Detecting and monitoring the development stages of wild flowers and plants using computer vision: approaches, challenges and opportunities

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ABSTRACT

Wild flowers and plants play an important role in protecting biodiversity and providing various ecosystem services. However, some of them are endangered or threatened and are entitled to preservation and protection. This study represents a first step to develop a computer vision system and a supporting mobile app for detecting and monitoring the development stages of wild flowers and plants, aiming to contribute to their preservation. It first introduces the related concepts. Then, surveys related work and categorizes existing solutions presenting their key features, strengths, and limitations. The most promising solutions and techniques are identified. Insights on open issues and research directions in the topic are also provided. This paper paves the way to a wider adoption of recent results in computer vision techniques in this field and for the proposal of a mobile application that uses YOLO convolutional neural networks to detect the stages of development of wild flowers and plants.

1. Introduction

Over the last years, farmers, horticulturalists, gardeners, and curious onlookers have been increasingly using new technologies for a more sustainable and efficient agriculture, and to gain experience caring for plants by identifying plant species and diseases. Detecting the stages of the lifecycle of a plant has been used to better understand the stages of growth of the crops to improve efficiency and productivity [1]. But it can be very interesting to apply this concept to wild flowers and plants, as it can help to protect endangered species in protected areas, such as genisteae, nettles or juniper. In some counties, one species of wildflower becomes extinct every two years [2]. Some wild flowers and plants may play a big part on the diet of certain animal species or play an essential role in ecosystems, which may collapse causing the extinction of other species [3]. Furthermore, some of these plants play a key role in the development of modern medications or beauty products [4].

The development stages of wild flowers and plants can be classified as follows: 1) sprout: this stage typically happens underground where the plant starts to grow out of its seed; 2) seedling: this stage is characterized by the spread of roots and the appearance of the first leaves; 3) vegetative: this stage is identified by the development of stems and foliage; 4 budding: this stage can be identified by the

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appearance buds on the plant; 5) flowering & pollination: this stage is recognized by the appearance of flowers, which in consequence causes pollination and can be accompanied by the appearance of fruits in early stages; 6) ripening: this stage is identified by the appearance of fruits already matured.

To the best of our knowledge, at the time of this research, no work has been undertaken to specifically detect and monitor the growing stages of wild flowers and plants using computer vision techniques. Computer vision is an application of machine learning and artificial intelligence that takes information from digital images and videos and makes meaningful decisions based on that information. Over the years convolutional neural networks have been widely used for object detection and classification, and various techniques have proven superior results in terms of detection accuracy, speed, objectiveness, reliability.

The work presented in this paper represents a first step in an ongoing effort to develop a system and a support mobile phone app, which on one hand can help park visitors in their enjoyment and awareness of the wild flowers and plants they find along the roadways and trails (flowers they observe, appreciate, and probably photograph), and on the other hand at the same time allows monitoring their development stages. Thus, contributing for wild flowers and plants understanding and preservation.

This paper first introduces the related concepts. Then, presents a survey that focuses on recent peer-reviewed studies (mainly from 2018 to 2022) searched in electronic databases, and existing mobile apps from AppStore and Play Store, guided by three research questions: (a) What types of modern computer vision techniques are commonly used in this area?; (b) What studies and mobile apps have been focused on plant identification?; (c) What studies and mobile apps have been focused on plant disease detection? It aims to identify the most promising approaches to apply to this specific scenario of detecting and monitoring the development stages of wild flowers and plants.

The rest of the paper is organized as follows. Section 2 presents computer vision techniques that have been used in the literature for plant identification and plant disease detection. Section 3 reviews related studies and applications. Section 4 discusses the challenges and provides directions for future developments and research. Finally, Section 5 presents the conclusions and draws some lines of future work.

2. Method

Computer vision makes it possible for systems and computers to take actions or make recommendations based on relevant information gleaned from digital images, videos, and other visual inputs. The field of computer vision has been fundamentally altered by deep learning, which is frequently used to teach computers to "see" and analyse the environment in the same way that people do.

Deep learning involves using a neural network to teach an algorithm through training. With the help of the neural networks, an algorithm can be trained with a large quantity of data and learn from it. Then, it will be able to receive an input such as an image and predict a value for the input based on the data it learned from [5]. Object detection and classification through deep learning can be divided into two tasks. The task of object detection deals with the identification of an object in an image. Thus, in the context of this work, it detects wild flowers and plants in a photo. The task of object classification deals with the categorization of the object based on previously defined classes or types [6]. In the context of this work, it allows determining the wild flowers and plants species and classifying their development stage.

In the last years object detection has made significant progress by using Convolutional Neural Networks (CNN). Due to the capacity of imitating neurons on the brain, CNNs have the characteristic to learn through a large quantity of data [5].

The object detection models that make use of CNNs can be classified in two categories: single-stage and two-stage. The single-stage object detection models produce bounding boxes around the detected object. These bounding boxes are the result of the process of assigning predictions to various regions of the image with the use of anchor boxes. These boxes are used to capture the object and contain a prediction value [7]. Then, the network will evaluate these predictions and detect the object creating a bounding box around it [8]. Examples of single-stage object detection models are YOLO, KNN, MobileNet and SVM. The two-stage object detection models add a classification stage to the process, which classifies the objects within the subsets of images or regional proposals. This additional stage increases accuracy, although it is slower than single-stage object detection models [8]. Examples of two-stage object detection models are Mask R-CNN and AlexNet.

The main principles of object detection models commonly used for plant identification and plant disease detection are described below.

2.1. Single-stage Object Detection

2.1.1. YOLO

YOLO (You Only Look Once) [9] is a real-time object detection algorithm. YOLO divides the input image into a grid of cells. Each of these cells is responsible for predicting a set of bounding boxes and class probabilities. This allows YOLO to process an entire image in a single pass, hence the name "You Only Look Once" [9].

YOLOv3, the third version of YOLO, uses the CNN Darknet-53 which has 53 convolutional layers for feature extraction. Furthermore, it is the first version of YOLO that can detect objects of different size. This is due to the anchor boxes being capable to be scalable. Consequently, it performs better at the task of object detection. In addition, this algorithm also uses feature pyramid networks (FPN) that allows the algorithm to be able to detect objects at different sizes [10].

YOLOv4 works by receiving an input, which is an image that is passed through three components: the backbone, neck, and head. The backbone is used to extract features by using the CNN CSPDarkNet53 for the feature extraction, which is the process of transforming data into numerical features [11], [12]. The neck is used to extract different features maps from the many stages of the backbone by using Path Aggregation Network (PAN) [11]. Finally, the head, which is composed by dense prediction and sparse prediction [12] is responsible to detect the objects drawing bounding boxes around them [11]. All these components work to produce as result a object surrounded by a bounding box [13]. The Fig. 1 illustrates how this algorithm works.

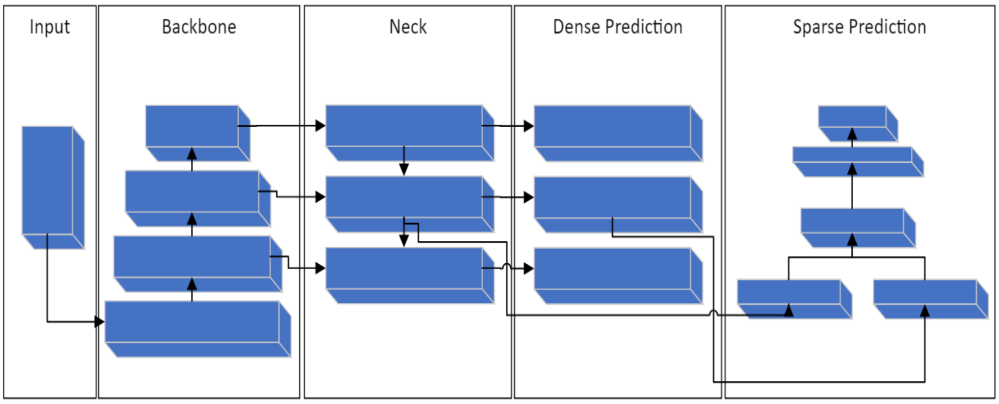

Fig. 1. Architecture of YOLOv4.

2.1.2. KNN algorithm

K-Nearest Neighbours (KNN) [14] algorithm is a classification and regression supervised machine learning technique [15]. This algorithm creates 'K' values by the extraction of features on a training dataset. These 'K' values are then positioned based on their values on a space and are aggregated into classes. After this process, when the algorithm receives an image to classify, it will calculate the 'K' value of the image. Then the 'K' value of the image is used to position the received data in the space. Then, to classify the image, it will compare the distances to the classes of the training dataset by using a formula to calculate the nearest 'K' value [16].

There are other classifier types based on KNN that use different distance metrics, such as: distance weight for Weighted KNN [17] that uses the distance weight; Cubic KNN [18] that uses the cubic distance; the cosine KNN [19] that uses the cosine distance; the Fine KNN [20] that uses the euclidean distance. Fig. 2 illustrates how this algorithm classifies new data.

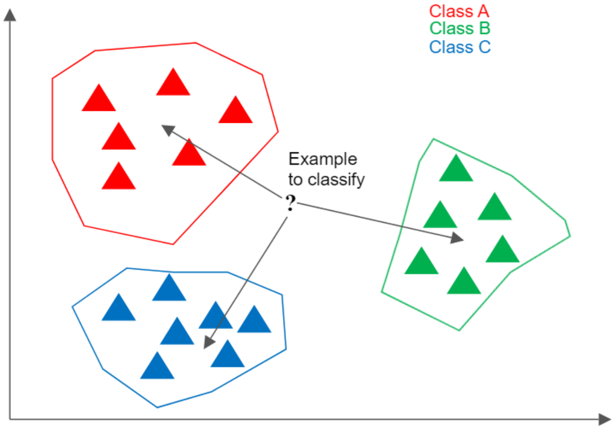

Fig. 2. KNN classifying new data based on the distances to the existing classes.

2.1.3. MobileNet

MobileNet [21] is an accurate and efficient lightweight convolutional neural network (CNN) designed for mobile and embedded devices with limited computational resources. MobileNet uses depthwise separable convolution to reduce the computation required by a traditional CNN. In depthwise separable convolution, a single filter is applied to each channel of the input image. Then, a pointwise convolution is applied to combine the results from each channel. This approach reduces the number of filters applied, and thus reduces the computation required. In addition, this CNN also introduces a technique called width multiplier and resolution multiplier. This technique allows to control the number of channels in the layers and the resolution of the input image, which is a trade-off between computational cost and accuracy.

Furthermore, MobileNet makes use of batch normalization. This is a technique that is used after the depthwise convolution and pointwise convolution layers, to normalize the activations before they are passed through the next layer [22]. By normalizing the activations, the batch normalization helps to reduce the internal covariate shift, which can improve the performance and stability of the network during training [22]. Fig. 3 illustrates how this algorithm works.

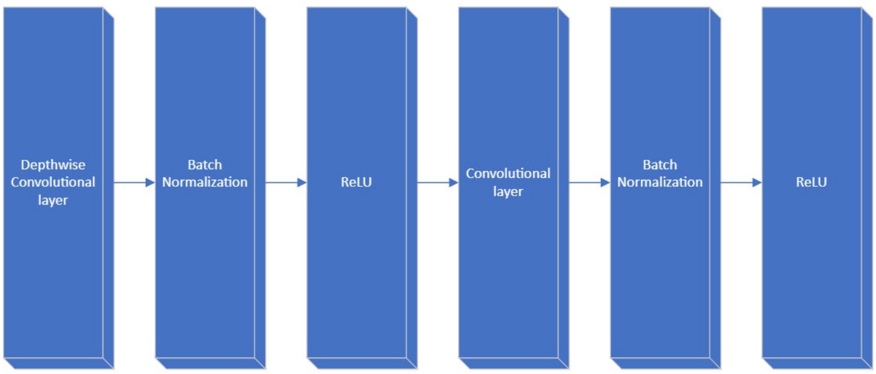

Fig. 3. Architecture of MobileNet.

2.1.4. SVM

Support Vector Machine (SVM) [23] approach consists of mapping data into a high-dimensional feature space so that this data can be categorized. After SVM is trained, it will classify the training data into vectors, which will be placed into a n-dimensional space. Then, a hyperplane will be drawn between the data categorized with the aid of the selected support vectors, which are the vectors closest to the hyperplane. These support vectors, which are used to represent these data points, form the basis for the SVM method. They are crucial to the algorithm's ability to correctly classify new data.

There can also be multiple hyperplanes to aid the classification of data. Once the hyperplane is drawn, data can be classified by determining on which side of the hyperplane it is placed [24]. Fig. 4 illustrates how this algorithm works.

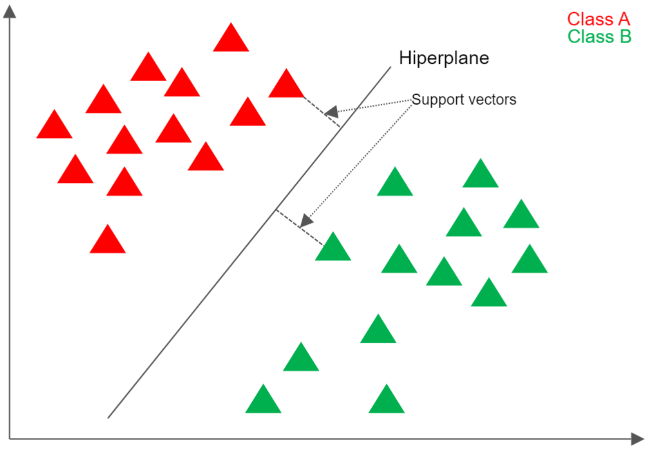

Fig. 4. Vectors divided into two classes by the hyperplane.

2.2. Two-stage Object Detection

2.2.1. Mask R-CNN

Mask R-CNN [25] is based on Faster R-CNN [26]. Faster R-CNN merges Fast R-CNN with a Regional Proposal Network (RPN), making it faster while maintaining its accuracy [27].

Faster R-CNN is a two-stage algorithm [28] that consists of two modules: RPN and Fast R-CNN. RPN is used to generate region proposals. This region proposals are passed to the component Region of Interest (RoI) pooling, which resizes each region proposal to a fixed size before feeding it into the fully connected layers. These layers will then output the class, which is the class label of the object and the bounding box [29].

The algorithm Mask R-CNN differentiates from the Faster R-CNN by replacing the RoI Pooling with RoI align, which is used for extracting a small feature map, and by adding a mask. A new branch was also added to this algorithm that takes regional proposals and inputs them into convolutional layers, which in turn will output a mask [25]. Thus, Mask R-CNN has 3 outputs: the bounding box, the class, and the mask [26]. Fig. 5 illustrates how the Mask R-CNN algorithm works.

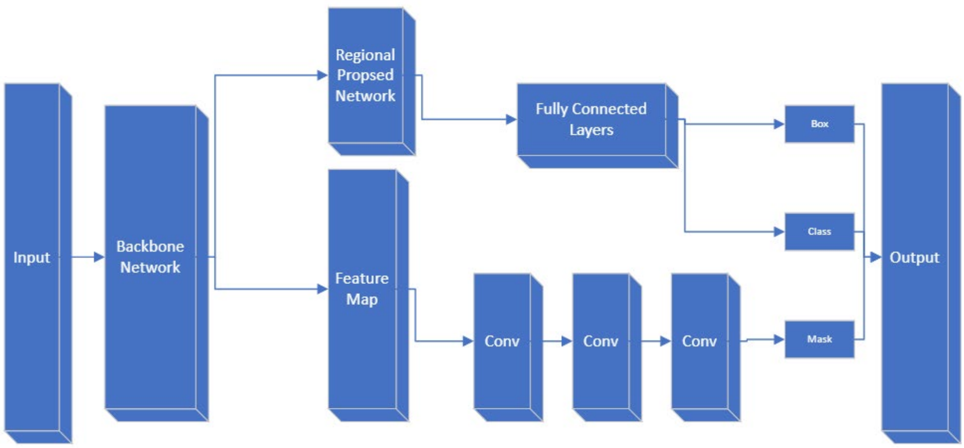

Fig. 5. Architecture of Mask R-CNN.

2.2.2. AlexNet

AlexNet [30] consists of eight layers of which three are fully connected (FC) layers and the other five are convolution layers, with Dropout on the first two layers to reduce overfitting. In addition, the final fully linked layer is followed by a Softmax function, which is used to convert the class scores into a probability distribution over all possible classes. The input picture is filtered by the first convolutional layer, which uses 96 11x11 kernels. The output of the first convolutional layer is filtered by the second convolutional layer, which uses 256 5x5 kernels. The image is then passed to the third, fourth, and finally to the fifth convolutional layers, respectively, each having 384, 384, and 256 3x3 kernels. Then, the output is passed through the first and second fully connected layers with Rectified Linear Unit (ReLU). Finally, the data is passed through the third last fully connected layer or output layer [31]. Fig. 6 illustrates how this algorithm works.

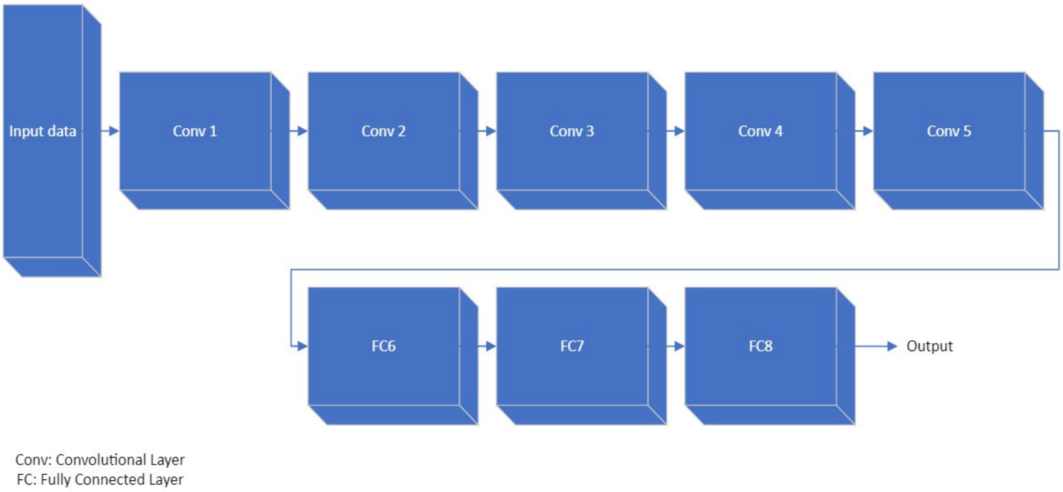

Fig. 6. Architecture of AlexNet.

3. Results and Discussion

To the best of our knowledge, no work to date utilized computer vision techniques to specifically detect and monitor the growing stages of wild flowers and plants. Therefore, the related work presented in this section focuses on recent research works and applications using computer vision techniques for plant identification and plant disease detection.

2.2.3. Plant Identification

Plant detection and identification can be achieved through a photo taken of a plant that is passed through a CNN algorithm, which then gives the output indicating the corresponding plant species. Several mobile applications (apps) available through platforms such as Google Play Store provide this capability. Example of such apps are [32], [33] which additionally present information related to the plant identified. Recent works in the literature have also tackled the same issue. The work in [34] aimed to improve the accuracy and the performance of real-time lemons detection in a natural environment. This improvement was made by switching the backbone of the algorithm YOLOv3 with SE_ResGNet3. The performance of the proposed algorithm was tested and compared with the standard YOLOv3. It was shown that it performs best with an accuracy of 96.28% and 90 frames per second (FPS), while standard YOLOv3 achieved an accuracy of 90.6% and 62 FPS.

Another work [35] had the objective of identifying 15 plant species through their leaves. To achieve this goal, AlexNet was used. It was observed that AlexNet achieved an accuracy of 72%. The work [36] proposed a new algorithm for the identification of poisonous and harmful plants, called Weight Bat-inspired Algorithm (WBA) with Deep Neural Network (DNN). The performance of this algorithm was tested and compared with other algorithms such as SVM, KNN, Naive Bayes (NB), C4.5, Random Forest (RF) and AdaBoost. The proposed algorithm achieved an accuracy of 98% after data augmentation. Whereas the algorithms SVM, KNN, NB, C4.5, RF and AdaBoost achieved accuracies of 92.7%, 92.7%, 90%, 94.7%, 94% and 94% respectively, after data augmentation.

Other work [37] tried to identify wild plants through their leaves, fruits, or both. Three algorithms were tested, AlexNet, RF, and SVM. It was concluded that AlexNet was the most suitable for the task, achieving the highest accuracy of 98%. The tests also showed that SVM and RF achieved an accuracy of 96.7% and 96% respectively. The work presented in [38] focused in identifying apple flowers in a natural environment. A combination of the algorithms YOLOv4 and channel pruning was considered. The performance of this combined algorithm was compared with Faster R-CNN, Tiny-YOLO v2, YOLO v3, SSD 300 and EfficientDet-D0. It was observed that the combined algorithm performed better than the other algorithms. It achieved a higher accuracy of 97.31%. While the other algorithms Faster R-CNN, Tiny-YOLO v2, YOLO v3, SSD 300 and EfficientDet-D0 obtained the accuracies of 85.10%, 81.75%, 83.12%, 91.64% and 89.52%, respectively. The work [39] had the objective of identifying medicinal plants. It used a variation of KNN called Weighted KNN, which alters the procedures to assign the weights to the 'K' points. This algorithm achieved an accuracy of 98.62%. Another work [40] combined two algorithms, Principal Component Analysis (PCA) and KNN, to identify medicinal plants. PCA was used for feature extraction, and KNN was used for image classification. The results of the study showed that this combination of PCA and KNN achieved an accuracy of 88.67%. In [41], the authors proposed a system to detect peaches using deep learning, based on the algorithm Faster R-CNN. This algorithm was tested, and it achieved an accuracy of 90%. A summary of the above-described applications and related works is reported in Table 1, highlighting their contributions.

Table 1. Approaches/techniques for plant identification.

Name	Type	Year of publication	Types of plants classified	Goal	Technique used	Accuracy
PictureThis - Plant Identifier [32]	App	2017	All types	Identify plants through a picture and deliver relevant information to the user	Unknown	Unknown
NatureID [33]	App	2020	All types	Identify plants or diagnose them through a picture and deliver relevant information to the user	Unknown	Unknown
Lemon-YOLO [34]	Paper	2021	Lemons	Improve the accuracy and the performance of real-time lemons detection in a natural environment	YOLOv3 with SE_ResGNet34 YOLOv3	96,28% 90.60%
Plant Species Image Recognition using Artificial Intelligence on Jetson Nano Computational Platform [35]	Paper	2021	Limited to 15 species	Identify the species of the plant trough their leaves	AlexNet	72%
WBA-DNN: A hybrid weight bat algorithm with deep neural network for classification of poisonous and harmful wild plants [36]	Paper	2021	Harmful wild plants	Classify poisonous and harmful plants	WBA-DNN SVM KNN NB C4.5 RF AdaBoost	98% 92.7% 92.7% 90% 94.7% 94% 94%

Table 1. (Continued)

Name	Type	Year of publication	Types of plants classified	Goal	Technique used	Accuracy
A New Deep Learning System for Wild Plants Classification and Species Identification: Using Leaves and Fruits [37]	Paper	2022	Wild plants	Identify wild plants through their leaves, fruits, or both	AlexNet SVM RF	98% 96.7% 96%
Using channel pruning-based YOLO v4 deep learning algorithm for the real-time and accurate detection of apple flowers in natural environments [38]	Paper	2020	Apple flowers	Identify apple flowers in a natural environment	YOLOv4 with channel pruning Faster R-CNN Tiny-YOLO v2 YOLO v3 SSD 300 EfficientDet-D0	97.31% 85.10% 81.75% 83.12% 91.64% 89.52%
Segmentation and identification of medicinal plant through weighted KNN [39]	Paper	2022	Medicinal plants	Identify medicinal plants	Weighted KNN	98.62%
Implementation of PCA and KNN Algorithms in the Classification of Indonesian Medicinal Plants [40]	Paper	2021	10 species of medicinal plants	Identify medicinal plants	Combination of PCA and KNN	88.67%
Peaches Detection Using a Deep Learning Technique A Contribution to Yield Estimation, Resources Management, and Circular Economy [41]	Paper	2022	Peaches	Detection of peaches	Faster R-CNN	90%

2.2.4. Plant Disease Detection

Plant disease detection can also be performed using a photo of a plant that is passed through a CNN algorithm [42]. Some mobile applications available through platforms such as Google Play Store provide this capability [43], [44]. Recent works in the literature show promising results and are described next.

The work presented in [45] aimed to classify rice diseases by using only colour features. It tested different classifiers such as SVM, DC, KNN, NB, DT, RF and Logistic Regression (LR). It was concluded that the SVM classifier presents the best results, achieving an accuracy of 94.65% while DC, KNN, NB, DT, RF and LR obtained the accuracies 92.34%, 91.39%, 75.72%, 83.18%, 92.52%, 75.85% respectively. Another work [46] proposed an algorithm to identify crop diseases. This algorithm makes use of a CNN to extract the features, which are then classified using an error-correcting output codes (ECOC) based on SVM classifier. This algorithm was tested using two CNN's, AlexNet and VGG19. It was concluded that the VGG19 presented the best accuracy of 98.9%. The algorithm with AlexNet achieved an accuracy of 98.8%.

The work in [47] tried to improve the standard AlexNet with Inception-V4 to increase the accuracy of plant disease diagnosis. The proposed algorithm was tested along with AlexNet, VGG11, ZFNet and VGG16. It was concluded that the improved algorithm achieved an accuracy of 96.5%. This accuracy was higher than the algorithms AlexNet, VGG11, ZFNet and VGG16 that obtained an accuracy approximately of 80%.

The work [48] also tested different algorithms to classify plant diseases to determine which has the highest accuracy. These algorithms were AlexNet, SVM Linear and SVM Radial Basis Function (RBF). It was concluded that the most suitable algorithm would be AlexNet. It achieved the highest accuracy of 91.15%, while SVM Linear and RBF achieved accuracies of 88.96% and 89.69% respectively. In [49], the authors aimed to create a technology to detect diseases on tomatoes through their leaves. To achieve this goal the following algorithms were compared - InceptionV3, ResNet50, AlexNet, MobileNetV1, MobileNetV2, MobileNetV3 Large and MobileNetV3 Small. These algorithms were trained and tested with a large range of optimizers, like Adam, Adagrad, SGD and RMSProp. It was concluded that the combination that presented the best accuracy was MobileNetV3 Large with Adagrad, obtaining an accuracy of 99.81%. Additionally, the study also concluded that the best optimizers for each algorithm were MobileNetV3-L with Adagrad, Inception V3 with SGD ResNet50 with SGD, MobileNetV1 with SGD, MobileNetV2 with SGD, MobileNetV3-S with Adagrad and AlexNet with SGD, achieving the accuracies of 99.81%, 99.62%, 99.62%, 99.49%, 98.93%, 98.99% and 96.68% respectively.

The work presented in [50] described a new algorithm to identify plant diseases in crops such as wheat, cotton, grape, corn, and cucumbers. This algorithm combines AlexNet with Particle Swarm Optimizer (PSO). To assess the accuracy of this proposal, the algorithm was tested against AlexNet and the results were compared. It was observed that AlexNet and AlexNet + PSO scored 95.6% and 98.83% respectively.

The work [51] focused on identifying diseases on crops trough images of the plants leaves. It used a more compact version of the algorithm YOLOv4, called YOLOv4-tiny. This algorithm was tested and it achieved an accuracy of 63.31%. In [11], two YOLO algorithms, YOLOv3 and YOLOv4, were tested with the goal of identifying seventeen diseases on thirteen plant species. This study concluded that YOLOv4 was the most suitable for the task of detecting diseases on crops. YOLOv3 and YOLOv4 achieved accuracies of 53.08% and 55.45% respectively. The work [52] aimed to create a system capable to identify early blight and late blight on potatoes through their leaves. The paper tested two algorithms to assess which was the most suitable, GoogleNet and AlexNet. Both algorithms achieved an accuracy of 98.51%. Nevertheless, AlexNet outperformed GoogleLeNet in terms of precision 99.44%, sensitivity 98.35%, specificity 99.72%, and F1 score 98.89%. GoogleLeNet achieved a precision of 98.88%, sensitivity 98.34%, specificity 99.44%, and F1 score 98.61%.

Other work [53] tried to identify 7 kinds of diseases that affect strawberries using Mask-R-CNN. It was observed that the algorithm Mask-R-CNN had an accuracy of 82.43%. In [54] a new algorithm was proposed to identify three major leaf diseases on tea plants. This new algorithm is based on Mask R-CNN and wavelet transform, which are then inputted into a four-channeled residual network (F-RNet). This new algorithm was compared with ResNet18, VGG16, AlexNet and SVM to assess its accuracy. The new algorithm achieved an accuracy of 88%. In contrast the algorithms ResNet18, VGG16, AlexNet and SVM registered accuracies of 82%, 80%, 73% and 65% respectively. Another work in [55] proposed the creation of a decision-making support system by classifying the diseases affecting peaches. MobileNetV2 algorithm was trained and tested for the task. It was observed that this algorithm achieved an accuracy of 96%.

A summary of the above-described applications and related works is reported in Table 2, highlighting their contributions.

Table 2. Approaches/techniques for plant disease detection.

Name	Type	Year of publication	Types of plants classified	Purpose of study/app	Technique used	Accuracy
Plant Disease Identification a [43]	App	2020	Fruits, vegetables, and crops	Identify the disease of a specific plant	Unknown	Unknown
Plantix [44]	App	2015	Plants, vegetables, and crops	Identify the disease of a specific plant	Unknown	Unknown
Rice plant disease classification using colour features: a machine learning paradigm [45]	Paper	2020	Rice Plants	Identify rice plant diseases trough machine learning	SVM DC KNN NB DT RF LR	94.65% 92.34% 91.39% 75.72% 83.18% 92.52% 75.85%
Plant Disease Identification and Classification Using Convolutional Neural Network and SVM [46]	Paper	2021	Crops	Identify crop diseases with a new algorithm	VGG19 AlexNet	98.9% 98.8%
Improved AlexNet with Inception-V4 for Plant Disease Diagnosis [47]	Paper	2022	Crops	Improve AlexNet with Inception-V4 to increase its accuracy for plant disease diagnosis	AlexNet with Inception-V4 AlexNet VGG11 ZFNet VGG16	96.5% 80% 80% 80% 80%
Comparison of Plant Leaf Classification Using Modified AlexNet and Support Vector Machine [48]	Paper	2021	Nine different plants	Propose an algorithm to classify plant diseases	AlexNet SVM Linear SVM RBF	91.15% 88.96% 89.69%
Optimized Deep Learning Algorithms for Tomato Leaf Disease Detection with Hardware Deployment [49]	Paper	2022	Tomatoes	Determine which algorithm and optimizer is most suitable to detect diseases on tomatoes through their leaves	MobileNetV3-L with Adagrad Inception V3 with SGD ResNet50 with SGD MobileNetV1 with SGD MobileNetV2 with SGD MobileNetV3-S with Adagrad AlexNet with SGD	99.81% 99.62% 99.62% 99.49% 98.93% 98.99% 96.68%
Optimization of Deep Learning Model for Plant Disease Detection Using Particle Swarm Optimizer [50]	Paper	2022	Wheat, cotton, grape, corn, and cucumbers	Detect plant diseases in five types of crops	AlexNet + PSO AlexNet	98.83% 95.6%
Real-Time Detection and Identification of Plant Leaf Diseases using YOLOv4-tiny [51]	Paper	2021	Tomato, mango, strawberry, beans and potato	Identify diseases on crops trough images of the plant leaves	YOLOv4-tiny	63.31%

Table 2. (Continued)

Name	Type	Year of publication	Types of plants classified	Purpose of study/app	Technique used	Accuracy
Plant Disease Detection Based on YOLOv3 and YOLOv4 [11]	Paper	2021	Thirteen plant species	Train two algorithms with YOLOv3 and YOLOv4 to identify seventeen diseases on thirteen plant species	YOLOv4 YOLOv3	55.45% 53.08%
Disease Detection In Plant Leaves Using Deep Learning Models: AlexNet And GoogLeNet [52]	Paper	2021	Potatoes	Create a system to identify early blight and late blight on potatoes through their leaves	AlexNet GoogLeNet	98.51% 98.51%
An Instance Segmentation Model for Strawberry Diseases Based on Mask R-CNN [53]	Paper	2021	Strawberries	Identify 7 kinds of strawberry diseases	Mask R-CNN	82.43%
Symptom recognition of disease and insect damage based on Mask R-CNN, wavelet transform, and F-Rnet [54]	Paper	2022	Tea plants	Propose a new algorithm to identify 3 major leaf diseases of tea plants	Algorithm based on Mask R-CNN, wavelet transform and F-RNet ResNet18 VGG16 AlexNet SVM	88% 82% 80% 73% 65%
Decision-making support system for fruit diseases classification using Deep Learning [55]	Paper	2020	Peach	Propose a support system for the classification of peach diseases	MobileNetV2	96%

4. Challenges and Opportunities

As stated in the introduction the main objective of this ongoing project, is to develop a system, that can help park visitors in their enjoyment and awareness of the wild plants and flowers. The system will be able to identify the plant and flowers species and their growth stages. To achieve this objective the system will be composed by two different components: a mobile application, which can be installed on the mobile phone of each visitor, and fixed devices to be mounted on the ground near the plants and flowers. The mobile application can be used by park visitors themselves. They can direct the camera to a plant or a flower and the application will detect and identify the plant species and growth stage, and provide other relevant information. The fixed devices must be mounted on the ground and equipped with a camera pointing towards the area of wild plants or flowers to be monitored. Each fixed device performs a daily photo capture and sends it to a central computer. Each capture is then classified and kept in a database in the cloud, where researchers, naturalists and enthusiasts can access it. This system will allow constant monitoring of wild flowers and plants which can help in their preservation.

To develop the proposed system four main challenges were identified that need to be overcome. The first challenge is that to the best of our knowledge, at the time of this research, a dataset of images with the growth stages of wild flowers and plants is not available. This represents one of the biggest obstacles, since a dataset is needed to train the algorithm that will be used to classify the flowers and plants development stages.

The second challenge to be considered is the network coverage. This problem occurs when the network signal is weak or even not available in certain areas, which can lead to poor network performance, slow data speeds, and dropped packets. For the mobile application, to avoid large amounts of data being transferred over the network, the classification can be performed directly in the users' mobile phones. Then, the mobile application would only retrieve from the central computer additional information related to the plant and its growth stage. In contrast, the fixed device would transfer the photos to the central computer for classification and storage. Since fixed devices will be mounted in remote areas with high forest density, network coverage may not be the most suitable for transferring large amounts of data. Thus, to carry out these transfers, it would be possible to take advantage of the multiple devices spread across the terrain. A wireless mesh network could be used to bring network coverage to all these devices. Mesh networks create a network of interconnected devices. These devices can relay data between one another, allowing for communication even in areas where there is no direct connection to the destination or to the Internet. This solution would allow photos to be transferred opportunistically via other devices to be delivered to the central computer.

The third challenge identified is related to the power supply for fixed devices. Since these devices would be applied in remote areas, it would be impractical to provide a constant energy supply. Therefore, the operation of this devices would need to rely on a battery. One possible solution would be to use solar panels to recharge devices batteries. However, in locations with high forest density this solution may not be suitable due to lack of sunlight. To mitigate this problem, some mechanisms could be used to minimize the operation of the devices (e.g., use duty cycles).

Finally, the fourth challenge would be the possible destruction of the fixed devices by wild animals. Wildlife may disturb the fixed device by tumbling it to the ground or changing the camera angle. As a possible solution, it would be advisable to install the system at some distance from the ground, out of reach of wild animals. Alternatively, camouflage could be used over the devices to avoid detection by wild animals.

The development of this system will also create some opportunities. Three identified opportunities are described below. One of the opportunities identified is that, to the best of our knowledge at the time of the development of this work, a technology has not yet been developed that allows the classification of the growth stage of a particular wild plant through a photo. Therefore, the creation of this system would contribute greatly for the preservation of endangered species of wild flowers and plants.

The second opportunity would be the improvement of pre-existing technologies, which are used for the identification of plants or plant diseases. An indication of this opportunity was show in the related work section. According to a study [50] using the App Plantix it was proven that only 10% of the infected plants had the right disease diagnosed. Despite this bad result, it shouldn't be assumed that all Apps have a bad accuracy, but it is a clue that some results may not be as accurate as expected.

The third opportunity is that the proposed system would provide information to researchers and park workers to help in the protection of specific wild flowers and plants species. In addition, it would also provide information and awareness to the public (i.e., park visitors) through the mobile application.

The proposed system will classify and identify the growth stages of wild flowers and plants on a central computer by using computer vision techniques. The analysis of the survey presented in this paper allows to conclude that for the fixed device the most suitable algorithms would be MobileNetV3-Large with the optimizer Adagrad or AlexNet. As presented in [49], using MobileNetV3-Large with the Adagrad optimising algorithm, an accuracy of 99.81% was achieved. In [37], [48], [52] and [35] it was proven that the AlexNet algorithm is also very reliable and accurate in many situations. Therefore, AlexNet can also be considered.

Based on the results obtained in [12], [34] and [11], YOLOv4 or YOLOv3 proved to be the best option to be used for the mobile application. These algorithms are fast, use relatively low processing power, and can perform results in real-time. These features fit perfectly with the requirements of the proposed mobile application.

5. Conclusion

Not only are wild plants and flowers beautiful, but they are also an important part of our lives. They feed both people and animals or can be used for aromatic or medical purposes. Wildlife like bees, birds, butterflies, and others would not exist without them. However, this irreplaceable natural heritage is in danger of being lost due to human activity and climate change. The work presented in this paper contributes to the conservation effort. It identified computer vision as a suitable technological platform for detecting and monitoring the development stages of wild flowers and plants. An overview of the most used computer vision techniques used in this area was provided. Then, a survey of plant identification and plant disease detection related research and applications was presented. It aimed to identify the most promising computer vision techniques. From the literature review, several open issues and challenges in the area were presented. The research that is presented in this paper is a first step in an ongoing effort to create a system and a mobile App that will support park visitors in their enjoyment and awareness of the wild flowers and plants they find along the roadways and trails. It will also allow the remote monitoring and collecting information regarding wild flowers and plants development stages. We are currently evaluating and comparing the precision of the above-identified computer vision techniques on different datasets of wild flowers and plants.

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Declarations

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