Adversarial Anomaly Detector

Use of Generative Adversarial Networks for the detection of tomato diseases

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December 13th, 2019

Content

Context

Tomato production

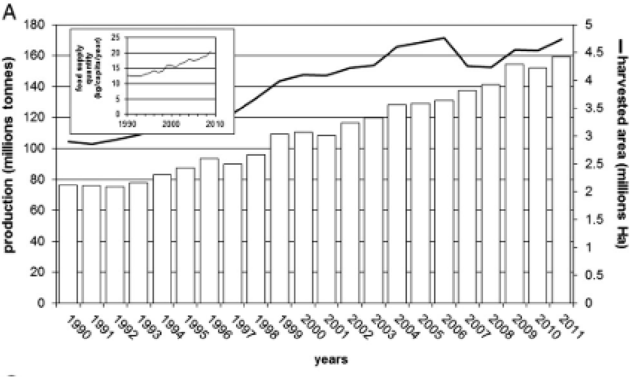


Figure: Tomato production worldwide. Reprinted from Bergougnoux, V. (2014). The history of tomato: From domestication to biopharming. Biotechnology Advances.

Context

Tomato production

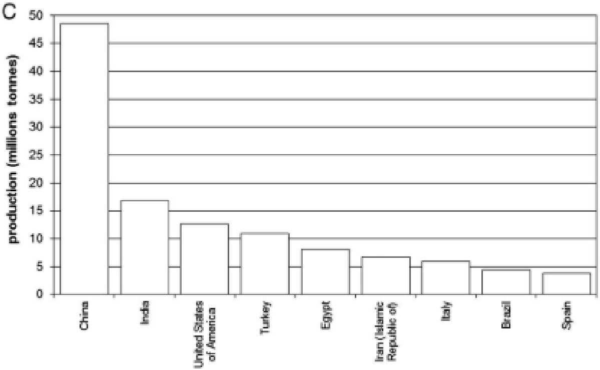


Figure: Tomato production per country. Reprinted from Bergougnoux, V. (2014). The history of tomato: From domestication to biopharming. Biotechnology Advances.

Problem

Diseases and pests in tomato crop, and the development of non-invasive systems for its early detection that mitigate the food security.

Objectives

General objective

Evaluation of different algorithms for anomaly detection, in the context of tomato images.

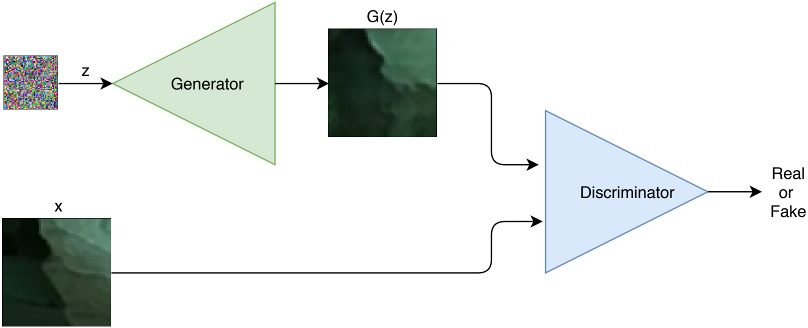
Objetives

Specific objectives

- To design a dataset to train the machine learning models.
- Selection of an anomaly detection algorithms.
- To evaluate the selected methods for detection anomaly in tomato images.

Anomaly detection with generative adversarial networks

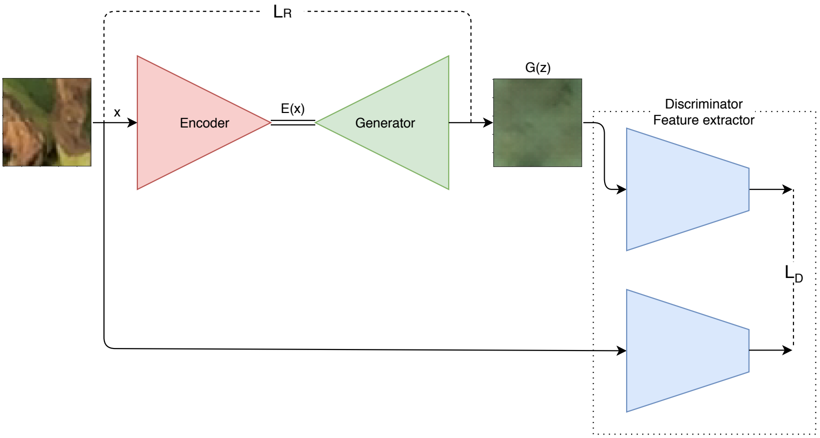
Generative Adversarial Networks architecture



$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z)))]$$

Anomaly detection with generative adversarial networks

Adversarial Anomaly Detector architecture



Anomaly detection with generative adversarial networks

Adversarial Anomaly Detector loss function

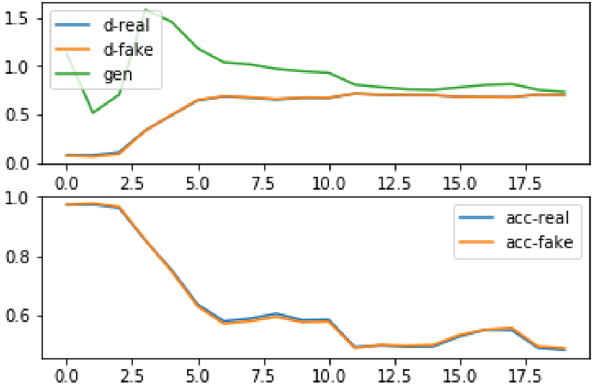
$$\mathcal{L}\left(\mathbf{E}(x)\right) = (1-\lambda)\cdot\mathcal{L}_R\left(\mathbf{E}(x)\right) + \lambda\cdot\mathcal{L}_D\left(\mathbf{E}(x)\right)$$

where the reconstruction error $\mathcal{L}_R$ and the discriminator error $\mathcal{L}_D$ are defined as follows:

$$\mathcal{L}_R\left(\mathbf{E}(x)\right) = \left\|\mathbf{x} - G\left(\mathbf{E}(x)\right)\right\|$$

$$\mathcal{L}_D\left(\mathbf{E}(x)\right) = \left\|\mathbf{f}(\mathbf{x}) - \mathbf{f}\left(G\left(\mathbf{E}(x)\right)\right)\right\|$$

GAN training



Reconstruction evaluation

Table: Reconstruction metric evaluation.

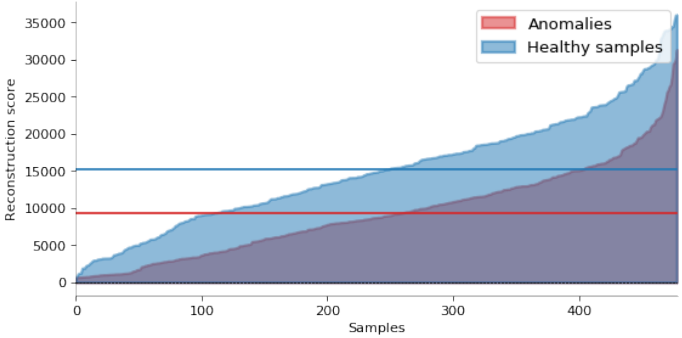
Model	Mean (healthy)	STD (healthy)	Mean (anomalies)	STD (anomalies)
sVAE	10410.6	7020.3	19858.8	18464.1
GM-VAE	15162.2	7597.3	9357.3	6071.7
AAD	3839.5	3251.1	8996.1	3308.8

Reconstruction evaluation

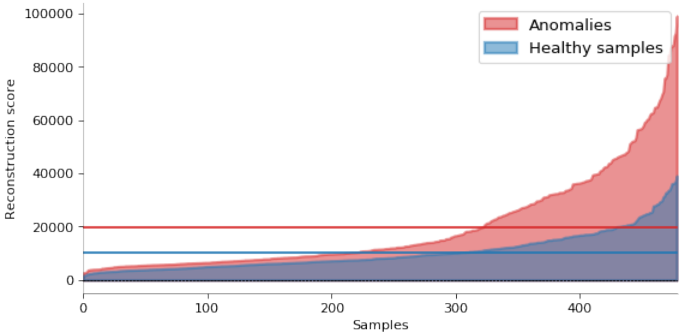
Table: Reconstruction time evaluation.

Model	Reconstruction time (ms)
sVAE	160.8
GM-VAE	1383.1
AnoGAN	6320.6
Adversarial Anomaly Detector	255.3

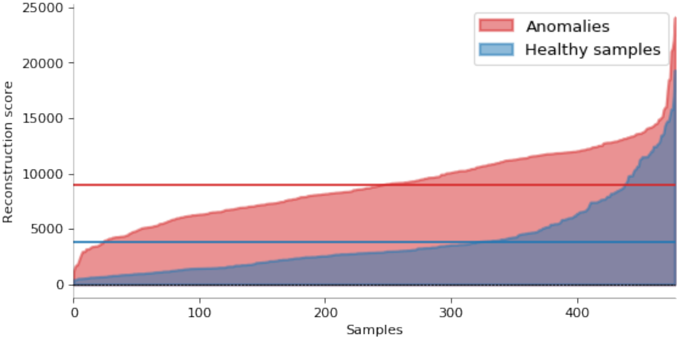
Reconstruction evaluation



Reconstruction evaluation



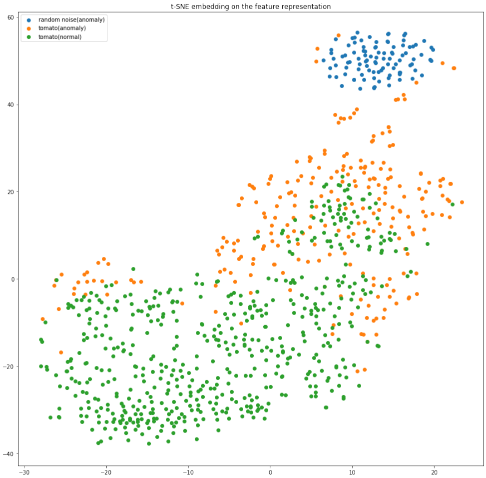
Reconstruction evaluation



t-SNE evaluation

Figure: Test image with regular samples

t-SNE evaluation



t-SNE evaluation

Figure: Test image with anomalous samples

t-SNE evaluation

Conclusions

- The experiments performed so far have shown a tendency of the variational autoencoder architectures to blur the reconstructed image
- The GAN-based architectures have more promising results with better reconstruction images
- A modification to the AnoGAN architecture is proposed, allowing to considerably improve the reconstruction time

Future work

- Improve the generator of the GAN
- Metrics that evaluate the GAN performance needs to be explored, along with more metrics for the evaluation of the anomaly detections
- A segmentation process should be implemented in order to mark possible anomalous regions

Summary