## A Reinforcement Learning Algorithm using

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## Motivation and background

Training object class detectors typically requires large amount of data in which images are manually annotated with bounding boxes (bbox) for every instance of each class. This is particularly true for lightweight object class detectors that progressively improve their mean average precision ( $m A P$ ) increasing the number of examples available. The presented research suggests a metodology to exploit generated data from the field and a collaboration with multiple independent deep neural networks to obtain an increasingly more performing embedded model for the designated tasks.

## Proposed Algorithm

A first architecture of the algorightm is shown in the graph at the bottom and it follows the following steps:

- An initial dataset is used to train a two-stage Faster-RCNN, a Single Shot Multibox Detector (SSD) and a lightweight version of it.
- Data generated by the embedded network (frames \& predictions) is sent to the cloud.
- Received images are elaborated by the ensemble network that generates new bbox.
- New data are merged with the old one and, through a re-training, novel weights of the embedded SSD are generated


Flow of Images
$\square$ Flow of Labels and Images
$\square$ Re-trained Weights

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## Materials and methods

- Dataset: (OIDv4_ToolKit)

| 0 |  | Apple | Grape | Lemon | Orange | Pear |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Train | 624 | 755 | 367 | 583 | 204 |
| D | Validation | 24 | 44 | 41 | 25 | 4 |
| $V$ | Test | 57 | 124 | 79 | 95 | 27 |
| 4 | Videos | $5^{\prime} 4^{\prime \prime}$ | $12^{\prime} 25^{\prime \prime}$ | $34^{\prime} 3^{\prime \prime}$ | 7' ${ }^{\prime \prime}$ | $9^{\prime} 43^{\prime \prime}$ |

- Hardware:
- Tesla K80 (4992 Cuda Cores)
- Networks:
- Faster R-CNN (with ROI-align)
- SSD (with Focal-Loss (1.1))

$$
\begin{align*}
& \operatorname{CE}\left(p_{t}\right)=-\log \left(p_{t}\right)  \tag{1}\\
& \operatorname{FL}\left(p_{t}\right)=-\left(1-p_{t}\right)^{r} \log \left(p_{t}\right) \tag{1.1}
\end{align*}
$$

## Simulation Results



## Conclusions and future work

The methodology presented is the first of its kind and preliminary results have proven a remarkable effectiveness of the overall system. However, the proposed research requirese further studies to improve the algorithm and asesess its limitations and drawbacks.

- Substitute the SVR block with a FC layer that exploits backbone extracted features
- Look for saturation value of $m A P$

