural plant growth or quality, the conclusions can be seen in table 4.

The Use of Artificial Neural Networks in Agricultural Products

Research on agricultural products using ANN has been carried out to determine the aroma and taste of tea and spices using an electronic nose system (E-nose) with temperature and humidity drift compensation techniques. The E-nose sensor is used with varying tea temperature and moisture. Results and experiments were carried out using four E-nose sensors based on Metal Oxide Semiconductor (MOS). ANN was used to discriminate and classify electronic nasal response data for different tea and spice flavors. They were using different ANN architectures, classifying tea types and tasting samples. The training results were obtained with an accuracy of 97% and 98% for the tea and spice samples, respectively [60]. The aroma of tea from the brewing system can also be detected using ANN with input from the nose sensor. The power spectral estimation results using the Welch periodogram with a maximum frequency range of 1 Hz from each sensor show specific characteristics so that the results can be used as input data sets for classification. The classification results using an Artificial Neural Network backpropagation multilayer perceptron (MLP) with 16 training data sets and nine testing data show recognition with an error of 11.11% [61].

Table 5. Search Results using Keyword "Artificial Neural Networks" and "Agricultural Products"

Crop	Observed	Models	Algorithms Result
Tea	Tea and spices	ANN	97% and 98% accuracy
Coffee	Coffee acidity level	ANN	About 95% accuracy
Cotton	Spinning and winding	ANN	The results are satisfactory.
Black tea	Aroma and taste quality	ANN	16 sets of training data and 9 sets of testing data show recognition with an error of 11.11%
Sugarcane	Bioelectricity of cane sugar yield	ANN	Accurate
Mango	Mango classification	ANN	80% accuracy
Rambutan	Rambutan skin thickness	ANN	The results showed that the best accuracy occurred in the case of maximum diameter on the Z axis as input and skin thickness on the Z axis as output

ANN is used for training on the system to measure the acidity level of Fresh Roasted Coffee. E-nose as an ANN input for the active application of robot baristas was explored with various observations, such as the effect of temperature on coffee aroma, classification of acidity levels, and the possibility of doing the job of tasting human coffee. E-nose reveals that the temperature of liquid coffee has a tremendous effect on the aroma and taste of coffee. This study demonstrated the ability of ANN to classify the acidity level of coffee and predict the value according to the human acidity score with an accuracy of about 95%. This system is a potential technology that allows robotic chefs and baristas to acquire a sense of smell and perform tasting tasks previously limited to humans [62].

The ANN model has also been used in the system to predict sugar recovery based on the bioelectric properties of the sample. The ANN structure uses two inputs, 30 nodes in the first hidden layer and 40 nodes in the second hidden layer, and one predictive network output (obtaining sugar cane). Recovery of cane sugar was highly predicted by bioelectric property data (MSE 0.04). An ANN model based on bioelectrical properties obtained accurate training results for sugar recovery from sugarcane measurements [63].

Mango classification system research with artificial intelligence can calculate the volume of mangoes by identifying the collected images of mangoes to classify them according to bruised mangoes. This is very necessary for positioning in image processing. This study describes the methods and terminology of several tools used for image processing and analysis in sorting and classifying mangoes based on Artificial Intelligence. Digital image processing is needed firstly to process mango image data into a format from which features can be extracted and secondly to extract and measure these features [64].

The ANN model is used for this system of rambutan skin thickness, which estimates the thickness of rambutan skin by measuring the length of its maximum average diameter on the X, Y, and Z axes. The results show that the best accuracy occurs in the case of the maximum diameter on the Z axis as input and skin thickness on the Z axis as output. The optimal ANN model for this case consists of one hidden layer with six neurons in the hidden layer, capable of producing a value of rambutan skin thickness with a curve R2 value between the predicted value of the optimal ANN and the actual value of 0.9401. And these results will be transformed into an equation for the relationship between the maximum diameter on the Z-axis and the skin thickness on the Z-axis to be applied to the rambutan peeler in subsequent work [65].

Based on the results of journal searches using the keywords artificial neural networks and agricultural products, the conclusions can be seen in table 5.

CONCLUSIONS

Artificial neural networks are used to detect and classify diseases on the leaves of agricultural plants, namely apples, cotton, tomatoes, corn, and coffee with high-accuracy training results. Detect and classify pests on surfgrass, strawberry, cereal and tomato, and corn strawberry plants with high accuracy training results. Artificial neural networks are used for the growth or quality of crops in chili plants to detect root growth, chicory for nitrogen absorption in chicory plants, optimizing air consumption connected to fruit and vegetable processing type and structure, and excessive segmentation of corn leaves. The use of artificial neural networks on agricultural products for tea and spice taste sensitivity systems and the aroma of brewed black tea to determine smell and taste using E-nose as input for ANN training. E-nose as input to the artificial neural network is also used in the system to predict the acidity level of Fresh Roasted Coffee. ANN is used in bioelectrical measurement systems for cane sugar yield and aqua manganese sorting systems, as well as the estimation of rambutan skin thickness with accurate results.

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