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OBJECT DETECTION TECHNIQUES FOR STRAWBERRY DISEASE DETECTION : A COMPREHENSIVE REVIEW

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ABSTRACT

Strawberry, which is a popular fruit, is known for its high content of vitamin C and antioxidants, thus contributing to cardiovascular health and blood sugar control. Faced with the challenges posed by diseases affecting its cultivation, such as anthracnose and powdery mildew, the integration of advanced technologies has become crucial to improve productivity compared to conventional agricultural methods. In recent years, deep learning techniques have been widely used in various fields of computer vision, demonstrating their potential for strawberry disease detection. However, the lack of in-depth discussions on the application of deep learning to this culture highlights the need for a comprehensive review of recent technologies. This article provides a comprehensive review of recent advances in this field and highlights four main models: YOLO, Mask R-CNN, RetinaNet, and SSD, which have been widely used in object detection. It also explores different databases available in the literature, while highlighting the challenges of using them for real-time research.

Keywords: *Strawberry Disease, Object Detection, Deep Learning, Yolo, Mask R-CNN, Retinanet, SSD*

1. INTRODUCTION

Strawberry cultivation is of fundamental importance globally, being an essential pillar of the agricultural and food economy [1]. This fruit is not only among the most popular, but also one of the most consumed worldwide. Its cultivation represents a major incoming source for many farmers and agricultural regions, thus actively participating in the economic dynamics of local and national communities [2]. However, strawberry production faces many challenges, including diseases that can cause considerable economic losses [3]. Diseases such as gray rot [4] (Botrytis cinerea), root rot [5](Phytophthora spp.), and various fungal, bacterial and viral infections can affect the growth, quality and quantity of strawberries produced.

To ensure strawberry health and maintain optimal yields, it is crucial to design and employ techniques to detect diseases as they emerge. Conventional detection approaches can sometimes be time-consuming and expensive, [6] which delay the implementation of control measures and promote the spread of diseases. This is where the need for fast and accurate detection methods comes into play. In recent years, the artificial intelligence technologies, including machine learning and deep learning, has revolutionized disease detection in crops [7, 8]. The use of image recognition through deep learning and computer vision has proven to be a highly accurate and cost-effective solution for spotting diseases affecting crops [9]. Available reports highlight convolutional neural network (CNN) as one of the most effective deep learning techniques for detecting crop diseases.

Visual identification and field sampling of plant material remain the conventional approaches to spotting infections in the field, but they are laborious and require specialized know-how [10]. These traditional methods cannot detect latent

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infections in the early stages of their development. Although various laboratory analyses, such as microscopy and molecular, biochemical and microbiological techniques, have been implemented to diagnose crop diseases, they have drawbacks. This is because the sampling process is destructive and provides limited diagnostic points, which does not facilitate scalable field detection or accurate representation of the variability of field conditions. The integration of computer vision technologies has generated great enthusiasm for precision agriculture over the last decade [11]. The computer vision, which positioned at the heart of robotics and artificial intelligence, offers the possibility of performing a multitude of tasks in an automated and efficient manner throughout the agricultural production cycle, from the planting phase to the harvest.

Currently, the adoption of the computer vision technology, especially the object detection, in the agricultural sector is growing steadily. This technology uses imaging devices to capture images and determine whether they contain weeds, pests or even plant diseases with their locations in the image using the object detection techniques [12].

For this review, we adopted a systematic and structured methodology to ensure rigorous selection and in-depth analysis of relevant articles. We began by defining precise inclusion and exclusion criteria to identify relevant studies on strawberry disease detection techniques. Articles were selected from recognized scientific databases such as IEEE Xplore and Google Scholar, using specific keywords related to strawberry disease detection and object detection techniques. Each selected article was analyzed in depth according to predefined criteria such as the methodology used, the results obtained and the contributions to current research. This systematic approach allowed us to provide a comprehensive and critical overview of existing techniques in this area.

Based on the opinions of the authors of the selected articles and the importance of the algorithms in the current literature, we chose to analyze the RetinaNet, Mask R-CNN, SSD, and YOLO algorithms in detail. These algorithms are among the most popular and recognized for their performance and unique characteristics.

This paper presents a review of the utilization of deep learning techniques to enhance the economic aspects of strawberry farming. It aims to summarize and analyze recent literature to facilitate researchers in comprehending the relevant methodologies and technologies in this field efficiently and systematically.

This paper is organized to provide a comprehensive understanding of the challenges and advances in disease detection in strawberry cultivation. The background section explores the importance of strawberries on a global scale, detailing their economic importance to farmers and the agricultural industry. Additionally, it highlights the impact of diseases such as anthracnose and powdery mildew on crop yield and quality, as well as economic losses, highlighting the need for advanced technologies. Object detection techniques are then discussed, including classic approaches such as image segmentation and rule-based systems, as well as deep learning methods and transfer learning concepts. The discussion extends to datasets, reviewing those that exist and addressing challenges related to their availability and diversity. Real-world applications and case studies illustrate successful implementations of object detection in strawberry disease detection, highlighting their practical importance on agricultural operations. Finally, the evaluation metrics are elucidated, covering commonly used metrics such as precision, recall, and F1 score.

The rest of this paper is organized as follow. Section 2 gives the background. The object detection techniques are presented in section 3. Section 4 presents the datasets. The applications and case studies are presented in section 5. Section 6 presents Evaluation Metrics. Finally section 7 gives the conclusions followed by the most relevant references.

2. BACKGROUND

Strawberries (Fragaria × ananassa) are among the most widely cultivated fruits across the globe, due to their distinctive flavor and remarkable nutritional qualities, as well as their versatility as a fresh or processed product. Additionally, strawberries play a major economic role globally and are considered a key commodity in many regions. Their economic value is not only limited to their local consumption,

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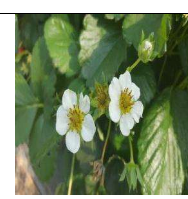
but they also represent a crucial element in international trade, with strong potential as an export product [13].

There are many important factors to consider when growing strawberries, including diseases that seriously affect them. For example, fungi and bacteria diseases, that attack fruits, flowers, and leaves in strawberry crops, can have an impact from the earliest stages of growth [14]. Among these diseases, there are some disease examples, which are shown in table 1, such as; gray rot, anthracnose, leaf spot disease, angular leaf spot, powdery mildew [15-19], and Blossom Blight [20]. Gray rot [15] is a significant example. This disease affects plants during the flowering period when the weather is cold and wet for long periods, creating favorable conditions for its spread. Symptoms vary; from gray spots on infected fruit to spread of the disease between different parts of the plant. Anthracnose [16] is a fungal disease that affects many plants, including strawberries. It is caused by different fungi of the Colletotrichumgenus. Anthracnose can cause black spots on the leaves, stems, and fruits of strawberries, leading to discoloration and deformation of the fruits, which often reduces their quality and yield. Leaf spot disease [17] is one of the serious conditions that affect the stems of strawberry plants as well as several parts of the plant. It significantly reduces crop growth and can even lead to complete death of plants if the disease is associated with drought or high temperatures. Among its symptoms, for example, we observe the presence of a dark purple color on the upper parts of the leaves of strawberry plants, and as the disease progresses, the tissues surrounding these spots take on a purple and red tint, giving the leaves a burnt appearance in many resistant cases. Angular leaf spot [18] is a bacterial disease caused by Xanthomonas fragariae. It affects the leaves of strawberries and causes characteristic angular lesions whose edges are soaked in water. Powdery mildew [19] is one of the major fungal diseases affecting strawberries, and its occurrence can lead to significant crop losses if not controlled effectively. The first signs of powdery mildew generally appear on the leaves, in the form of white powdery spots. This white substance is made up of fungal spores that spread easily from plant to plant, especially in hot dry weather. Flower stems and fruits may also be affected, reducing the quality and quantity of the harvest. Blossom Blight[20] is a disease that affects strawberry flowers. It is characterized by the initial formation of a gray fungus on the stigma of the flower, which gradually leads to flower burn, followed by black rot and complete flower necrosis.

Table 1. Strawberry disease examples

Strawberry disease	**Image disease characteristics**	
Gray rot [15]		
Anthracnose [16]		
Leaf spot [17]		
Angular leaf spot [18]		
Powdery mildew [19]		
Blossom Blight [20]		

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In the past, farmers using traditional methods often faced major challenges in plant disease management. Manual recognition and expert systems were the primary methods for identifying diseases, but their efficiency and accuracy were limited, making real-time crop monitoring difficult. Early detection of diseases during their initial infection phase is crucial for effective prevention, but was often difficult to achieve quickly. So, it is essential to accurately and quickly identify plant diseases, particularly when growing strawberries, and to implement effective corrective measures to limit their spread. This helps prevent reduction in crop yield and quality, while reducing dependence on pesticides [21]. In this context, the adoption of advanced technologies becomes essential for smarter agriculture.

Traditional image recognition methods have yielded satisfactory results, but they have limitations such as complex image preprocessing, high subjectivity, and interference in complex environments [22]. However, thanks to technological advancements in the fields of deep learning and computing, deep learning-based detection algorithms are increasingly used in agricultural research. These algorithms provide significant advantages, including high speed, increased accuracy, generalization ability, and robustness in varying environments [23]. By integrating these technological advances, farmers can benefit from real-time monitoring of plant diseases, allowing them to take more effective and targeted preventive and corrective measures. This contributes to more sustainable crop management, reducing yield losses and excessive use of pesticides.

In conclusion, it is imperative to consider the implications of excessive pesticide use on the environment, fruit quality and human health. By reducing dependence on pesticides, we not only preserve ecological balance and biodiversity, but we also improve fruit quality. Reducing exposure to pesticide residues helps ensure healthier and safer fruits for human consumption. By protecting the health of consumers, we also help preserve the health of ecosystems and agricultural communities in the long term. This shift towards more sustainable and environmentally friendly agricultural practices is essential to ensuring a secure and sustainable food future for future generations.

3. OBJECT DETECTION TECHNIQUES

Object detection is a crucial process in computer vision and image processing, involving locating and identifying specific objects in images or videos. Basically, it involves detecting the presence of objects in a scene and determining their location and class.

Object detectors generally operate by analyzing visual information in an image or video frame and generating bounding boxes that delineate the regions where objects are detected. Besides localizing the objects, object detectors also classify them into predefined categories or classes, specifying the type of object identified.

There are multiple approaches to object detection, including traditional methods and deep learning-based techniques. Traditional methods typically involve handcrafted feature extraction and machine learning algorithms, such as the Viola-Jones Detector, Histogram of Oriented Gradients (HOG) Detector, and Deformable Part-based Model (DPM).

Conversely, deep learning-based approaches have garnered significant attention and success in recent years. Convolutional Neural Networks (CNNs) play a crucial role in deep learning for object detection, as they can automatically extract relevant features from images and learn complex patterns representative of various object categories. CNN-based object detection architectures can be categorized into two types: one-stage detectors and two-stage detectors.

In this section, we explore various object detection techniques, to provide innovative solutions for agriculture and crop health.

3.1. Classical Approaches

Object detection is a fundamental pillar of computer vision, relying on various classical methods to identify and interpret elements present in an image [24]. Among these methods, image segmentation plays a vital role. This approach consists of subdividing an image into distinct regions or objects, thus making it possible to discern the different visual components. By isolating these regions, segmentation facilitates the understanding and analysis of the various elements contained in the image, thus facilitating object detection [25].Meanwhile, feature extraction represents another crucial method in the object detection process. This technique involves the identification and isolation of specific features within the image that are relevant for object recognition and classification. By extracting distinctive features such as patterns, textures or shapes, this method provides valuable clues to identify target objects in the image [26]. Furthermore, rule-based systems play a significant role in object detection. These systems rely on the definition of specific rules that encode criteria or conditions to identify particular objects or events. By applying these predefined rules, systems can determine the presence or absence of target objects in an image, providing a structured approach for object detection and classification [27]. However, despite their usefulness, these traditional computer vision methods have limitations when faced with complex scenes, lighting variations, and dynamic environments. Image segmentation can face challenges when distinguishing between objects that are overlapping or have similar textures, while feature extraction can be sensitive to subtle variations in the appearance of objects. Similarly, rule-based systems can be limited by their rigidity and inability to generalize to new or unexpected contexts. These methods can also struggle to handle the diversity of objects and situations encountered in real-world environments, compromising their ability to provide accurate and reliable results [28].

To address these challenges, new approaches based on deep learning and artificial intelligence has emerged, providing enhanced capabilities for object detection in complex environments. By leveraging deep neural networks and advanced machine learning techniques, these approaches enable more sophisticated analysis of visual data, improving the accuracy and robustness of object detection in a variety of contexts. As a result, the integration of these emerging technologies opens new avenues for computer vision and object detection, paving the way for innovative applications in various fields, including surveillance, security and image analysis [29].

3.2. Deep Learning Approaches

Deep learning, a branch of machine learning, has revolutionized computer vision, a crucial area for interpreting the growing avalanche of images and videos recently available [30]. Faced with this flood of visual information, the extraction of relevant data has become essential. The foundations of computer vision are based on machine learning techniques and in particular on deep learning [31]. With increasing computing power and abundance of data, deep learning has emerged as a leading method to efficiently process huge data sets and extract features from unstructured data. These advances have been deployed in various sub-domains of computer vision, which are enabled the prowess in tasks such as classification, localization, detection, and segmentation, with remarkable performance. The development of object detection methods perfectly illustrates the impact of deep learning in the field of computer vision. These methods aim to locate and classify objects that presented in images or videos; this complex task requires a deep understanding of the visual context. There are many deep learning architectures designed specifically for object detection, such as you only look once (YOLO), single-shot detector (SSD), mask region-based convolutional neural network (Mask R-CNN) and RetinaNet, which have revolutionized the way of computers interpreting and understanding visual information [32]. These architectures combine sophisticated image processing techniques with deep neural networks to extract meaningful features from visual data and make precise inferences about the presence, location and class of detected objects. Table 2 highlights the strengths and limitations of Mask RCNN, RetinatNet, SSD and YOLO approaches for object detection in images, based on different experiments carried out by various authors specializing in the field of deep learning.

- **You Only Look Once(YOLO)**

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YOLO represents an innovative object detection algorithm which is based on CNNs and offers a distinct approach from previous networks [33]. YOLO applies a single neural network to the entire image, avoiding the need to generate separate region proposals. This process consists of subdividing the image into several sub-regions, then predicting the bounding boxes and class probabilities for each of these subdivisions. Figure 1 shows the architecture of YOLO algorithm.

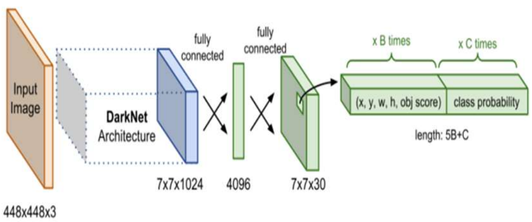

Figure 1. The YOLO algorithm architecture

The heart of YOLO's architecture is a convolutional neural network (CNN), usually considered as backbones and built using deep classification models like Darknet or ResNet, which is responsible for extracting relevant features from the image at different scales and resolution levels. This feature extraction is crucial for accurate detection of objects in the image. YOLO divides the image into a grid of cells, with each cell responsible for predicting a set of bounding boxes and their associated confidences. Each bounding box also predicts the class scores for different categories of objects present in the image. Prediction of bounding boxes and class scores is performed using specific techniques, such as box regression and softmax classification, ensuring accurate detection of objects in the image. Finally, YOLO applies a non-max removal technique to eliminate redundant detections and merge overlapping bounding boxes.
In summary, YOLO's architecture enables real-time object detection by applying a single neural network to the entire image, providing an efficient and accurate approach for object detection in a variety of scenarios of application. There are several versions of this model, each with specific improvements and adjustments at different levels.YOLOv8 represents the latest iteration of the YOLO object detection model; This version, while retaining the fundamental architecture of its predecessors, introduces several significant improvements; These improvements include a new neural network architecture leveraging both the Feature Pyramid Network (FPN) and the Path Aggregation Network (PAN). Additionally, YOLOv8 includes a new labeling tool that significantly simplifies the data annotation process. This tool offers various features such as automatic labeling, labeling shortcuts, and customizable hotkeys. This combination of features greatly facilitates image annotation for model training, thereby increasing the efficiency and accuracy of object detection [34].

- **Single-Shot Detector (SSD)**

The SSD algorithm has similarities to YOLO in that it avoids generating distinct region proposals and performs object detection in a single pass through the neural network [35].
The mechanism of the SSD algorithm is based on using a single pass through a convolutional neural network to detect objects in an image. It works by extracting features at different spatial scales from the image and then using special detection layers to predict bounding boxes and confidence scores for each object class. These predictions are made at several scales to detect objects of varying sizes. The algorithm is trained in an end-to-end manner, which means that it is optimized for object detection directly from the training images [32]. In summary, SSD is an efficient and fast method for real-time object detection thanks to its single-pass approach through the neural network. Figure 2 shows the architecture of SSD algorithm.

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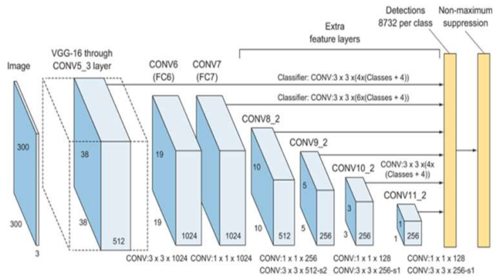

Figure 2. The SSD algorithm architecture

The SSD architecture is an efficient solution for object detection in images, designed around a single pass through a convolutional neural network. First, SSD uses a convolutional backbone to extract image features at different scales and resolution levels. This step allows capturing relevant information about the objects present in the image, using popular architectures such as VGG, ResNet or Inception. Then, the SSD uses a feature pyramid to detect objects at different spatial scales. This pyramid is built by applying convolutions on the intermediate layers of the network, which allows information to be captured at different spatial resolutions. At each scale, special detection layers are used to predict bounding boxes and confidence scores for each object class. Bounding boxes are predicted using default boxes defined at different scales and aspect ratios to cover a variety of object sizes and shapes. The detection layers predict both the confidence scores for each object class and the coordinates of the bounding boxes associated with each class.

Finally, to eliminate redundant detections, SSD uses the Non-Maximum Suppression (NMS) algorithm which merges overlapping bounding boxes with high confidence scores. This step ensures that the final detections are accurate and non-redundant.

- **Mask Region-based Convolutional Neural Network (Mask R-CNN)**

Mask R-CNN is an extend version from the Faster R-CNN model by introducing Instance segmentation functionality for object detection. Mask R-CNN operates in three main steps; it begins by generating object proposals via an R-CNN. Then, it refines these proposals with increased spatial precision using convolutional regional of interest (ROI) pooling. Finally, it creates segmentation masks for each detected object. This evolution of the R-CNN architecture is motivated by the limits of traditional object detection which did not take into account pixel-by-pixel segmentation of objects. Successive improvements, including Fast R-CNN and Faster R-CNN, led to Mask R-CNN, providing a more comprehensive solution for the precise detection and segmentation of objects in images [36, 37]. Figure 3 shows the architecture of Mask R-CNN algorithm.

The concept of Mask R-CNN is quite simple to understand: it is an extension of Faster R-CNN which, for each object candidate, not only generates a class label and bounding box offset, but also an accurate mask of the object itself. This extension is intuitive, but the additional mask output requires extraction of finer spatial details from objects, which represents a distinct challenge from class and box outputs.

To explain how the Mask R-CNN works, let's start by looking at the Faster R-CNN detector. The latter is divided into two main stages: the first stage, called region proposal network (RPN), proposes bounding boxes for candidate objects. The second stage, which is essentially a Faster R-CNN, extracts features from each candidate box using RoIPool, and then performs bounding box classification and regression. The extracted features can be shared between the two stages to speed up inference.

The Mask R-CNN, on the other hand, follows the same two-step procedure with an identical first step, i.e. RPN. In the second step, in addition to predicting the class and offset of the box, Mask R-CNN also produces a binary mask for each region of interest (RoI).

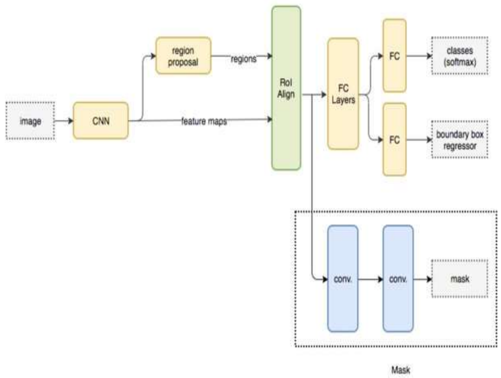

Figure 3. The Mask R-CNN algorithm architecture

- **RetinaNet**

RetinaNet [38, 39] presents itself as an innovative architecture that integrates a main network and two distinct sub-networks. The main network, often referred to as the backbone, operates on the input image to calculate a convolutional map. This map is then used by sub-networks for specific tasks which making RetinaNet a comprehensive and efficient model for object detection in images.

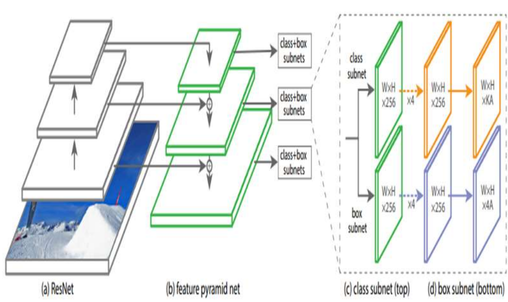

Figure 4. The RetinaNet algorithm architecture

The single-stage RetinaNet network architecture, figure 4, uses a Feature Pyramid Network (FPN) on a forward-propagating ResNet architecture (a) to generate a rich, multi-scale convolutional feature pyramid (b). To this backbone, RetinaNet associates two sub-networks, one for classification of anchor boxes (c) and the other for regression of anchor boxes to reference object boxes (d). The network design is intentionally simple, allowing this work to focus on a novel focal loss function that eliminates the accuracy gap between our single-stage detector and state-of-the-art two-stage detectors such as Faster R- CNN with FPN while running at higher speeds.

Generally, the architecture of RetinaNet is based on a convolutional "pyramid" neural network (FPN) and a recurrent neural network (RPN). FPN is used to extract features from images at different scales, while RPN is used to generate potential ROIs. These regions of interest are then classified and refined to detect objects of interest. One of the main features of RetinaNet is its use of a loss function called "Focal Loss", which allows rare objects to be processed more efficiently and avoids the class imbalance problem. This innovative architecture enabled exceptional disease detection results, surpassing traditional methods [40].

Table 2. The strengths and limitations of the Mask RCNN, the RetinatNet, the SSD and the YOLO models

Model	Advantages	Disadvantages
YOLO[41]	Its high processing speed, which allows it to detect objects in real time in images and videos, making it an effective option for applications such as video surveillance and autonomous vehicles.	Its poor detection to small or poorly defined objects, which can lead to difficulties in accurately detecting these objects, particularly in complex or cluttered environments.
SSD[42]	The use of a single network allows faster	Object detection accuracy is lower than Fast

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	localization of objects compared to the Fast R-CNN and Faster R-CNN approaches.	R-CNN and Faster R-CNN, although the latter are faster.
Mask R-CNN[43]	It stands out for its ability to detect objects precisely, segment their contours with high accuracy and manage multiple instances of objects in an image, thus providing a versatile and powerful solution for computer vision	Using an external candidate region generator causes a bottleneck in the detection process
RetinaNet[44]	Effective use of a focal loss function to overcome class imbalance	Compared to SSD, Mask R-CNN and YOLO, its higher computational complexity may limit its performance in applications requiring higher

		computing cost large number of negative samples Require high VRAM

3.3. Transfer Learning

Transfer learning consists of reusing a model already developed for one task as a starting point for another model intended for a second task. This approach, widely used in deep learning, uses pre-trained models to initiate tasks in computer vision and natural language processing. It is favored because of the significant computational resources and time required to develop neural networks on these problems, as well as the significant advances it brings to similar tasks. Pre-trained models are derived from prior training on large datasets, and their weights are retained for later use [45].In practice, for agricultural disease detection, transfer learning involves taking a pre-trained deep learning model (e.g. ResNet, VGG, Inception) and re-tuning it on a smaller dataset containing images of plants with and without diseases. The weights of the pre-trained model are adjusted during the training process to adapt to the specific characteristics of agricultural images and disease detection task.

Transfer learning in deep learning involves using pre-trained models as a starting point to train a new model on a similar or related task.

A pre-trained model is a deep neural network that has been trained on an extensive dataset to perform a specific task, such as image classification or object detection. This pre-trained model has acquired the ability to extract relevant features from the input data, and these features can be reused to solve similar tasks.

In the context of transfer learning, pre-trained models are typically leveraged in two main ways. First, the pre-trained model can serve as a feature extractor, where the output of one or more layers of the pre-trained model is used as input to a new model. Next, the pre-trained model can be fine-tuned, which involves adjusting the weights of

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some or all layers of the pre-trained model during training to better fit the new task.

4. DATASETS

For training and evaluation of strawberry disease detection models, several datasets are widely used in the research community and agricultural industry.

4.1. Smaller Dataset Problems

Currently, crop disease detection techniques rely largely on advances in deep learning, particularly in the field of computer vision. Crop disease detection is a crucial specialized application for modern agriculture. However, the availability of samples of agricultural diseases and pests are remains limited. Compared to open standard libraries, datasets collected by farmers themselves are often more restricted and require laborious effort to label [46, 47]. The small size of these datasets represents a major challenge for detecting crop diseases and pests, especially when considering the disparity with large datasets such as those from ImageNet, which include over 14 million of samples. The scarcity of training data, due to the low prevalence of diseases and the high cost of image acquisition, poses a significant obstacle to the effective application of deep learning methods for the identification of diseases and diseases crop pests.
Data augmentation methods represent crucial solutions to compensate for the lack of data in various scenarios. They encompass a range of techniques designed to enrich both the characteristics and size of training datasets. Therefore, deep learning networks that integrate these approaches tend to have better performance. Some examples of these techniques used to address challenges associated with limited datasets include flipping, color space, translation, cropping, rotation, and adding noise [48-53].

Flipping

The flipping operation consists of inverting an image either horizontally or vertically. This technique generates new images by rotating the image by a multiple of 90 degrees. However, it is important to note that some frameworks do not support vertical flipping natively. In such cases, vertical flipping can be simulated by rotating the image 180 degrees and then applying a horizontal flips [54].

Color Space

Color space transformation, also known as photometric transformation, is a techniques used in image processing. The operation consists of creating three stacked matrices representing the image, each of these matrices having the dimensions of height and width. Each matrix corresponds to pixel values for the red, green, and blue (RGB) color components. This approach makes it possible to modify the color distributions of the image in order to correct the lighting problems encountered [55].

Cropping

Cropping, also known as randomly sampling a specific section of an original image, involves selecting a random portion of the image and resizing it to the size of the original image. It is therefore a selected part of the initial image which is adapted to a specific scale if necessary. This method is often referred to as "random cropping." It is important to note that random cropping differs from translation in that it reduces the size of the image, while translation maintains its spatial dimensions [54, 56].

Rotation

Rotation allows you to adjust the image in 90 degree increments or at finer angles as needed. When rotated in 90 degree increments, the image maintains its integrity without introducing background noise. However, this is not true for rotations at finer angles, where background noise may be added to the image during orientation. Additionally, if the background of the image is black or white, any noise introduced will likely blend into the image. Conversely, if the background contains different colors, the noise may not blend

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in, allowing the network to perceive it as a distinctive feature of the image [54, 55].

Alternatively, rotational augmentation is a technique used to increase data diversity by rotating images clockwise or counterclockwise around an axis. The degree of rotation can vary from 1 to 359 degrees, which provides great flexibility in transforming images. The safety of this increase depends on the degree of rotation applied. Indeed, a slight rotation, say 20 degrees, can often retain the integrity and semantics of the original data while introducing sufficient variability to enrich the dataset.

It is important to note that when applying this technique, the data label or annotation is usually preserved for light rotations. However, as the degree of rotation increases, it is possible that the annotation of the data will be changed, which may require special attention when using this augmentation in machine learning or data processing applications and image processing.

The degree parameter for rotation governs the conservatism of the augmentation. It proves beneficial in digit recognition tasks for light rotations. However, increasing the degree of rotation may alter the data label after transformation.

Translation

Translation, when applied to images, makes it easier to identify objects in different regions of the image. It involves moving the image along the X or Y axis, or both which allowing adjustments left, right, up or down. This technique is very useful for mitigating positional biases in the data because it allows the network to explore different parts of the image. However, this increase can introduce background noise into the image [57].

Noise Infusion

The process of foleying involves injecting an arbitrary matrix of values into the data. Generally, this matrix is generated from a Gaussian distribution. Moreno Barea et al. [58] studied noise injection using nine datasets from the UCI repository. Introducing disturbances into images allows convolutional neural networks (CNNs) to acquire additional robust features.

4.2. Dataset availability

To effectively deploy deep learning techniques in agriculture, the availability of large and high-quality datasets is essential. These datasets can be acquired through various means including; self-collection efforts, network collaboration, and public repositories [26, 49, 32, 53]. Methods for self-collecting image datasets are often involve ground camera photography, monitoring via Internet of Things (IoT) devices, and aerial photography using unmanned aerial vehicles equipped with cameras, hyper-spectral imagers or near-infrared spectrometers. Datasets collected in real agricultural contexts are particularly valuable because of their relevance to practical applications.

Although an increasing number of researchers are making field-collected images publicly available, uniformly comparing datasets across different disease classes, detection objects, and scenarios remains a challenge.

Table 3. Strawberry disease detection datasets example

Dataset Name	Total Images	Training Images	Validation Images	Test Images	Link
PlantVillage [59]	61,486				https://data.mendeley.com/datadata/tywbtsjrjv/1
The Strawberry Disease Detection Dataset [60]	2,500	1450	307	743	https://www.kaggle.com/datasets/usmanafzaal/strawberry-disease-detection-dataset

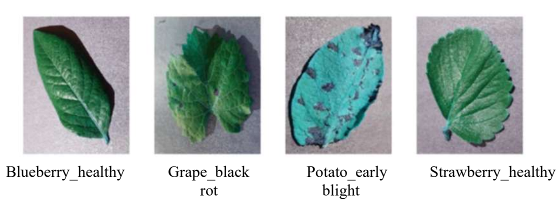
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

PlantDoc-Object-Detection-Dataset [61]	2,598				https://github.com/pratikkayal/PlantDoc-Dataset
strawberry-disease-detection-dataset_dataset [62]	4918				https://universe.roboflow.com/strawberry-disease/strawberry-disease-detection-dataset

Table 3 presents a selection of publicly available datasets from existing research efforts. These datasets provide valuable resources for researchers and practitioners in the field of agriculture and plant pathology.

- **PlantVillage Dataset**

The PlantVillage dataset [59] was designed to provide effective solutions in the detection of 39 distinct plant diseases. It includes a total of 61,486 images of plant leaves and backgrounds. This dataset was enriched through the use of six different augmentation techniques. These methods allowed for the creation of more diverse data sets, exhibiting a variety of background conditions. The augmentations applied include resizing, rotation, noise infusion, gamma correction, image flipping, and PCA color augmentation.

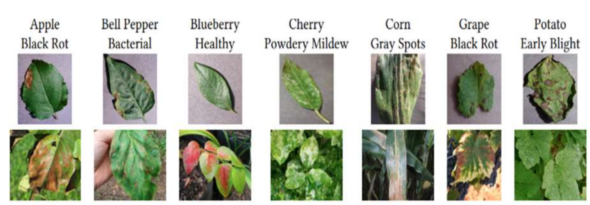


- **The Strawberry Disease Detection Dataset**

The Strawberry Disease Detection dataset [60] includes 2,500 images showing cases of strawberry diseases, collected from different greenhouses using camera-equipped mobile phones. These data were collected in numerous greenhouses located in South Korea, under natural lighting conditions, to encompass a diverse range of environmental variables. Disease validation was carried out by experts in the field.

- **PlantDoc Dataset**

PlantDoc dataset [61] is a dataset for visual detection of plant diseases. This dataset contains 2,598 total data points across 13 plant species and up to 17 disease classes, involving approximately 300 hours of human effort to annotate images retrieved from the Interne.



- **Strawberry-disease-detection-dataset Dataset**

Strawberry-disease-detection-datasetdataset [62] contains 4918 open source strawberry disease images, accompanied by a pre-trained model and strawberry disease detection API.

blossom_blight anthracnose_fruit_rot angular_leafspot

5. APPLICATIONS AND CASE STUDIES

In this section, we will look at a summary of the applications of deep learning algorithms used for strawberry disease detection from the reviewed studies. We will explore advances and real-world applications of deep learning techniques in the early and accurate detection of diseases affecting strawberry crops. These studies will shed light on how deep learning models have been deployed to identify symptoms of various diseases on strawberry leaves, thereby providing innovative solutions for farmers to prevent economic losses and drive better crop management crops.

5.1 Multiple Disease Detection

Diseases are a predominant factor in reducing the quality and productivity of vegetables, thereby causing economic losses for farmers, and are closely linked to daily economic activities [63, 64]. Strawberries, among the major greenhouse crops, are no exception and face various disease problems. The ability to quickly detect and identify strawberry diseases, as well as take appropriate control measures, is of crucial importance to ensure their growth, treat infections and increase farmers' income. Although different diseases may present symptoms visible in the light spectrum, their identification remains complex and subject to variations, requiring the expertise of specialists trained in the field of plant pathology for an accurate diagnosis. With advances in computer vision, a range of methods have been developed to address the challenges of detecting plant diseases, including first observing lesions and infection patterns on leaf surfaces. So, many researchers were proposed precise techniques for detecting and classifying plant infections [65, 66, 68].

Many studies have developed deep learning models to identify different diseases grouped into different classes. We took the approach of detecting multiple diseases as distinct categories. The Background section provides information on common diseases and their essential characteristics, while Table 4 summarizes the deep learning algorithms used in strawberry disease detection studies. At the same time, several researchers have developed models to early predict the appearance of specific plant diseases. The use of CNNs by several researchers has enabled the detection of multiple diseases (categories) in strawberries, leading to the creation of various specialized models capable of detecting multiple pathologies. For example, the study in [67] developed models such as GoogLeNet model, Resnet50, and VGG 16 to detect strawberry diseases.

In [69, 70], authors used the AlexNet model so that this model is used to train the strawberry diseases and pest image dataset. An enhanced residual network G-ResNet50 is used to identify healthy strawberry plants, powdery mildew, strawberry anthracnose and leaf spot disease images in [6]. In [71], this study explored the recognition of common strawberry diseases using deep convolutional neural network technology. Moreover, it presented a new method based on the strawberry disease recognition algorithm of deep convolutional neural networks (DCNN). In [72], this study used a recent approach to build a system capable of detecting and classifying plant diseases. By analyzing and comparing previous works based on deep learning, we concluded that these studies mainly use two CNN architectures (AlexNet and GoogleNet). By evaluate state-of-the-art CNN architectures using a public plant disease dataset, the results of this evaluation clearly showed that we can improve accuracy using new CNN architectures such as InceptionV3, which achieved an accuracy of 99.76%. Furthermore, this study investigated

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increasing the transparency of deep models using visualization techniques, introducing the saliency map method to locate infected regions of plants after disease identification. In [73], authors proposed a simple but effective strawberry disease detection system with unknown diseases that can produce reasonable performance. In [63], authors used a computer vision model based on the YOLO v5 architecture to perform real-time research on seven of the most common strawberry diseases. This model demonstrated effective disease detection with 92% accuracy. In [74], authors presented a plant disease detection model based on deep learning. This model is designed to identify different diseases from images of plant leaves. To develop this disease detector, a methodology steps was: first, data augmentation was carried out to expand the sample, then, a CNN, with multiple convolution and pooling layers, was employed. In [65], authors proposed a model based on Mask R-CNN architecture that effectively performs instance segmentation for seven diseases. They used a ResNet backbone and follow a systematic approach to data augmentation that enables segmentation of target diseases under complex environmental conditions. Authors achieved a final average accuracy of 82.43%. In [75], authors trained a deep CNN to identify 14 crop species and 26 diseases (or lack thereof). The trained model achieved 99.35% accuracy, demonstrating the feasibility of this approach. In [76], authors presented a model for detecting strawberry leaf diseases. This research used AlexNet and GoogLeNet architectures to develop strawberry leaf disease detector based on dual-channel residual network with multi-directional attention mechanism.

5.2 Specific Disease Detection

This research work in [68] developed a method for diagnosing powdery mildew disease on strawberry leaves based on RGB images using deep learning techniques. The optimized models such as AlexNet, SqueezeNet, GoogLeNet, ResNet-50, SqueezeNet-MOD1 and SqueezeNet-MOD2 were subjected to exhaustive evaluation. To avoid over-fitting and to take into account the variability of leaf shapes and orientations in the field, data augmentation was carried out using 1450 photos of healthy and diseased plants. The used six deep learning algorithms presented an overall average classification accuracy exceeding 92%. ResNet-50 stood out by achieving a classification accuracy of 98.11% to distinguish healthy leaves from infected leaves. However, considering the processing time, AlexNet processed 2320 images with a classification accuracy of 95.59% in just 40.73 seconds. Due to its performance with classification accuracy of 92.61% and memory requirements for hardware deployment, SqueezeNet-MOD2 is recommended for particle detection on strawberry leaves. Although ResNet-50 achieved statistically higher classification accuracy (98.11%), the other methods did not show a notable difference in classification accuracy. SqueezeNet-MOD2 turned out to be the least demanding in terms of hardware memory. ResNet-50 was the slowest in processing the 2320 photos, requiring 178.20 seconds, while AlexNet was the fastest, taking just 40.73 seconds. The CNN algorithms tested exhibited significantly different processing times, with AlexNet and SqueezeNet-MOD2 being the fastest.

A recent study used deep learning networks, including UNet, to detect the presence and assess the severity of gray mold on strawberries [66]. Three groups of strawberries were inoculated with different levels of the pathogen. Using an RGB camera, symptoms were recorded on leaves non-invasively. A set of 400 leaf images was divided into training and testing sets. The model was trained and evaluated with five cross-validations. UNet showed an accuracy rate of 82.12%, low memory usage (~22 MB), and fast test times (0.2 s per frame on a standard computer). Incorporating VGG16's pre-trained convolutional layers improved the performance of the XGBoost classifier. The researchers concluded that UNet's performance is superior due to the concatenation of feature maps from the encoder and decoder, as well as the network's ability to detect fine image details. The decoder ensures that the input and output images have the same dimensions, facilitating the calculation of disease severity.

In [77], authors described the development of convolutional neural network models to detect and diagnose plant diseases from simple images of

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healthy and diseased leaves using deep learning techniques. The models were trained with an open database of 87,848 images, including 25 plants in 58 different classes of [plant, disease] combinations, including healthy plant samples. The highest performers achieved a success rate of 99.53%. In another investigation [80], the UNet architecture was employed to assess the impact of fungal diseases on plant leaves. Research conducted by Kim et al. [81] used a standardized deep neural network to detect fungal diseases on strawberry leaves. Disease categories include leaf spot, leaf blight, leaf blight, and a category where leaf blight and leaf blight coexist. Their method achieved 98% classification accuracy, 97% precision, 95.7% recall, and 96.3% F1 score. Previous research [82] used multi-task learning and attention networks to detect verticillium wilt in strawberries. This study presents a technique for identifying verticillium wilt in strawberry images, using faster R-CNN and multi-task approaches. Hu et al. [83] developed a CNN model using deep metric learning to classify known and unknown diseases in strawberry leaf samples.

Table 4. Summary of applications of deep learning algorithms used for strawberry disease detection from the reviewed studies

Category	Parameters	Used tools and techniques
Disease detection	Multiple classes	AlexNet [69,70] Improved ResNet50 [6] DCNN [71] AlexNet, DenseNet-169, Inception v3, ResNet-34, SqueezeNet-1.1 andVGG13 [72] GoogLeNet model, Resnet50, and VGG 16 [67] DNN (PlantNet) [73] YOLO [63] CNN (a location network, a feedback network, and a classification network) [74] Mask R-CNN [65] CNN [75] AlexNet and GoogLeNet [76]
	Fungal leaf disease	Multi-directional Attention Mechanism-Dual Channel Residual Network [77] DCNN [78] DCNN [79] UNet [80] CNN, VGG 16, GoogleNet, and Resnet 50 [81]
	Gray mold disease	UNet [66]
	Verticillium Wilt	Faster R-CNN and multi-task learning [82]
	Powdery mildew disease detection (Leaf)	AlexNet, SqueezeNet, GoogLeNet, ResNet-50, SqueezeNet-MOD1, and SqueezeNet-MOD2. [68]
	Known and unknown diseases	Deep Metric Learning-Based KNN Classifier [83]

6. DISCUSSION

Recent research in strawberry disease detection has shown significant advancements through the use of deep learning algorithms, particularly convolutional neural networks (CNNs). Several studies have proposed innovative approaches to improve the accuracy and speed of detection, addressing specific challenges such as the variety of diseases and the conditions in which images are captured in real-world environments.

The study by [68] demonstrated that architectures such as AlexNet, ResNet50, and SqueezeNet can effectively diagnose specific diseases like powdery mildew. Although ResNet50 achieved the highest accuracy at 98.11%, it was slower in processing images, which can be problematic for real-time applications. On the other hand, AlexNet, while slightly less accurate, processed images much faster. This highlights a common trade-off in disease detection systems: the balance between accuracy and speed, especially critical for real-time applications where quick detection is essential to prevent large agricultural losses.

Furthermore, the approach proposed by [63] using YOLOv5 for real-time detection of seven common strawberry diseases is notable for its efficiency, achieving 92% accuracy. However, while YOLOv5 shows promise, its performance is constrained by

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the complexity of real-world environmental conditions and the challenge of generalizing to diseases not included in the training dataset.

More recent architectures, such as UNet, used in the study by [66], have proven their ability not only to detect diseases but also to assess their severity. This approach is particularly valuable for enabling farmers to prioritize treatments based on the severity of infections. UNet's ability to capture fine details in images is a significant advantage for real-time monitoring, although it comes at the cost of higher memory usage and computational resources.

Some studies, such as [67], also focused on image segmentation to isolate infected areas using models like Mask R-CNN. These techniques not only detect the presence of diseases but also precisely segment the affected regions. However, while Mask R-CNN demonstrated good performance with an accuracy rate of 82.43%, its complexity may limit its deployment in resource-constrained environments, such as in-field systems used by farmers.

In summary, previous studies have shown that different CNN architectures have their own strengths and weaknesses. Models like AlexNet and SqueezeNet offer speed and lightweight architecture, making them suitable for real-world conditions, whereas more complex architectures like ResNet50 or Mask R-CNN provide higher accuracy but require more computational and memory resources. For practical use, especially in agricultural environments where quick data processing is essential, a trade-off between these factors is often necessary. Future approaches must not only focus on improving accuracy but also consider the feasibility of models in environments where speed and resource efficiency are critical.

7. EVALUATION METRICS

Metrics for evaluating strawberry disease detection algorithms must be carefully adapted to the particularities of this complex task. Symptom variability is one of the major challenges where disease signs can vary widely depending on many factors such as; the type of pathogen, weather conditions, stage of plant development, and other environmental variables. Metrics must therefore be sensitive to this variability and be able to understand the diversity of disease manifestations.
There are different evaluation metrics to measure the performance of machine learning algorithms [84]. Some focus on evaluating each individual class prediction, while others evaluate the overall predictive performance. This section highlights several of these metrics, including confusion matrix, precision, recall, F1 score, average precision, and mean average precision which are specifically designed to accurately evaluate the performance of each class prediction whether for image classification, object detection, or instance segmentation.

7.1 Confusion Matrix

The Confusion Matrix, also known as a contingency table, constitutes a fundamental tool in the field of machine learning for visualizing the results of predictive analysis [85]. Although it is widely used in data science, data mining and statistical analysis, its main role is in evaluating the performance of a model during a classification task. Unlike other performance indicators, the confusion matrix is not limited to displaying accuracy. Indeed, it offers a more in-depth view of the performance of the classifier by comparing the real values to the values predicted by the model. This comparison helps visualize metrics such as precision, accuracy, recall, specificity, sensitivity, and f1-score.
By providing a detailed view of error types and their occurrences, the confusion matrix allows classification results to be analyzed more comprehensively. Thus, it distinguishes correctly classified examples from incorrectly classified examples, classifying them into true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). This approach makes it possible to identify the strengths and weaknesses of the model precisely, thus facilitating its continuous improvement. Figure 5 shows the confusion matrix for binary classification problem.

- **TP (True Positive):** A true positive occurs when a model correctly predicts a positive class. This means that the model's prediction is positive and the truth (or actual label) is also positive.
- **FP (False Positive):** A false positive occurs when a model incorrectly predicts a positive class when the truth is actually negative. In other words, the model made a mistake by incorrectly classifying a negative example as positive. False positives are

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often associated with Type I errors in statistical tests.

- **FN (False Negative):** A false negative occurs when a model incorrectly predicts a negative class when the truth is actually positive. This means that the model failed to detect a positive occurrence. False negatives are associated with type II errors in statistical tests.
- **TN (True Negative):** In classification, a true negative occurs when the model correctly predicts a negative class. This means that the model's prediction is negative and the truth is also negative. True negatives represent correct predictions of negative examples by the model.

Figure 5. The confusion matrix for binary classification problem [86]

7.2 Precision, Recall, Specificity, Sensitivity, and F1-score

To facilitate the interpretation of the Confusion Matrix and evaluate the performance of the model, different metrics can be employed; precision, recall, specificity, sensitivity, and f1-score

Recall

In the context of classification, recall [87], represents the percentage of positive examples that a model has correctly classified among all positive examples. It is calculated by dividing the number of true positives (TP) by the sum of true negatives (FN) and false negatives (FN). Sometimes called the success rate, recall measures the model's ability to correctly identify positive examples

$$recall = \frac{TP}{TP + FN} \tag{1}$$

Precision

Like recall, precision evaluates the percentage of positive examples. However, it focuses on data identified as positive by the model. In other words, it divides the total number of positive examples by the sum of true positives (TP) and false positives (FP). Precision quantifies the proportion of examples correctly identified among those identified as positive by the model [88].

$$precision = \frac{TP}{TP + FP} \tag{2}$$

Specificity

Specificity measures the ability of the test to correctly identify true negatives among all true negative occurrences [89]. Mathematically, it is formulated as follows:

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{3}$$

Sensitivity

Sensitivity measures the ability of the test to detect true positives among the set of truly positive items [90]. Mathematically, it is formulated as follows:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

F1-score

The F1 score, also known as the F-measure, provides a combined measure of precision and recall through harmonic averaging. It is calculated by doubling the product of the two metrics, then dividing it by their sum. This metric is particularly useful for evaluating models where the balance between precision and recall is essential [91].

$$f1 - score = 2 \times \frac{precision \times recall}{precision + recall} \tag{5}$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

- **Overall Accuracy**

The Overall Accuracy (OA) is a metric that indicates the percentage of correctly mapped reference sites relative to the whole. It is usually expressed as a percentage, where 100% indicates perfect classification of all reference sites. To calculate it, we divide the total number of correctly classified pixels (which corresponds to the sum of the elements along the main diagonal) by the total number of reference pixels. OA is the primary metric used to evaluate classification accuracy [92, 93].

$$OA = \frac{Number\ of\ Corrected\ Predictions}{Total\ Number\ of\ Predictions} \quad (6)$$

- **Intersection over union (IoU) and Non-max Suppression**

Intersection over union (IoU)

Intersection over Union (IoU) [94] represents a crucial metric in the evaluation of object detection algorithms. This metric, based on the Jaccard Index, evaluates the similarity between two data sets, often used to determine what constitutes "correct" or "incorrect" detection in object detection.

In the process of object detection, the IOU measures the degree of overlap between the predicted bounding box and the actual ground bounding box. By dividing the intersection area between these two boxes by their union area, the IOU provides an indication of detection accuracy. This measurement thus makes it possible to evaluate the performance of detection algorithms by taking into account the spatial precision of the predictions in relation to the ground truths.

$$IoU = \frac{Area\ of\ Intersection}{Area\ of\ Union} = \frac{|Ground\ Truth\ \cap\ Predicted|}{|Ground\ Truth\ \cup\ Predicted|} \quad (7)$$

Non-max Suppression

Non-max Suppression is a technique utilized in object detection to eliminate redundant detections generated by object detection algorithms that produce multiple bounding boxes for the same object within an image [95]. Object detection algorithms typically produce confidence scores for each detected object, reflecting the algorithm's confidence level in the accuracy of the bounding box prediction. The process of Non-max Suppression involves several steps; eliminate all predicted boxes with confidence scores below a predetermined threshold set by the user, then Iterate through the list of predicted bounding boxes, then select the bounding box with the highest confidence score and use it to make a prediction, and then compare the IoU of this bounding box with every other predicted bounding box of the same class. If the IoU threshold exceeds the user-defined IoU threshold, discard it as a duplicated detection, and then remove the predicted bounding box from the list of bounding boxes.

- **Average Precision (AP)**

Average Precision (AP) is a measure used in the field of information retrieval and machine learning to evaluate the performance of classification or search models. It combines both recall and precision of classification or search results. In short, it represents the average of the precisions obtained after the recovery of each relevant element [96].

The average precision is a key performance indicator that seeks to eliminate dependence on selecting a confidence threshold value and is defined by the AP, which summarizes the Precision Recall Curve into a scalar value. Average precision is high when both precision and recall are high and low when either is low for a range of confidence threshold values. Additionally, the range for AP is between 0 and 1.

There are two approaches generally used to find the area under the PR curve: The 11-point interpolation and the all-point interpolation. In the 11-point interpolation, the precision × recall curve's shape is condensed by averaging the maximum precision values at 11 evenly distributed recall levels ranging from 0 to 1, as given by:

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$$AP_{11} = \frac{1}{11} \sum_{R \in \{0,0.1,\ldots,0.9,1\}} Pinterp(R) \qquad (8)$$

Where

$$P_{interp}(R) = \max \mathrm{P}(\tilde{\mathrm{R}}) \qquad (9)$$

In this definition of Average Precision (AP), instead of utilizing the precision P(R) observed at each recall level R, AP is determined by considering the maximum precision $\mathrm{P_{interp}}(\mathrm{R})$ where the recall value surpasses R, as shown in figure 6. In the all-point interpolation approach, rather than interpolating solely at 11 evenly spaced points, interpolation can be performed across all points in such a manner that:

$$AP = \int_{R=0}^{1} P(R)dR \qquad (10)$$

$$AP_{all} = \sum_{n} (R_{n+1} - R_n) P_{interp}(R_{n+1}) \qquad (11)$$

Where

$$P_{interp}(R_{n+1}) = \max \mathrm{P}(\tilde{\mathrm{R}}) \qquad (12)$$

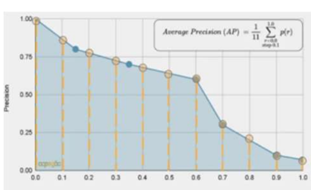

Figure 6. Precision × Recall curves of points using the 11-point interpolation approach.

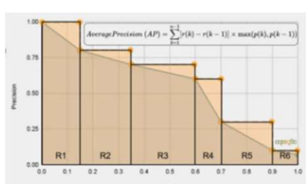

Figure 7. Precision × Recall curves of points applying interpolation with all points

In this case, rather than relying on precision observed at limited points, the Average Precision (AP) is calculated by interpolating precision at each level, considering the maximum precision where the recall value is greater than or equal to R_{n+1}.

- **Mean Average Precision (mAP)**

Mean Average Precision (mAP) is a metric used to evaluate the accuracy of object detectors across classes in a specific database. The mAP simply corresponds to the average of the AP (Average Precision) across all classes [97].

$$\mathrm{mAP} = \frac{1}{\mathrm{N}} \sum_{\mathrm{K}=1}^{\mathrm{N}} \mathrm{AP_k} \qquad (13)$$

With $\mathrm{AP_K}$ being the AP of the Kth class and N being the total number of classes evaluated.

8. CONCLUSION

This research has examined the application of deep learning techniques to the detection of strawberry diseases, contributing to the growing body of work aimed at improving agricultural productivity and disease management. By leveraging object detection models such as YOLO, SSD, and RetinaNet, this study has demonstrated the potential of advanced technologies to accurately identify diseases like anthracnose and powdery mildew in strawberry crops.

While the results are promising, particularly in terms of precision and detection speed, there are still some limitations to consider. One of the key challenges identified is the variability in real-world conditions, such as lighting and environmental factors, which can impact the generalizability of the models. Additionally, the dataset used, while effective for training and testing, could benefit from further expansion to include more diverse disease images and different growth stages of the strawberry plants.

Despite these challenges, the strengths of this work lie in its systematic approach to evaluating different object detection models, its use of state-of-the-art techniques such as transfer learning, and its practical implications for real-world agricultural use. Moving forward, future research should focus on addressing these limitations by expanding datasets, refining models, and exploring the integration of real-time monitoring systems to further enhance the economic benefits for farmers.

In conclusion, this study provides a solid foundation for researchers and practitioners looking to implement deep learning in strawberry disease detection. It highlights the value of continued innovation in this field, paving the way for more robust and scalable solutions to be applied across a range of agricultural challenges.

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