Seeds Germination Detection Using Convolutional SSD-like Architectures

Juan Valencia

***Abstract*—In this article ssd-like models are implemented to identify seeds in germination using a methodology based on [1] work.**

***Index Terms*—Mean Average Precision (mAP), Bounding Box, Anchor Boxes**

I. Introduction

II. Materials and Methods

A. Dataset

The dataset used was taken from the image acquisition process made by a project with the same goal [1]. It consists of 3 folders which contain the annotation of three seeds species (ZeaMays, SecaleCereale and PennisetumGlaucum) during its germination, figure II-A shows one example of the image with its annotations.

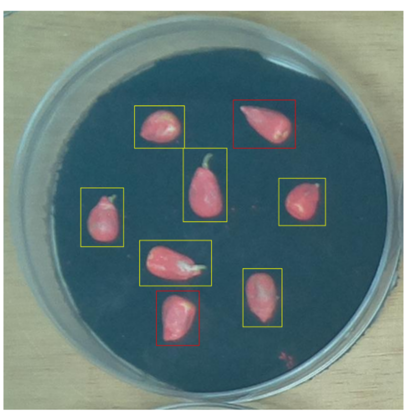

Fig. 1. Seeds with their respective bounding boxes

B. Multiple Objects Detection Problem

Let $\{I_n \in \mathbb{R}^{R\times C}, B_n \in \mathbb{R}^{M_n \times 4}, L_n \in \{l_1, l_2\}^{M_n}\}_n^N$ be an 1 input - 2 outputs set holding N labeled images, where I_n is the n-th image with R rows and C columns. B_n and L_n contains the bounding boxes and the classes of the M_n objects of interest from the image I_n respectively.

C. Model Architecture

There are two approaches to perform object detection over multiple elements. The first is based on two stage processing which is present in architectures like R-CNN [2] and Faster R-CNN [3] where is necessary to process the images twice to generate proposal regions an then classify them, while in architectures like YOLOv3 [4] or SSD [5] the image is passed once through the network. Models like R-CNN and Faster R-CNN tend to be more accurate than YOLO or SSD architectures but are slower [6]. We decided to use SSD framework due to its improvements in speed/accuracy made in architectures like RetinaNet [7].

SSD architectures are made of three parts (see the Figure II-C):

- **Backbone**: Is responsible of generate the feature maps which will be processed by the bottleneck.
- **Neck Bottle**: Its task is extract and mix relevant features taking as input layers at different heights of the backbone.
- **Head**: The Head of an SSD detector decode the features extracted from the bottleneck to produce the predictions

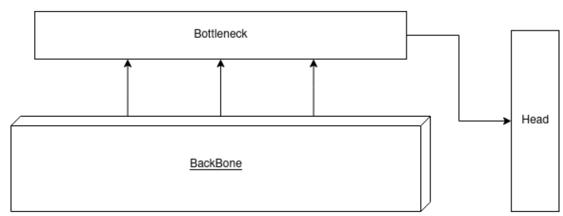

Fig. 2. SSD Architecture

D. Evaluation Metrics

In Many Object detection challenges the *mean average precision* (mAP) is used to measure the performance of the model

E. Data

III. Experimental set-up

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