Plant Disease Detection Using Mask RCNN

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Abstract - In this study, we introduce a new approach to automate the identification of plant diseases using machine learning methods, particularly focusing on the Mask R-CNN model. Plant diseases pose a significant threat to agricultural productivity and economic value, requiring efficient detection methods. Leveraging various morphological features and properties of plant leaves, our framework aims to accurately identify different types of plant diseases. Furthermore, we present Mask R-CNN, an all-encompassing system for segmenting individual objects within an image, crucial in various computer vision tasks. Mask R-CNN builds on the Faster R-CNN model by effectively identifying objects within images and producing detailed segmentation masks for each instance. We show the success of Mask R-CNN in addressing various complex problems, including instance segmentation, outperforming existing methods.

Keywords :- *Plant Disease Detection, Mask RCNN, Instance Segmentation, Object Detection*

I. INTRODUCTION

Object detection is vital in computer vision, identifying objects and where they are in images. Key algorithms like RCNN, Fast RCNN, Faster RCNN, and SSD have limitations like needing lots of data and not pinpointing locations accurately. Mask RCNN is innovative, combining object detection and segmentation for precise labeling of pixels across different objects. Its capability extends to complex instance segmentation tasks, accurately delineating individuals across various categories and pixel-wise labeling to differentiate individuals within the same category [4].

India, as a rapidly developing nation, relies heavily on agriculture as a cornerstone of its early-stage development. However, the agricultural sector encounters numerous challenges, notably substantial crop production losses. Among these challenges, plant leaf diseases stand out as significant contributors to reduced yields. Identifying plant leaf diseases proves to be particularly challenging in agricultural settings[3].

The presence of plant diseases significantly hampers agricultural production, potentially leading to food insecurity if left undetected. Early detection is essential for effectively preventing and controlling plant diseases, playing a critical role in agricultural production management and decision-making. In recent years, identifying plant diseases has become a pressing concern. Infected plants typically exhibit distinct marks or lesions on their leaves, stems, flowers, or fruits. Each disease or pest condition tends to manifest a unique visible pattern, aiding in precise diagnosis of abnormalities. Leaves are often the primary indicators of plant diseases, with symptoms typically first appearing on them.

The health of humans depends significantly on the quality of the food they consume. When crops are unhealthy, they can lead to various health issues due to inadequate nutrition. Thus, ensuring healthy nutrition hinges on cultivating healthy crops. Diseases in plants result in unhealthy crops, underscoring the critical importance of detecting leaf diseases as a vital and effective measure in cultivating robust crops.

Detecting diseases in leaves manually is time-consuming and often inaccurate. Fortunately, modern technologies such as Artificial Intelligence (AI), especially Deep Learning, provide a solution. These technologies can accurately predict leaf diseases, unlike human observation. This system aims to assist farmers in protecting their crops from pests and diseases without harming their cultivation. It identifies the type of pest or disease in a leaf and precisely marks the infected area. With AI integration, traditional agricultural practices are transforming into Digital Agricultural Systems. Testing has shown that technological advancements lead to higher agricultural yields.

The process involves several steps: creating datasets for disease prediction, labeling, preprocessing leaf images, training CNN models for disease prediction, creating datasets for masking, annotating data, applying the Mask R-CNN algorithm to mask infected areas, and obtaining region and mask information over the infected area.

Plant diseases commonly present as visible spots or lesions on leaves, stems, flowers, or fruits. Each disease or pest issue usually shows a specific visual pattern, allowing for the unique identification of abnormalities. Leaves serve as the primary source for identifying plant diseases, with symptoms usually appearing there first [2].Traditionally, agricultural and forestry experts or farmers rely on subjective, labor-intensive, and inefficient methods based on experience to identify fruit tree diseases and pests on-site. This approach can lead to misjudgments and indiscriminate pesticide use, resulting in environmental pollution and economic losses. To tackle these challenges, research into applying image processing methods for recognizing plant diseases has gained significant traction.[5]

II. LITRATURE REVIEW

An examination of various plant diseases and the diverse machine learning methods employed to classify diseases in different types of plant leaves.

We cover a broad spectrum of plant diseases and explore various machine learning classification techniques employed to detect these diseases across different types of plant leaves, through this paper [3]. Mask R-CNN enhances the Faster R-CNN architecture by adding an additional branch specifically for predicting segmentation masks for each Region of Interest (ROI). This branch works alongside the existing classification and bounding box regression branches.

(see Figure 1).

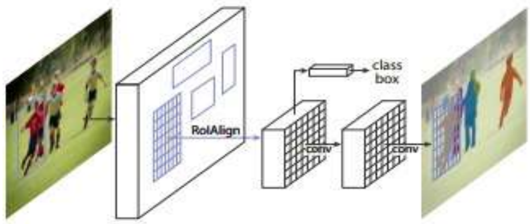

Fig 1: The Mask R-CNN framework for instance segmentation

The mask branch includes a streamlined Fully Convolutional Network (FCN) that is applied to each ROI, providing pixel-by-pixel predictions of segmentation masks. Implementation and training of Mask R-CNN are straightforward within the Faster R-CNN framework, allowing for versatile architectural designs. Furthermore, the additional computational load introduced by the mask branch is minimal, ensuring efficient performance and facilitating rapid experimentation [2].

Thus, to implement our idea of leaf disease detection using object detection and image segmentation of Mask RCNN, we integrated an application to have the instance level segmentation for disease detection.

III. RELATED WORK

This tech is super precise and can even estimate how much yield a crop will give. Scientists have also been studying how to judge the quality of fruits and veggies by looking at their texture and color using this technology. Digital technology in agriculture is changing how farming works, making it more efficient and sustainable. By using things like computers and cameras, farmers can tackle challenges better and get higher-quality crops while spending less money. In recent years, a technology called computer vision has become really useful in farming. It helps farmers do things like map soil, check crops for diseases, and even inspect fruits automatically, without needing people to do it.

Mask R-CNN is essentially an expansion of Faster R-CNN, which is designed for object detection in images. In Faster R-CNN, we get two main things for each object we're interested in: what type of object it is (like "car" or "dog") and where it is in the image (the bounding box). With Mask R-CNN, we add a detailed outline, or "mask," of the object. This helps us get a really precise idea of the object's shape. It might seem like a straightforward idea, but figuring out these masks is actually quite complex because it involves understanding the exact layout of every pixel that belongs to the object.

To make this work, Mask R-CNN introduces a few important things. One of the key elements is something called "pixel-to-pixel alignment," which basically means making sure that the mask we generate lines up perfectly with the object in the image. This was a missing piece in earlier versions like Fast and Faster R-CNN, but it's crucial for getting those detailed object outlines right.

Formally, during training, we calculate a multi-task loss for each sampled ROI as defined in [2].

A. Instance Segmentation

We conduct a detailed comparison of Mask R-CNN with the state-of-the-art approaches and perform extensive ablation experiments. We fine-tune the Mask R-CNN model for detection using the COCO dataset and additional datasets sourced from online resources. We report the standard COCO metrics defined in ”Mask R-CNN Kaiming He, Georgia Gkioxari, Piotr Dollar, Ross Girshick ”.

Google's TensorFlow Object Detection API is an open-source system for identifying items. It is built on TensorFlow, allowing users to define, train, and use models for object detection. ”Automated Detection of Plant Diseases Using Image Processing and Faster R-CNN Algorithm”.

B. Tensorflow in disease detection

TensorFlow, a popular tool for building and training machine learning models, has a handy feature called Tensorboard. It's like a dashboard that shows you everything about your model while it's learning. You can see graphs and charts that help you understand how the model's doing and how its performance changes as it learns.

With TensorFlow, there's also something called the Object Detection API. It's like a library of ready-made models that can spot objects in images. These models are already trained on lots of data, so they're pretty good at what they do. For example, there are models like SSD with MobileNet, Faster R-CNN with ResNet, and R-FCN with ResNet.

In our case, let's say we're building a disease detector. Instead of starting from scratch, we can pick one of these pre-trained models as a starting point for our training. The model we choose depends on what we want our disease detector to do.

The Object Detection API also helps us understand the trade-off between speed and accuracy for different models. So, depending on what's more important for our application, we can choose the model that fits best.

C. Steps for disease detection

To identify diseases, we begin by dividing our dataset into two sections. We allocate 80% of the images for training and 20% for testing. Because our dataset is small due to a lack of enough images of affected leaves, we don't have many samples for training and testing.

Next, we create a text file called a label map. This file helps us assign a unique ID and a name to each category of disease. It's like giving our model a list of what to look for and how to recognize it during training.

Two JSON files are created from the training and testing samples, where information about the images is stored. Then, from the JSON file, the JSON file is fed up to the model to train the algorithm for the accuracy even if we use the COCO dataset.

IV. MATERIALS AND METHODS

The plant disease, characterized by various symptoms such as discoloration and deformities, poses a significant threat to crop health. Once the pathogen infects a plant, it can rapidly spread throughout the entire crop. Therefore, there is a pressing need for accurate detection and localization of each diseased area on the plant leaves. IIn this study, we suggest using the Mask-RCNN object detection model to identify and pinpoint each diseased area on plant leaves. The proposed framework for plant disease detection is illustrated in Figure 1.

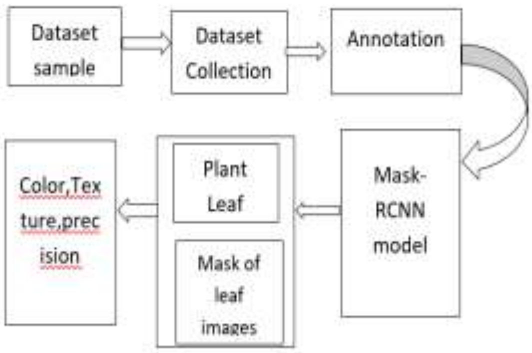

Fig 2: Proposed Structure for plant disease detection

A. Dataset Sample

This paper focuses on studying pictures of plant leaves. To do this, we have collected images of plant leaves from online download. These images were split into 125 for training and 50 for testing. We had to follow two main steps to create a dataset for detecting infected areas in different environments:

Image Collection: We took pictures of plant leaves from different angles and scenes, both from the internet. Since these images came in various sizes, We needed to make them all the same size (1024×1024 pixels) to work with a specific tool called Mask RCNN. We used a script to resize the images and filled in any empty parts with zeros.

Image Processing: We used a annotator tool to mark the damaged areas on the plant leaf images. Then, We divided the marked images into two sets: one for training and one for testing. They organized these images into folders named "train" for training samples and "val" for test samples. Each image in these folders had a corresponding .json file with annotation information, detailing where the scratches were.

Fig 3: Image dataset collection

B. Image notation

Image annotation is a pivotal step in enabling the detection of plant diseases using the Mask-RCNN model. Accurate annotation is essential for the model to effectively identify and delineate diseased areas on the plant leaves. To accomplish this, we employed the VIA, an open-source annotation tool. The annotation process consisted of several stages: initially, labeling the healthy plant leaf images; followed by segmenting the plant leaf images; and finally, By annotating the regions affected by various diseases on each plant leaf, the plant leaf images were carefully marked using the annotation tool. This allowed for the subsequent training of the Mask-RCNN model for accurate disease detection, as illustrated in Figure 3.

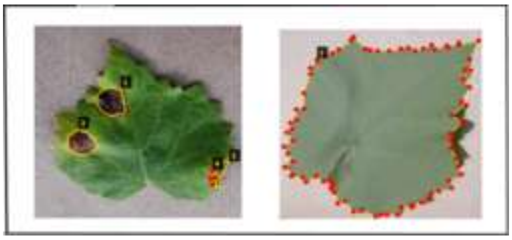

Fig 4: Diseased Image and Healthy Image Annotation

C. Mask RCNN

This research used the Mask-RCNN model for detecting plant diseases on each leaf. By utilizing the Mask-RCNN model, we were able to easily identify and accurately pinpoint plant diseases on leaves. The architecture of the Mask-RCNN model utilized in this study is illustrated in Figure 5. With the assistance of the Mask-RCNN model, identifying and pinpointing the locations of plant diseases on leaves became straightforward.

In the Mask-RCNN model, the Region Proposal Network (RPN) generates various anchor boxes to identify potential regions of interest for object detection. These boxes are then assessed to see if any objects are present within them.

During this process, the RPN calculates two types of losses: mask loss and boundary box losses, refining the detection accuracy. It also produces binary masks for each image, improving object delineation. The anchor boxes help delineate regions for feature alignment, achieved through Region of Interest (ROI) alignment.

Following alignment, fully connected layers are utilized for bounding box regression and object classification. These layers fine-tune the bounding box coordinates and assign class labels to detected objects. Finally, each object's detection is represented by a mask, generated through various convolutional layers. This approach ensures precise object identification and delineation.

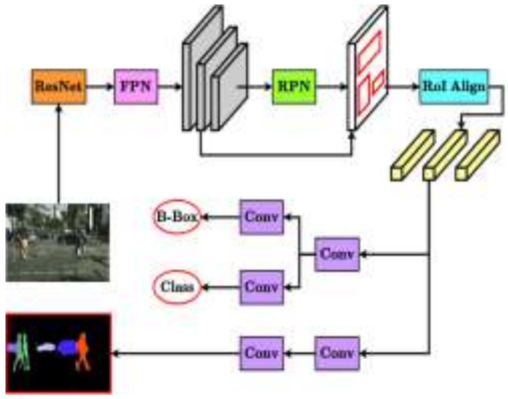

Fig 5: Structure of Mask RCNN Model

V. EXPERIMENTAL RESULTS

We extended the training duration to 100 iterations, during which the learning rate decreases over 70 iterations. Additionally, we adjusted the threshold to 0.9, meaning that detections with confidence below 90% are disregarded.

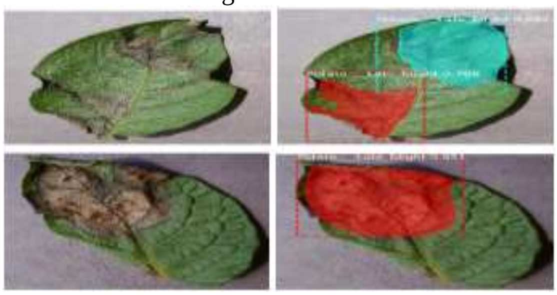

Fig 6: Results of Mask R-CNN Model

Following the segmentation of individual plant leaves, the subsequent task of the Mask-RCNN model involves pinpointing the precise locations of infected areas on each leaf. Consequently, the model not only segments the leaves but also accurately identifies and delineates disease spots on individual leaf images. Therefore, the Mask-RCNN model proves to be highly effective in detecting disease areas on plant leaves at a granular level.

VI. CONCLUSION AND FUTURE SCOPE

In conclusion, our research demonstrates the efficacy of Mask R-CNN in the domain of plant disease detection. Through our experimentation and analysis, we have confirmed that Mask R-CNN effectively identifies and locates plant diseases, providing valuable insights for farmers to manage their crops efficiently. By streamlining the detection process, Mask R-CNN empowers farmers with timely information, enabling proactive measures to mitigate crop diseases and ensure optimal yield. This research underscores the significance of advanced technologies like Mask R-CNN in revolutionizing agricultural practices and lays the groundwork for future advancements in plant disease detection and management. We used Mask-RCNN to detect diseases in plant leaves. Numerous studies evaluate this technology using a dataset called Plant Village, which contains a wealth of images of diseased plants. So, we plan to create a bigger dataset with real plant diseases. In the future, we plan to use Mask-RCNN on satellite images to detect plant diseases across large areas.

VII. REFERENCE

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