Adversarial Anomaly Detector

Use of Generative Adversarial Networks for the detection of tomato diseases

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Content

Context

Tomato production

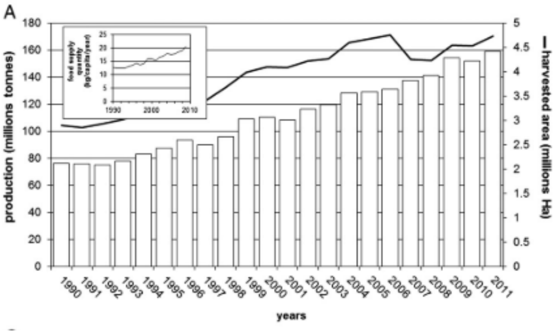


Figure: Tomato production worldwide. Reprinted from Bergougnoux, V. (2014). The history of tomato: From domestication to biopharming. Biotechnology Advances.

Context

Tomato production

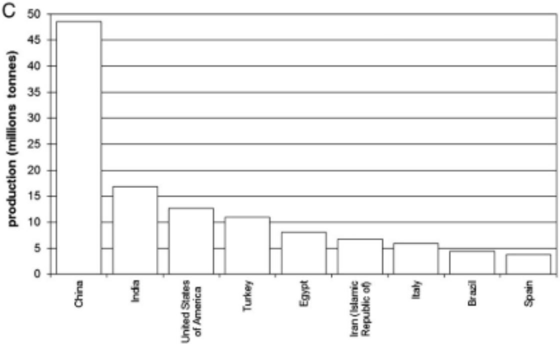


Figure: Tomato production per country. Reprinted from Bergougnoux, V. (2014). The history of tomato: From domestication to biopharming. Biotechnology Advances.

Problem

Detection of disease and pest in tomato crops with the use of non-invasive systems that help mitigating the consequences of climate change on food security.

Objectives

General objective

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

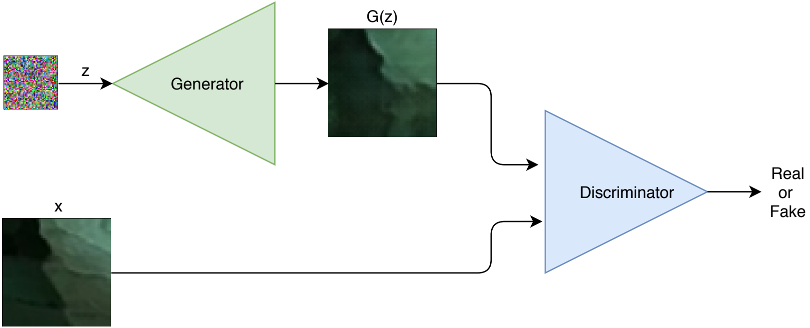
Objetives

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

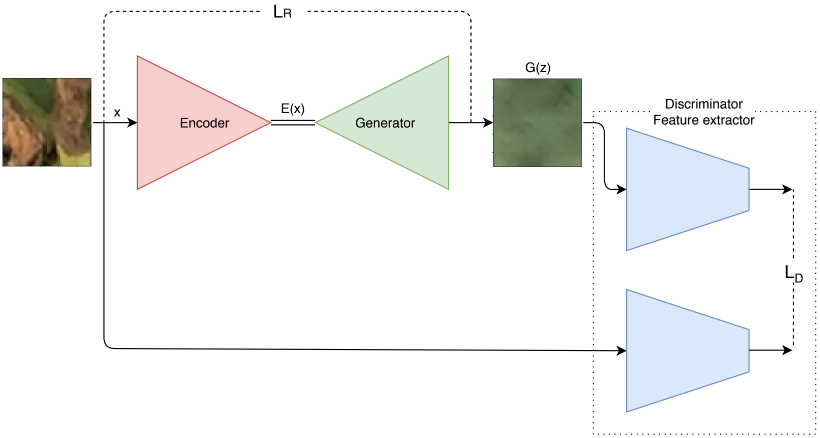
Generative Adversarial Networks architecture



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

Anomaly detection with generative adversarial networks

Adversarial Anomaly Detector architecture



Anomaly detection with generative adversarial networks

Adversarial Anomaly Detector loss function

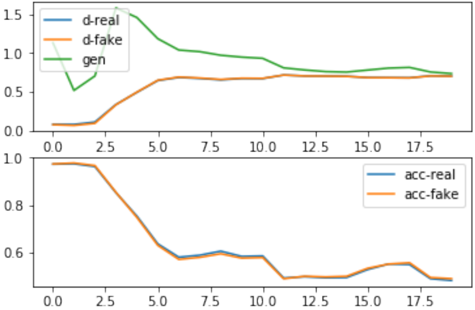
$$\mathcal{L}\left(\mathbf{E}(x)\right) = (1-\lambda)\cdot\mathcal{L}_R\left(\mathbf{E}(x)\right) + \lambda\cdot\mathcal{L}_D\left(\mathbf{E}(x)\right)$$

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

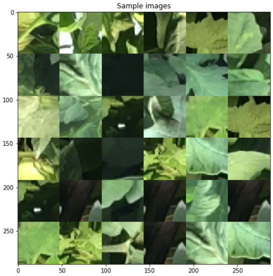
$$\mathcal{L}_R\left(\mathbf{E}(x)\right) = \left\|\mathbf{x} - G\left(\mathbf{E}(x)\right)\right\|$$

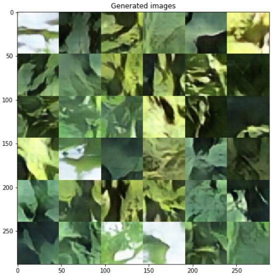
$$\mathcal{L}_D\left(\mathbf{E}(x)\right) = \left\|\mathbf{f}(\mathbf{x}) - \mathbf{f}\left(G\left(\mathbf{E}(x)\right)\right)\right\|$$

GAN training



GAN training





Reconstruction evaluation

Table: Reconstruction metric evaluation.

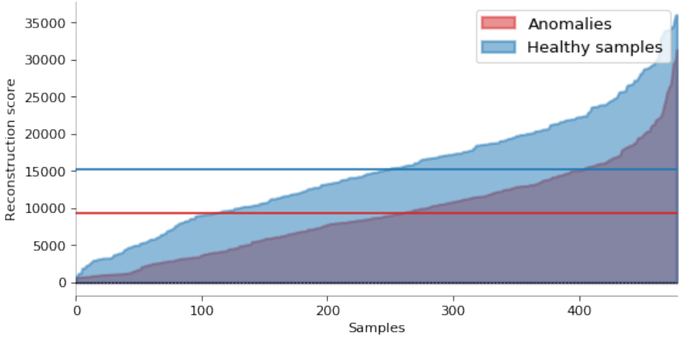
Model	Mean (healthy)	STD (healthy)	Mean (anomalies)	STD (anomalies)
sVAE	10410.6	7020.3	19858.8	18464.1
GM-VAE	15162.2	7597.3	9357.3	6071.7
AAD	3839.5	3251.1	8996.1	3308.8

Reconstruction evaluation

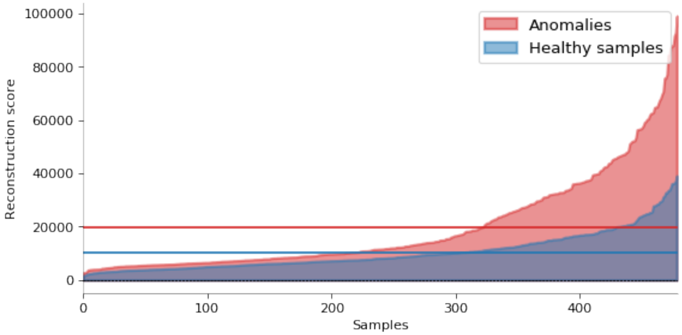
Table: Reconstruction time evaluation.

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

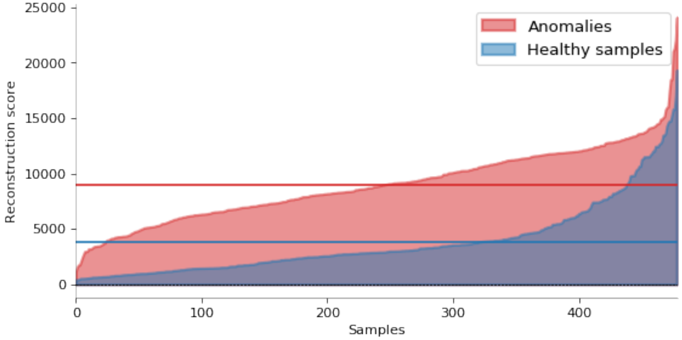
Reconstruction evaluation



Reconstruction evaluation



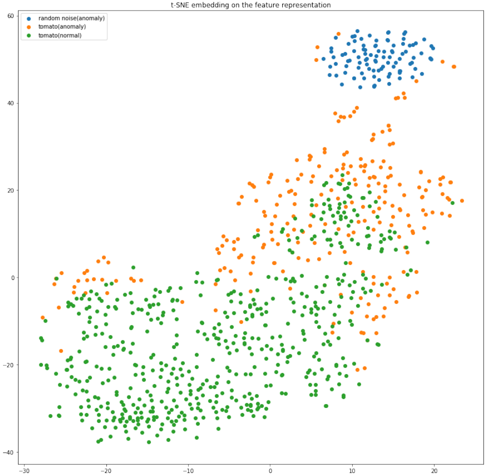
Reconstruction evaluation



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