APPLICATION OF DEEP LEARNING

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Application of Deep Learning

Abstract:

In the last decade, there has been a significant increase in the number of papers related to machine learning and the application of machine learning in various fields of science. Belmonte et al. observed that between 2010 and 2018, the growth in the number of papers related to machine learning topics and big data was exponential. They analysed 4240 scientific publications from the Web of Science citation database [1]. Xu et al., in the analysis of publications in the International Journal of Machine Learning and Cybernetics, noted that from 2010 to 2017, the number of publications, the cooperation rate, the total number of authors, and the degree of cooperation had shown an increasing trend [2]. Dokic et al. analysed the publication of papers in which deep learning is applied in the field of agriculture and noticed that the first papers were published in 2014, and in the second half of the second decade of the 21st century, exponential growth in the number of published papers was observed [3].
The objectives of this paper are primarily to analyze the literature related to the application of deep learning in apple growing, to propose the division of these papers depending on the area, and to analyze the observed trends in publishing papers related to this topic. In the analysis, only papers published in scientific journals were considered, and the condition is that they be found in the citation databases of the Web of Science or Scopus. The second section gives a brief overview of deep learning and its development and a presentation of the importance of apple growing in agriculture. The third section is an overview of papers that use deep learning methods and solve some problems in growing apples. The third section is divided into four parts, depending on the area the paper deals with. The fourth section is a discussion and conclusion.

Keywords:

Apple; deep learning; convolutional neural network

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Introduction

In the last decade, there has been a significant increase in the number of papers related to machine learning and the application of machine learning in various fields of science. Belmonte et al. observed that between 2010 and 2018, the growth in the number of papers related to machine learning topics and big data was exponential. They analysed 4240 scientific publications from the Web of Science citation database [1]. Xu et al., in the analysis of publications in the International Journal of Machine Learning and Cybernetics, noted that from 2010 to 2017, the number of publications, the cooperation rate, the total number of authors, and the degree of cooperation had shown an increasing trend [2].

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Overview of the areas of analysis

Deep learning

Deep learning (DL) is one of the methods of machine learning (ML) based on neural networks, and machine learning is a subcategory of artificial intelligence (AI). The relationship between these terms can be seen in Figure 1.

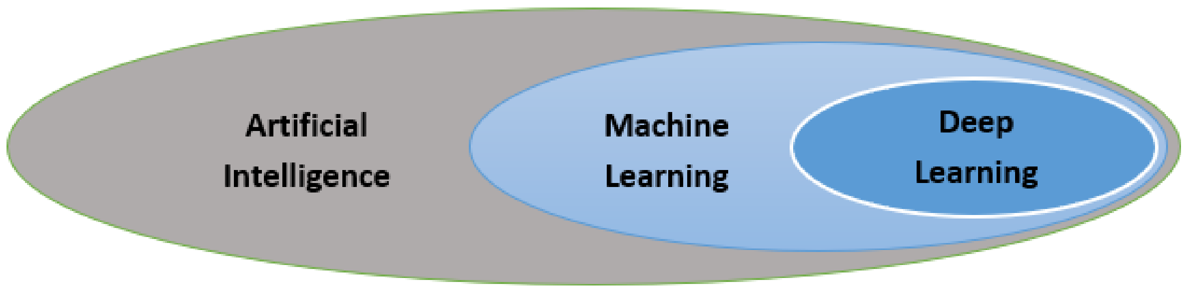

Figure 1. Relations of the terms AI, ML and DL

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The adjective “deep” refers to the fact that there are multiple layers between inputs and outputs in deep neural networks. Goodfellow et al. state that we are currently in the third wave of deep learning development. The first wave lasted between the 1940s and 1960s, and then the concept of stochastic gradient descent was set. The second wave lasted from the 1980s to the 1990s and began with the discovery of backpropagation. The third wave is thought to have started in 2006 with Hinton’s deep belief network and is still ongoing [4].

Deep learning is applied in several areas: computer vision, machine translation, drug design, material inspection, speech recognition, and natural language processing. In this paper, most analysed papers apply deep learning to recognise and segment objects in images that belong to the computer vision application category.

Apple growing

The apple is an edible fruit that is grown all over the world. The apple tree is the most widely grown species in the genus Malus. It is believed to have originated in Central Asia and has been cultivated for thousands of years. The FAO website states that in 2019, 87 million tons of apples were produced, over 10 kilograms per person in the world [5].

The fruits and apple tree are prone to pest, bacterial and fungal problems, and most often, various organic and non-organic means are used for this reason. With the advent of machine learning, there is an opportunity to automate much of the work involved in disease detection and fruit picking. This paper provides an overview of research in this area, and the focus is on the application of deep learning because the best results are achieved with it.

Paper analysis

Before the analysis of published papers related to the application of deep learning in apple growing, it was decided that only papers published in scientific journals indexed in the Web of Science and Scopus databases would be analysed. The terms "deep learning" and "apple" were chosen, and search engines were used in the mentioned databases. Words are searched in abstracts and keywords. The number of papers is listed in Table 1.

Year	Web of Science	Scopus
2021	8	15
2020	34	35
2019	12	10
2018	2	5
2017	3	2
2016	3	2
2015	1	2

Table 1. The number of papers in WOS and Scopus databases

About a quarter of the papers were excluded from the analysis because they were thematically related to the Apple Inc corporation's products. Also, some of the papers were listed in both databases, and some were not available at all. Papers published in 2021 are also excluded because these data are not complete.

There are 43 papers left that have been analysed in terms of content and are divided into four categories: Recognition of fruit and apple tree parts, Recognition of diseases and pests, Recognition of fruit damage before packaging and Miscellaneous. Below are paper descriptions divided into the four categories listed.

Recognition of fruit and apple tree parts

Anazco et al., in their paper, proposed a model for moving objects with the help of a robotic arm similar to a human hand. The model is based on Deep Reinforcement Learning, and the authors achieved an average success rate of 89.40% for the grasping and relocation tasks. One of the objects they used was an apple, and their model can be applied when picking apples [6].

Apollo-Apollo et al. proposed a model for estimating the amount of apple yield using images obtained by the unmanned aerial vehicle. Images are analysed using a convolutional neural network, and the goal is to get the most accurate yield estimate [7].

Biffi et al. proposed a model for recognising apple fruit on a tree using the Adaptive Training Sample Selection deep learning method. This method uses images of the apple tree as input and helps producers to predict production. The authors state that the accuracy of the proposed model is 0.3% to 2.4% higher than other known models (High-Resolution Network, RetinaNet, Cascade RCNN, Libra Regions with Convolutional Neural Network, Faster R-CNN, and Feature Selective Anchor- Free) [8].

Bresilla et al. have proposed a model for fruit detection on a tree. The input data are tree images, and the output is rectangles surrounding the fruit with a percentage probability of estimation accuracy. The model's accuracy is over 90%, and its speed is above 20 frames per second. High speed allows the use of models to automate apple picking. The authors used convolutional neural networks based on single-stage detectors [9].

Chen et al., in their paper, proposed a model for counting the fruits of apples and oranges using deep neural networks. The proposed model achieves a mean Intersection over Union (IU) of 0.838 on the apples. The proposed model uses images and can be used to automate yields apple picking [10].

Fan et al. proposed a model for segmentation of apple fruit on the tree to easier harvesting automation. The method considers the appearance of shadows, and its accuracy is 99.26% [11].

Gao et al., in their paper, proposed a model based on deep neural networks, which recognises apple fruit on a tree categorised into four categories, namely branch / wire-occluded, non-occluded, leaf-occluded, and occluded fruit. The average accuracy in non-occluded detection is 90.9%, while for other types, it is lower. The authors proposed the described approach because automated picking a robotic vehicle can adjust the strategy depending on the fruit category [12].

Gene-Mola et al., in their paper, presented a model for detecting apple fruit on a tree based on the R-CNN model with the use of additional sensors next to the camera. The input to the neural network consists of depth (D), colour (RGB) and range-corrected intensity signal (S). The authors state an average accuracy of 94.8% [13].

In their paper, Jia et al. proposed a model for detecting apple fruit on a tree based on the Mask Region Convolutional Neural Network. The model is specially trained to detect fruits that overlap in the images. They used a combination of Residual Network and Densely Connected Convolutional Network to reduce the input parameters. The authors state a model accuracy of 97.31% [14].

Majeed et al. cited the problem of trunk and branch segmentation in images in apple orchards. They proposed a solution based on convolutional neural networks that use data obtained from a Kinect V2 sensor. The authors state accuracy between 92% and 93%, intending to remove trunks and branches in the background, i.e. in adjacent rows, from existing tree images [15].

Kang et al. proposed a model for detecting and segmentation of apple fruit on a tree based on the deep-learning model Dasnet. With the help of the model, the central point of the fruit is defined and, using the Hough Transform, the place of fruit capture. The accuracy of determining the centre of the fruit is 95.5%, while the accuracy of defining the position for grasping the fruit is 92.3% [16].

Kang et al. presented in their paper a model for segmentation and determination of proper grasp pose based on deep neural networks. The model is intended for robotic fruit harvesting, and the authors state a model accuracy of 90% for detection and 82% for segmentation [17].

Kang et al. proposed a model for recognising apple fruits based on the Label Generation algorithm that utilises the multi-scale pyramid and clustering classifier. The model achieves 85.3% accuracy on apple detection in orchards. The authors state an inference time of 28 ms, and the model is intended for robotic apple picking [18].

Lyu et al. proposed in their paper a model for recognising apple trees in orchards by testing six different models based on machine learning. They chose the best model, and the specificity of the model is that it is intended for a small-scale agricultural unmanned ground vehicle. The neural network takes as input data grayscale images with a resolution of 320 × 240 pixels, and the authors state that the model's accuracy is 90% [19].

Majeed et al. proposed a model intended for apple tree segmentation in trellised fruiting-wall cultivation systems. They emphasised several advantages of this cultivation, especially in automated processing and harvesting. The authors used a Kinect V2 sensor to obtain the RGB and point cloud data of target trees. The achieved segmentation accuracy is between 82% and 89% for simple RGB images and about 92% for foreground-RGB images [20].

Zhang et al., in their paper, described a modified single shot multibox detector model of general-purpose, which they used to detect the apple fruit in the image. The reduction of the parameters was 50%, while they used a light multiple dilated convolution operator to compensate for the drop of accuracy. The paper was not written to improve agricultural production, but an apple dataset was used. The input data are images of 300 x 300 pixels, and the achieved accuracy is 98.99% with a speed of 85 frames per second [21].

Wang et al. proposed in their paper a model used to estimate the growth of apple fruits on a tree. An edge detection network that fused convolutional features has been proposed for fruit segmentation. The authors state the F1 score of the model of 53.1%, and the primary purpose of the model is seen in the plan of applying nutrients and pesticides during apple maturation [22].

Wang et al. in their paper described the model developed to categorise apple black rot levels. The achieved accuracy is 90.4%, and the authors achieved the mentioned result with a deep VGG16 model trained with transfer learning. The severity of the disease is categorised into four levels [23].

Wang et al. proposed a model for detecting flowers on an apple tree to estimate the amount of flowers and possible chemical thinning. The proposed segmentation method on a pixel level is based on a fully convolutional network. The output is a network that can be used in chemical thinning systems. The authors state an F1 score at pixel-level of 85.6% [24].

Wu et al. presented a model for detecting and segmenting apple trees and further analysis using remote imagery acquired from unmanned aerial vehicles in their paper. The authors used the Faster R-CNN object detector to detect an individual tree from images and the U-Net deep learning network for segmentation. The model then calculates the crown parameters. The accuracy in counting trees is 91.1% while segmenting their branches is 97.1% [25].

Wu et al. presented in their paper a model for rapid detection of apple flowers with the aim of eventual thinning. The authors used the channel pruned YOLO v4 deep learning algorithm. The number of model parameters was reduced by 96.74%, the inference time was decreased by 39.47%, and the accuracy was 97.31% [26].

Xuan et al. proposed in their paper a model for recognising the fruit of an apple on a tree. They used existing models, namely Faster RCNN based on AlexNet, Faster RCNN based on ResNet101, YOLOv3 based on DarkNet53 and improved YOLOv3. The best results were achieved with the improved YOLOv3 model. The authors state the F1 value of 95.0%, 94.6% and 94.1%, depending on the illumination for the red apple. For green apples, the results are slightly worse, 94.9%, 94.0% and 91.1% [27].

Recognition of diseases and pests

Attiqu Khan et al. have proposed in their paper a method for detecting fruit diseases based on a deep convolutional neural network using pre-trained models. VGG and AlexNet were used, and the authors state an accuracy of 97.8% in detecting three-leaf diseases in apples. These are apple scab, apple black rot and apple rust [28].

Bi et al. have proposed a model based on the well-known MobileNet model to detect two apple leaf blotch and rust leaf diseases. The authors emphasise the advantage of a model that is not demanding and can be implemented on smartphones. Compared to the InceptionV3 and ResNet152 models that achieve an accuracy of 75.59% and 77.65%, the authors state their model of 73.50% [29].

Boniecki et al. analysed classification models based on perceptron and radial neural networks to classify pests in apple orchards. The authors concluded that they achieved the best results using a multilayer perceptron neural network, citing an RMS value of 0.0001063 for test data. The inputs used are pest images [30].

Chao et al. presented in their paper a model that uses a convolutional neural network to recognise apple leaf diseases. The model recognises five common diseases, and its accuracy is 98.82%. After extracting the features using a convolutional network, a support vector machine algorithm was used for classification. Images of apple leaves were used to train the models [31].

Francis et al. have proposed a new model for recognising apple leaf disease with the help of deep neural networks. The authors state the accuracy of the model of 99.6% [32].

In their paper, Jiang et al. proposed a model to detect five apple leaf diseases based on convolutional neural networks. The model is trained to recognise Brown spot, Alternaria leaf spot, Gray spot, Mosaic, and Rust. The model includes Rainbow concatenation and GoogLeNet Inception structure. The authors state accuracy of 78.8% with a speed of 23.13 frames per second [33].

Khan et al. proposed a DeepLens Classification and Detection Model based on scalable transfer learning on Amazon Web Services. Its purpose is to recognise leaf diseases in fruit trees (apple, grape, peach and strawberry) and vegetable plants (potato and tomato). The authors state accuracy of 98.78% and availability in the cloud makes this model easy to implement [18].

Liu et al. proposed a model based on the well-known deep learning convolutional neural network AlexNet to detect apple leaf diseases. The model recognises four diseases: Brown spot, Mosaic, Rust, and Alternaria leaf spot. The authors managed to reduce the number of parameters to 51,206,928, while the model's accuracy is 97.62%. The authors used a dataset of 13,689 images of diseased apple leaves [34].

In their paper, Tian et al. proposed a model for detecting anthracnose lesions on apple surfaces in orchards. The model is based on the YOLO-V3 model, with which a densely connected neural network was used and is utilised to optimise feature layers. The authors state the accuracy of disease detection of 95.57%, which is slightly better than other known models (AlexNetOWTBn, VGG, GoogleNet) [35].

Turkoglu et al., in their paper, used LSTM-based Pre-trained Convolutional Neural Networks to detect apple diseases and pests. For feature extraction, the authors used AlexNet, GoogleNet and DenseNet201, and features were entered into LSTM. The authors state accuracy of 99.2% [36].

Yan et al., in their paper, described the model for recognising scab, frogeye spots, and cedar rust on an apple leaf. The proposed model is based on VGG16, and the authors state accuracy of 99.01%. Compared to the classic VGG16, the number of parameters is reduced by 89%, and the accuracy is improved by 6.3%. The training time was reduced to 0.56% of the original model [37].

Yang et al., in their paper, described a disease detection model in tomato, potato, grape, corn and apple. The authors propose a new model of deep learning called wide residual networks, and the accuracy in detecting scab and Frogeye Spot on an apple is 97% and 98%, respectively. The overall accuracy in detecting 35 different diseases is 91%, significantly more than the GoogLeNet Inception V4 model used for comparison, which is 57% [38].

Recognition of fruit damage before packaging

Fan et al. proposed in their paper a model for the detection of defective apple fruits on a conveyor belt for packaging. The model is based on a convolutional neural network, and the achieved accuracy is 96.5%. The proposed model processed an image with six apple fruits in 72 ms on a test computer [39].

In their paper, Hekim et al. proposed a model for categorising healthy and bruised apple fruits using iterative thresholding approaches based on different types of convolutional neural networks. The authors state an accuracy between 95.58% and 98.33%. The proposed method is intended for use on a conveyor belt before packaging [40].

Hu et al. proposed in their paper a model for bruised apple detection based on convolutional neural networks using a 3D infrared imaging system. Images are transformed from three dimensions into two-dimensional ones and further processed, and the method is based on the fact that bruised apple has deformations at the places of damage. The authors state the accuracy of the model as 97.67%. The model is intended for use on conveyors before packaging [41].

Ismail et al. proposed a model of visual inspection of apple and banana fruit based on deep neural networks. The authors used transferred learning and the DenseNet, MobileNetV2, ResNet, EfficientNet, and NASNet models. The proposed model achieves an accuracy of 99.2% and 98.6% for apples and bananas and is based on the EfficientNet model. In addition, the authors implemented this model on a cheap Raspberry Pi development board with a camera and touch-sensitive display [42].

Lashgari et al. proposed in their paper two models for the detection of mealiness in apple fruit. One is based on AlexNet and the other on VGGNet pre-trained convolutional neural networks, and the input information is the sound obtained by a weak blow of a plastic ball on an apple. The classification accuracy in these models in the classification into mealiness and non-mealiness was 91.11% and 86.94%, depending on the pre-trained convolutional neural network used [43].

Li et al., in their paper, proposed a model for classifying apple fruit depending on whether they contain a larva of codling moth or not. Codling moth larvae bore deep into the fruit, making it unmarketable. Using acoustic methods and convolutional neural networks, it is possible to categorise apples with high accuracy. The authors state an accuracy between 91% to 100% for the training set and 83% to 100% for the test set [44].

In their paper, Roy et al. proposed a model for classifying healthy and rotten apples during processing and before packaging. A modified version of the UNet model was used for classification, and the input was an apple image. The accuracy of the model was 97.54% [45].

Miscellaneous

Bai et al. used spectral analysis in their paper to better predict solid soluble content in the apple.

The problem they solved was the prediction of solid soluble content with multiple geographical origins in apples. The authors used deep learning with multivariate regression analysis [46].

Liu et al., in their paper, provided an analysis of global interest in organic food using Google Search Engine Data and deep learning methods. The authors conclude that organic milk, oil, chicken, and apples are the most exciting products. The countries where residents are most interested in organic products are New Zealand, the United States, Singapore, the United Kingdom, Australia, and Canada. The authors point out that there is no correlation between life expectancy and GDP with the population's interest in organic products. As part of the paper, a recurrent neural network was developed for predicting people's interests in major organic foods over time [47].

In their paper, Liu et al. proposed a model for recognising apple varieties based on a deep convolutional neural network, using an image of an apple leaf as an input. TensorFlow was used to develop the model, and they used a data set of 12,435 sheet images. The model has an accuracy of 97.11% and is trained to recognise 14 varieties of apples [48].

Discussion and conclusion

Four basic categories were identified by analysing papers describing the application of deep learning related to apple growing. The first category includes papers in which deep learning is applied to discover and segment apple fruits or parts of an apple tree. The objectives of these studies are primarily related to the automation of apple picking, and some papers aim to create models for estimating apple yield. In the second category are papers that apply deep learning in detecting diseases and pests. All analysed papers from this category use images of leaves, fruits, and plantations as input data. The third category includes papers in which deep learning is applied to detect fruit damage after picking but before packaging. In that category, photographs are most often used as input. There are only four papers in the fourth category, and they could not be categorised into the previous three categories.

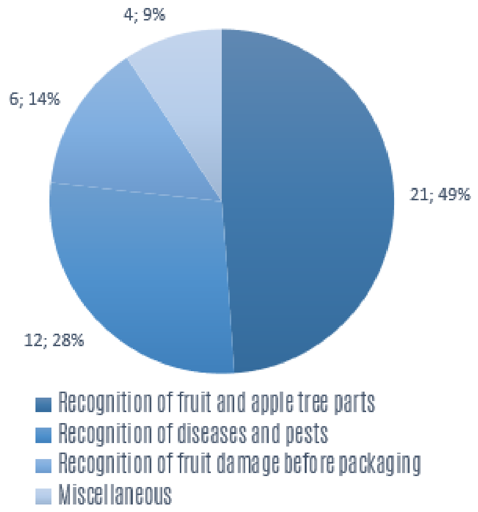

Figure 2. The number of published papers in each of the categories

Figure 2 shows the number of published papers in each category and is also offered as a percentage. Over three-quarters of the published papers are related to the automation of picking and detecting diseases and pests. Considering that unmanned aerial or ground vehicles can treat diseases and pests and harvest fruits, we can expect that almost all manual jobs will be taken over by unmanned vehicles soon.

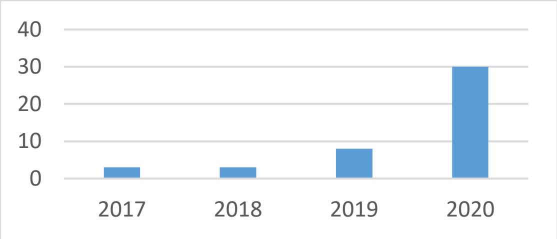

Figure 3. Number of papers by year

An increase in published papers can be observed from 2017 to 2020, as seen in Figure 3. If we compare the number of published papers in 2017 with 2020, we see a tenfold increase. Papers published in 2021 have not been analysed, but if we consider only their number, it can be seen that the number of papers will remain at the same level in the current year or continue to grow further.

In the paper, only papers from the journal are analyzed, which is a weakness that can be remedied in future research. In addition, a small number of papers were published in Chinese and were not included in the analysis. Finally, paper analysis would be more valuable if it included various types of fruit, as well as several different subcategories of artificial intelligence.

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