PAPER TITLE :- A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition

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AUTHOR:- Alvaro Fuentes, Sook Yoon, Sang Cheol Kim and Dong Sun Park

PROBLEM MENTIONED/SOLUTION OBTAINED:- The problem addressed is the detection of diseases and pests in tomato plants using deep learning-based approaches. The proposed solution involves utilizing deep meta-architectures and feature extractors to detect and localize diseases and pests in tomato plants from images captured in real scenarios. Extensive data augmentation techniques are applied to the dataset to avoid overfitting during experiments. The system is trained and tested on a dataset divided into training, validation, and testing sets, with evaluations conducted using GPUs for efficient learning and lower error rates

ALGORITHM USED:- The deep-learning-based approach in the study utilized three main families of detectors: Faster Region-based Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN), and Single Shot Multibox Detector (SSD). The system implemented batch normalization for each feature extractor and trained end-to-end using an ImageNet Pretrained Network. The study extended the application of Faster R-CNN for object recognition and utilized its Region Proposal Network (RPN) to estimate the class and location of object proposals. Various deep feature extractors were combined with the meta-architectures, such as VGG net and Residual Network (ResNet).

TOOLS USED: deep meta-architectures such as Faster R-CNN, R-FCN, and SSD, combined with deep feature extractors like VGG net and Residual Network (ResNet)

RESULTS AND DISCUSSION:-

The system achieved effective recognition of nine different types of diseases and pests in tomato plants, handling complex scenarios. Data augmentation techniques significantly improved the Average Precision for various disease classes, reducing false positives. Extensive data augmentation was applied to the dataset to avoid overfitting, resulting in successful training and evaluation processes

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