



Data Mining

Unit 2. Unstructured data mining

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Contenido

- Unstructured data
- Shallow features
- Deep features
- Problems in computer vision
 - Image segmentation
 - Image classification
 - Object detection
 - Instance segmentation
- Examples

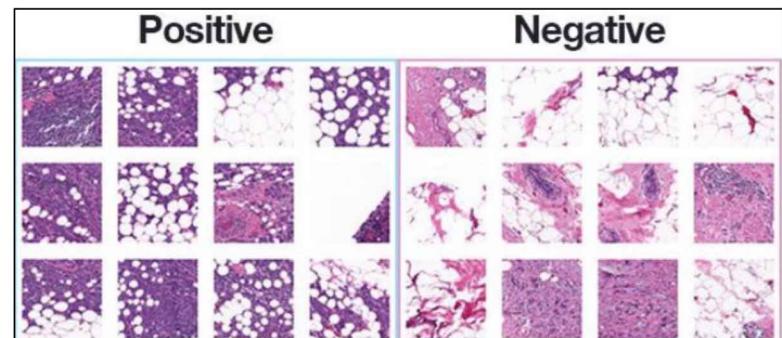
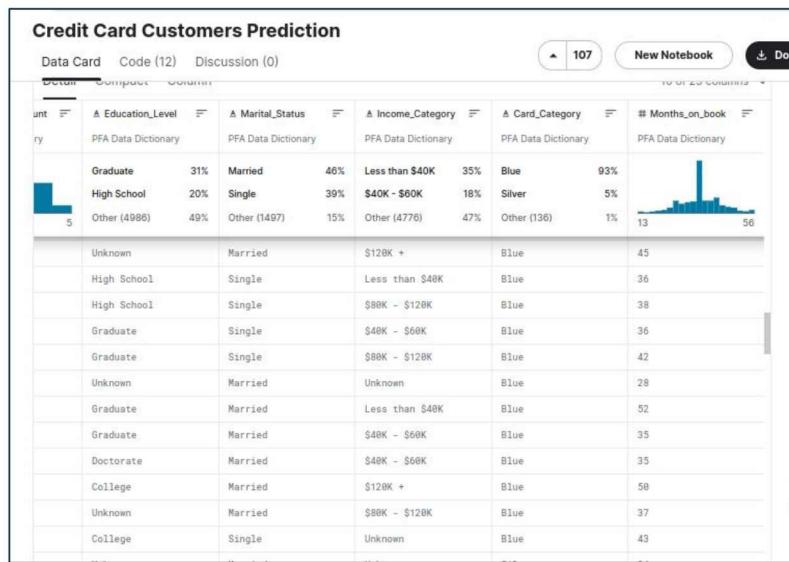
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Structured Data vs Unstructured Data

Estructurados		No estructurados (complejos)
Categorías y Numéricos {Enteros, Reales, Fecha}		Imágenes, audios, videos, electrocardiograma, etc.

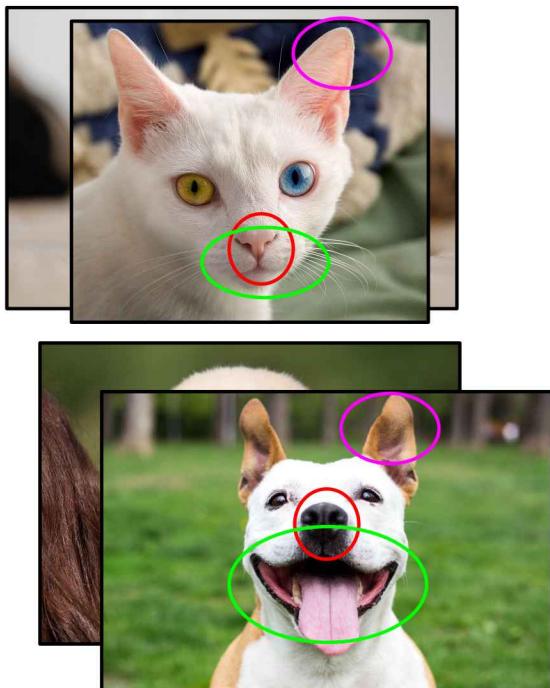


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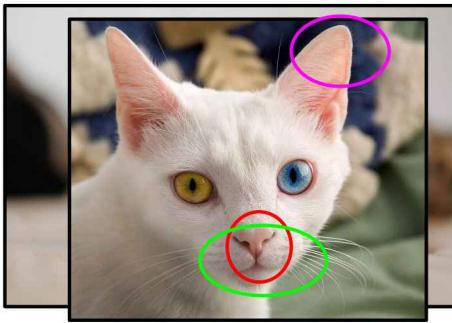
Shallow features



X	y
○	Cat
○	Dog
...	...
○	Cat

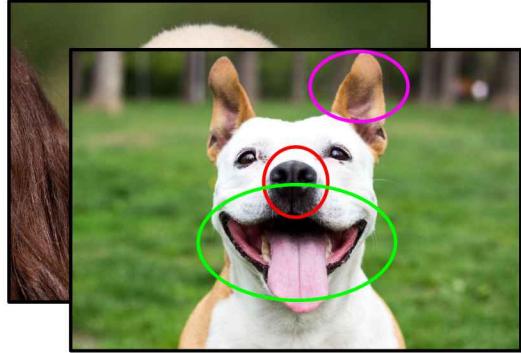
Features descriptors: Color, Shape, Texture, etc.

Shallow features



Feature descriptors: Color, Shape, Texture, etc.

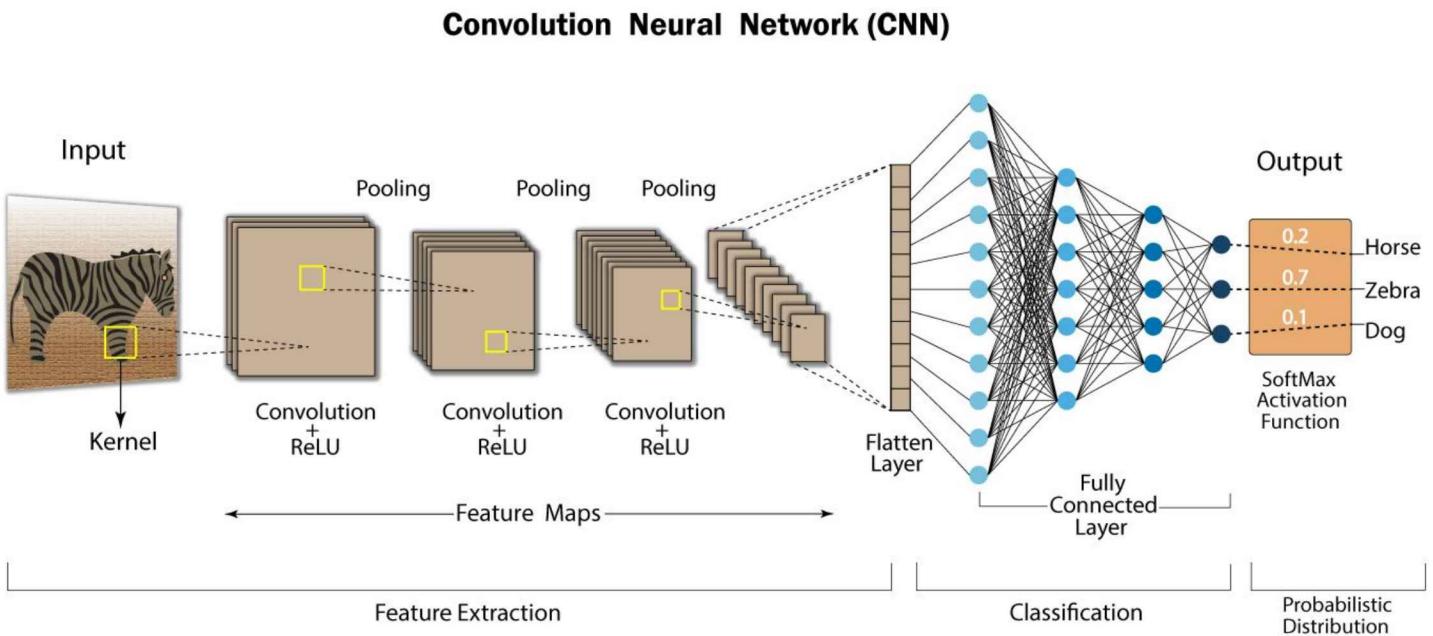
- Co-occurrence matrix (Haralick's coefficient):
https://scikit-image.org/docs/stable/auto_examples/features_detection/plot_glcm.html
- Local Binary Pattern for texture classification (LBP):
https://scikit-image.org/docs/stable/auto_examples/features_detection/plot_local_binary_pattern.html



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Deep features



<https://nafizshahriar.medium.com/what-is-convolutional-neural-network-cnn-deep-learning-b3921bdd82d5>

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Deep features - Transfer learning

Incorporating a Novel Dual Transfer Learning Approach for Medical Images

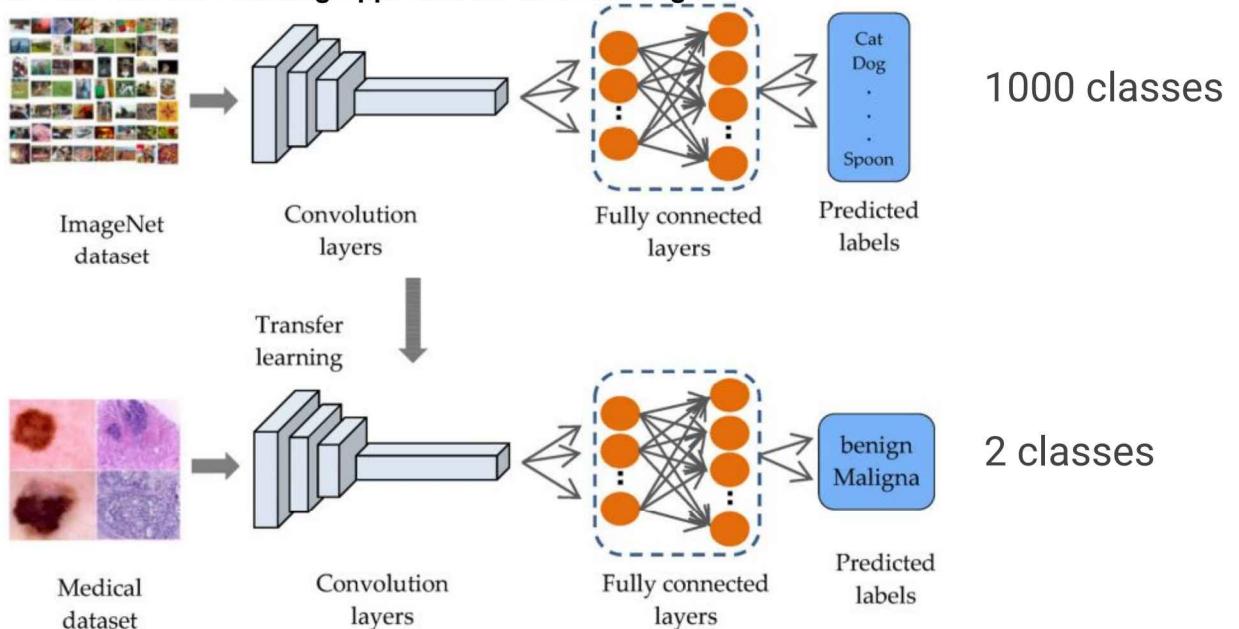


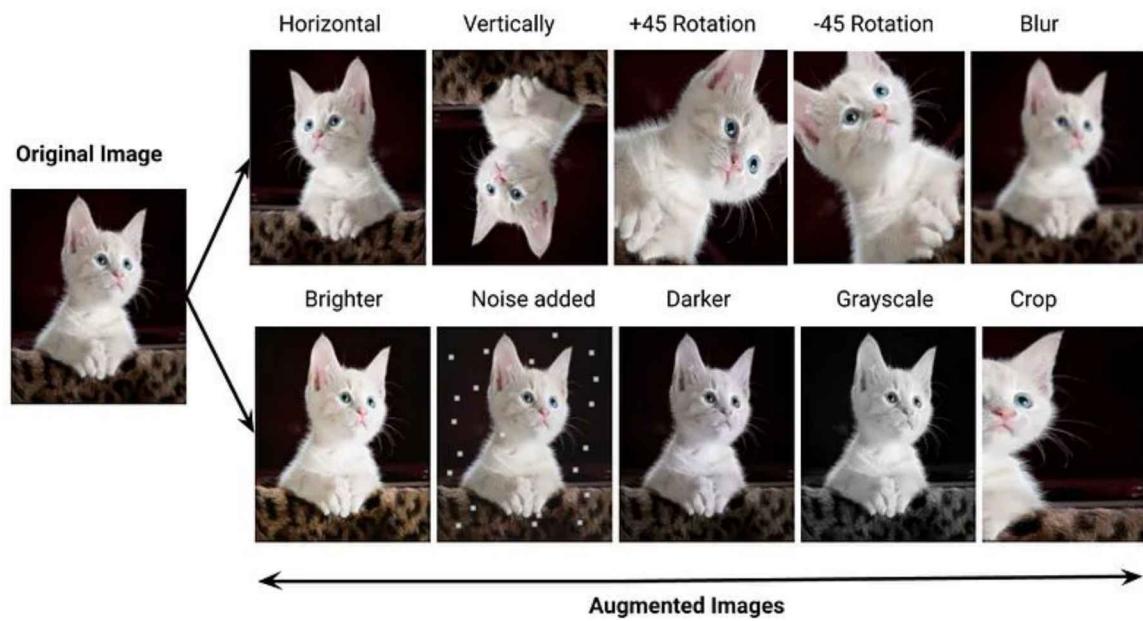
Figure 1. Transfer learning from ImageNet.

[7] <https://doi.org/10.3390/s23020570>

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Deep features - Data augmentation



<https://ubiai.tools/what-are-the-advantages-and-disadvantages-of-data-augmentation-2023-update/>

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Deep features - Data augmentation

Original Image	Basic	Light deformation	Extreme deformation	Color deformation	Image overlapping	Background swapping

<https://medium.com/@marcc22/data-augmentation-benchmark-for-deep-learning-2db712c6eb3e>

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Deep features - Convolutional neural network architectures

CNN Variants for Computer Vision: History, Architecture, Application, Challenges and Future Scope

Table 1. Performance summary of various CNN variants with its architectural categories.

Architecture Name	Year	Category	Main Role	Parameter	Error Rate
LeNet	1998	Spatial Exploitation	It was the first prevalent CNN architecture	0.060 M	distMNIST: 0.8 MNIST: 0.95
AlexNet	2012	Spatial Exploitation	<ul style="list-style-type: none">• Deeper and wider compared to LeNet• Used RELU, dropout and overlap pooling GPUs NVIDIA GTX 580	60 M	ImageNet: 16.4
ZfNet	2014	Spatial Exploitation	Provided visualization of intermediate layers	60 M	ImageNet: 11.7
VGG	2014	Spatial Exploitation	It used small-sized kernels and had homogeneous topology	138 M	ImageNet: 7.3
GoogleNet	2015	Spatial Exploitation	It was first architecture to introduce block concept. It used split transform and then merge idea	4 M	ImageNet: 6.7
InceptionV-3	2015	Depth + Width	It was able to handle bottleneck issue and applied small filters rather than using large filters	23.6 M	ImageNet: 3.5 Multi-Crop: 3.58 Single-Crop: 5.6
Highway Network	2015	Depth + Multi-Path	First architecture to introduce the idea of multi path	2.3 M	CIFAR-10: 7.76
Inception V-4	2016	Depth + Width	It used asymmetric filters with split transform and merge concept	35 M	ImageNet: 4.01
Inception ResNet	2016	Depth + Width + Multi-Path	It used residual link with split transform and merge concept	55.8 M	ImageNet: 3.52
ResNet	2016	Depth + Multi-Path	Identified mapping-based skip connections with residual learning	25.6 M 1.7 M	ImageNet: 3.6 CIFAR-10: 6.43

[8] <https://doi.org/10.3390/electronics10202470>

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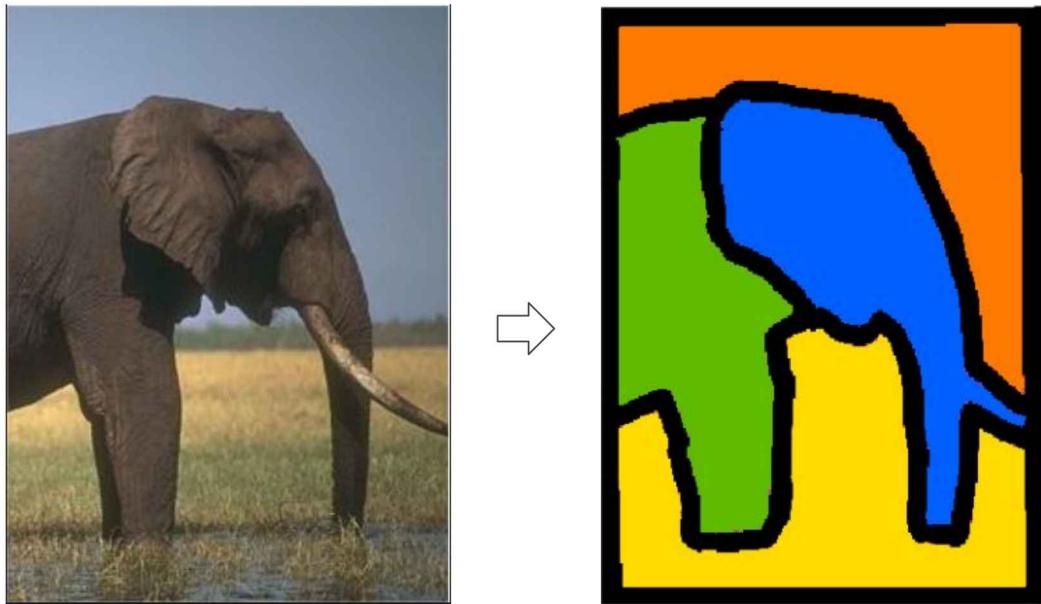
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Image segmentation



Segmentación: Agrupar pixels que sean similares entre si. La idea es que los segmentos formados tengan potencial de integrar algunas categorías de objetos.

Classification

Classification

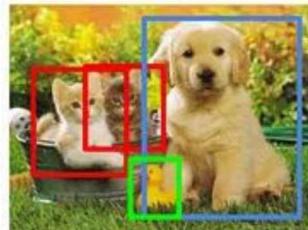


CAT

<https://paperswithcode.com/task/image-classification>

Object Detection

Object Detection



CAT, DOG, DUCK

<https://paperswithcode.com/task/object-detection>

Instance Segmentation

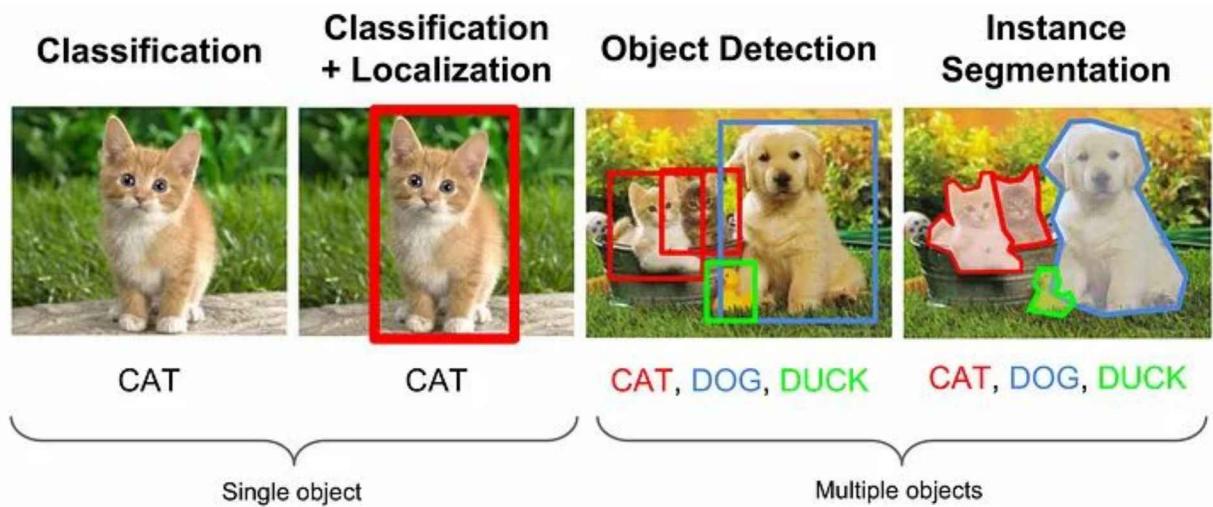
Instance Segmentation



CAT, DOG, DUCK

<https://paperswithcode.com/task/instance-segmentation>

Classification x Object Detection x Instance Segmentation



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Example: Image segmentation

Automatic image segmentation based on label propagation

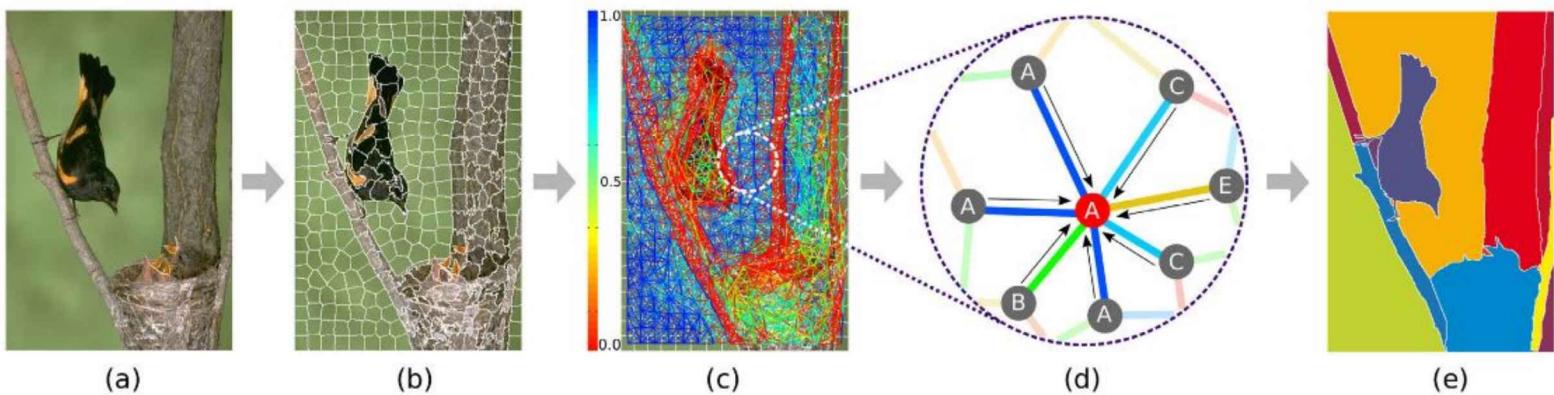


FIGURE 1 Illustration of our method. (a) Input image; (b) super-pixel extraction; (c) graph building. Blue edges indicate high similarity among vertices, whereas red edges represent low similarity; (d) label propagation. The red vertex is assigned the most frequent label in its neighbourhood, (e) segmentation result, that is, regions containing super-pixels with the same label

[11] <https://doi.org/10.1049/ipr2.12242>

Example: Image segmentation

Multi-level Graph Label Propagation for Image Segmentation

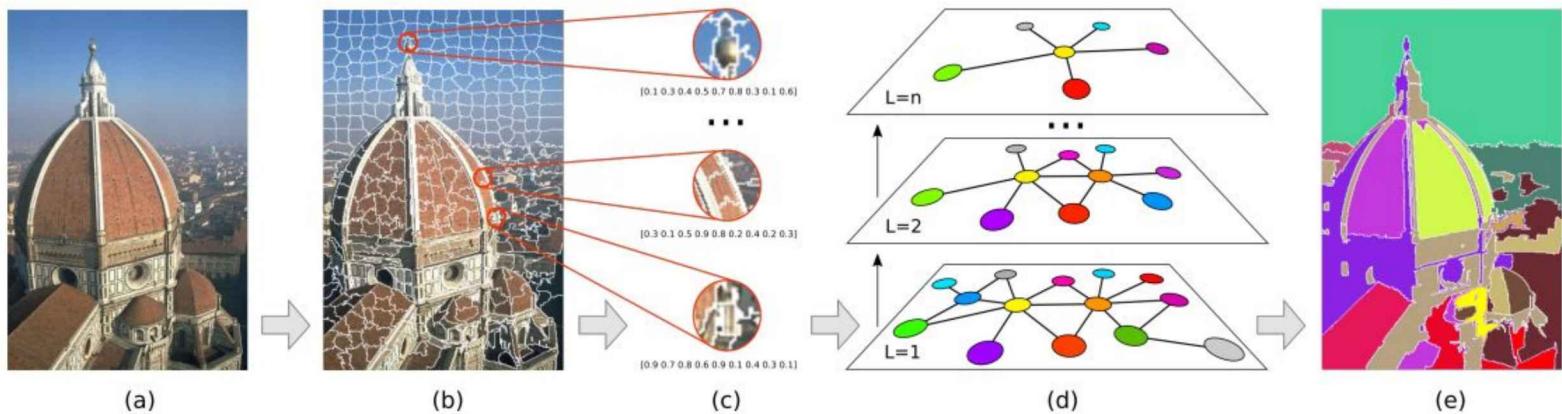


Fig. 1. The proposed method: (a) Input image; (b) super-pixel pre-segmentation; (c) feature extraction; (d) multi-level propagation where new graphs are created by merging similar super-pixels from the previous level; (e) final segmentation at the last level.

[12] <https://doi.org/10.1109/SIBGRAPI51738.2020.00034>

Example: Image classification

Analysis of vertebrae without fracture on spine MRI to assess bone fragility: A Comparison of Traditional Machine Learning and Deep Learning

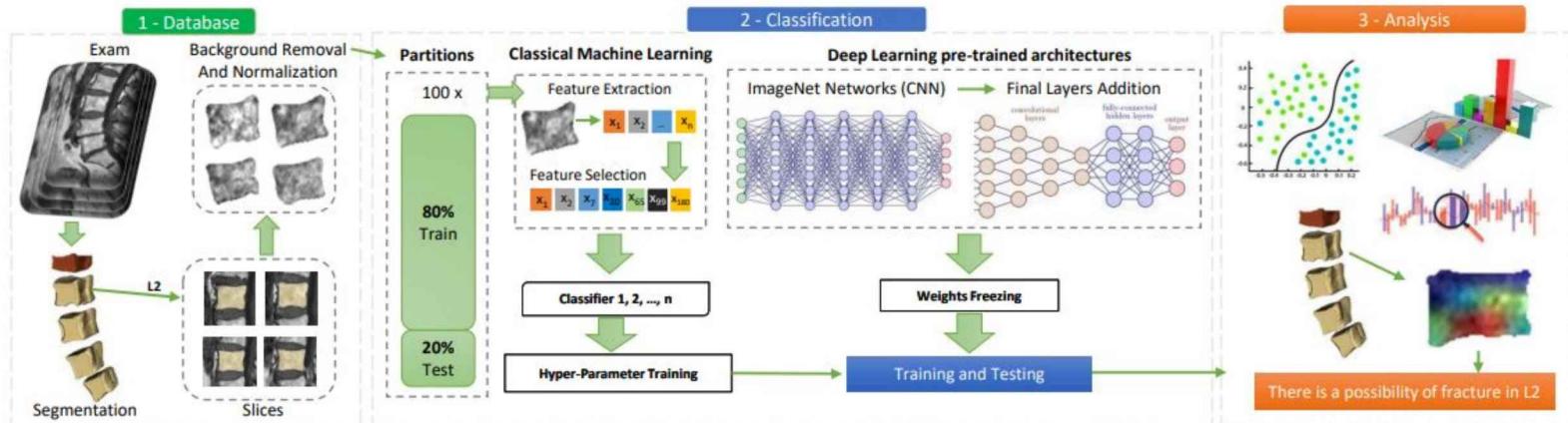


Fig. 1. Workflow employed in this study.

[13] <https://doi.org/10.1109/CBMS55023.2022.00021>

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Example: Object detection

Object Detection Using Deep Learning, CNNs and Vision Transformers: A Review

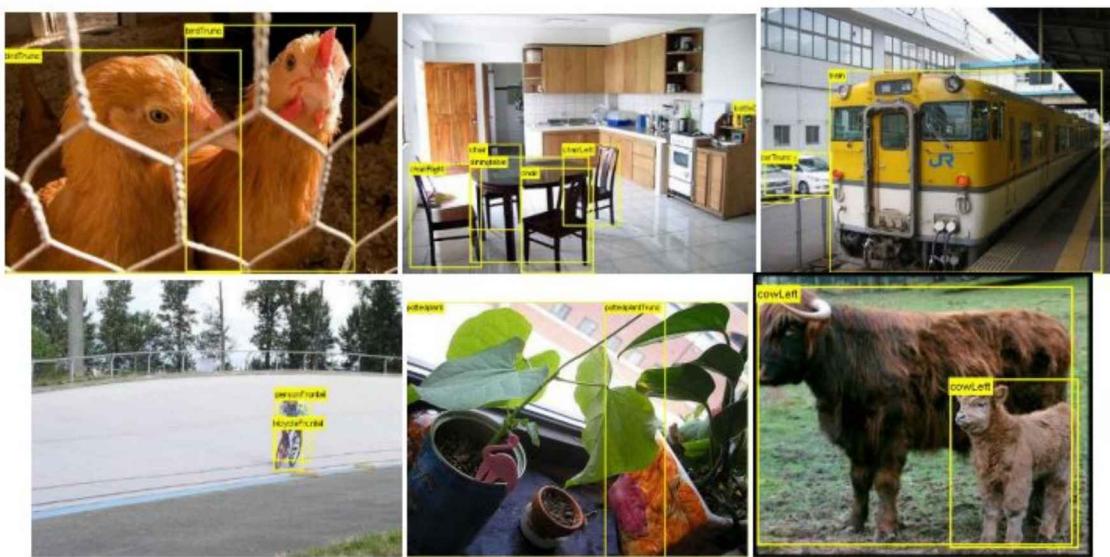


FIGURE 1. Samples from Pascal VOC 07.

[14] <https://doi.org/10.1109/ACCESS.2023.3266093>

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Example: Object detection

Automatic detection of Aedes aegypti breeding grounds based on deep networks with spatio-temporal consistency



Fig. 1. Selected frames of video sequences from the MBG database, showing annotated bounding boxes.

[15] <https://doi.org/10.1016/j.compenvurbsys.2021.101754>

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Example: Object detection

Automatic detection of Aedes aegypti breeding grounds based on deep networks with spatio-temporal consistency

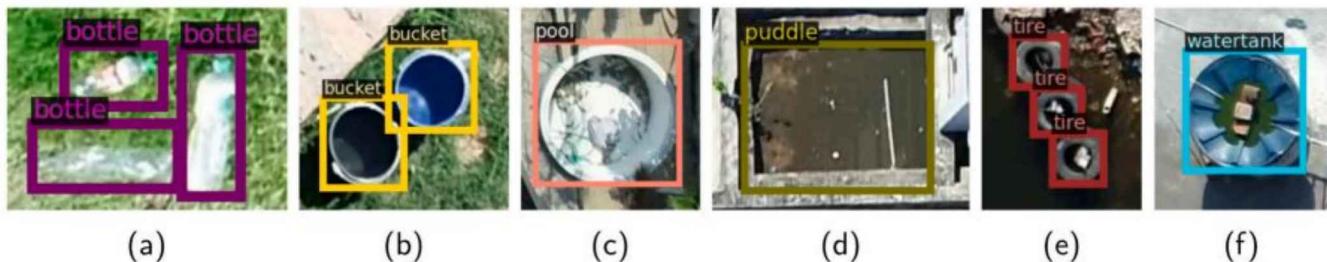


Fig. 2. Examples of objects associated to potential mosquito breeding grounds in the MBG database: (a) 'bottle', (b) 'bucket', (c) 'pool', (d) 'puddle', (e) 'tire', and (f) 'water tank'.

[15] <https://doi.org/10.1016/j.compenvurbsys.2021.101754>

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Example: Instance segmentation

Application of one-stage instance segmentation with weather conditions in surveillance cameras at construction sites

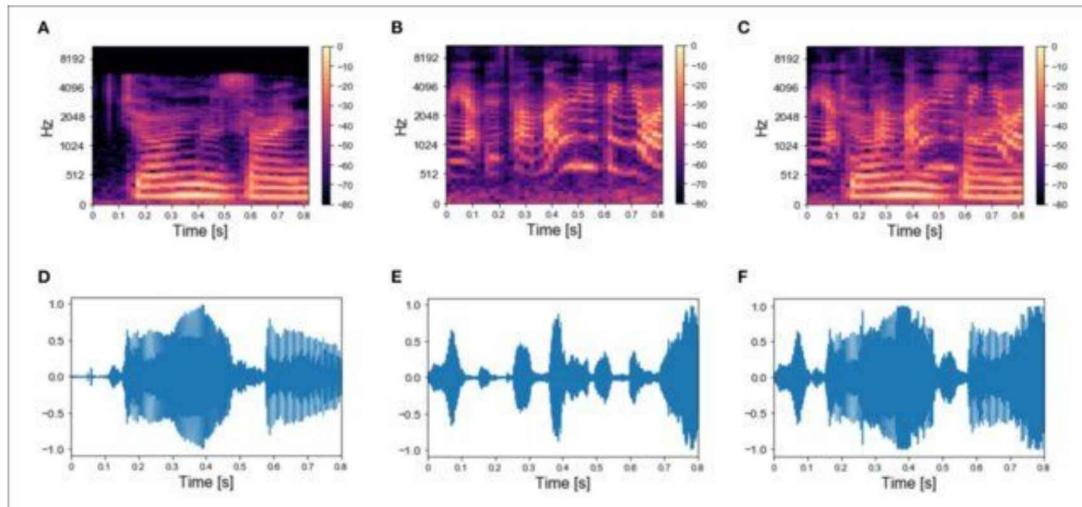


Fig. 10. Qualitative evaluation of models with and without weather augmentation, with a focus on the quality of the polygon masks.

[16] <https://doi.org/10.1016/j.autcon.2021.104034>

Sound event classification

Modeling the Repetition-Based Recovering of Acoustic and Visual Sources With Dendritic Neurons



[9] <http://dx.doi.org/10.3389/fnins.2022.855753>

Sound event classification

Mel-spectrogram and Deep CNN Based Representation Learning from Bio-Sonar Implementation on UAVs

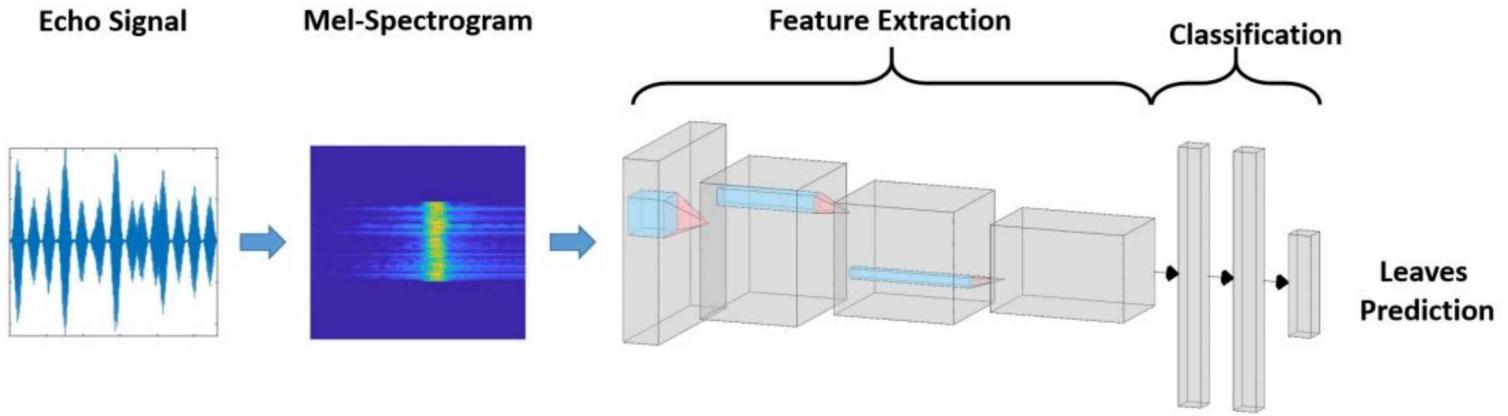


Fig. 1: The proposed pipeline. Mel-spectrogram converts the audio signal to an equivalent image. This image is then used for feature extraction using CNN. The number of leafs in the biosonar lobe is then returned as the output.

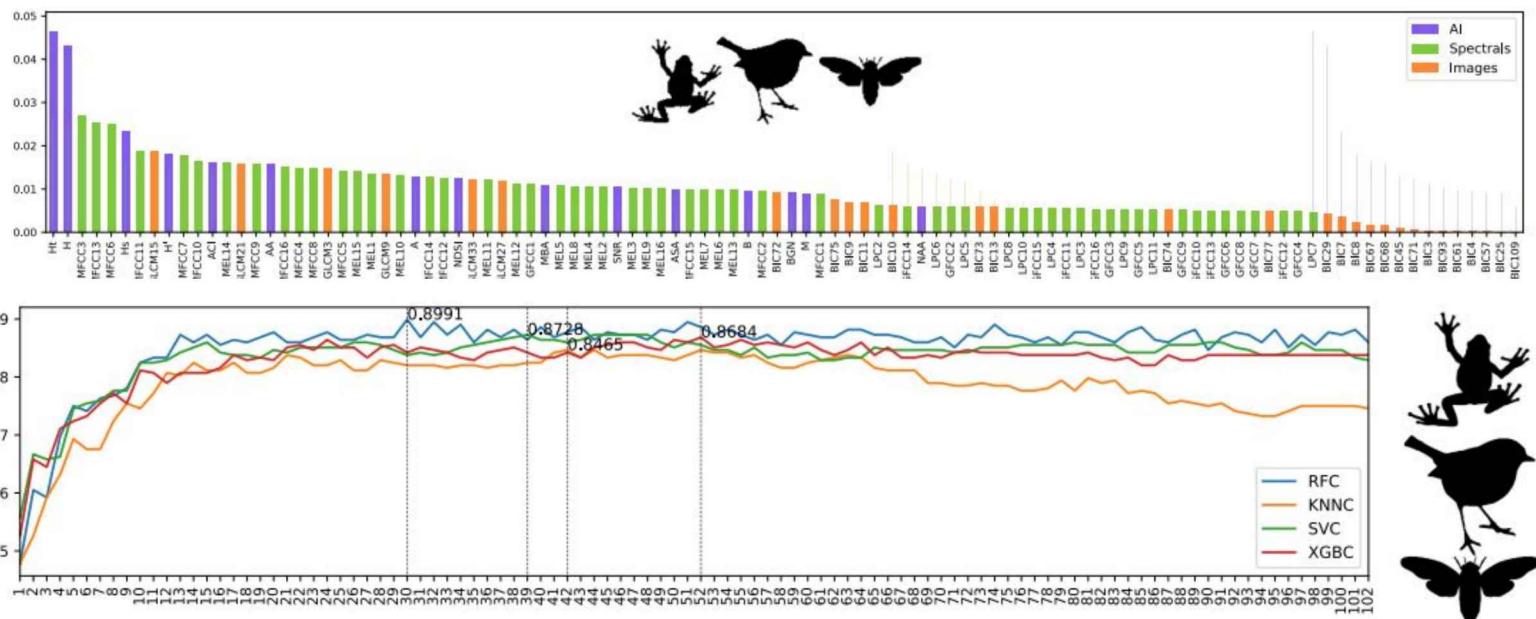
[10] <https://doi.org/10.1109/ICCCR49711.2021.9349416>

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Example: Sound event classification

Visualization and categorization of ecological acoustic events based on discriminant features



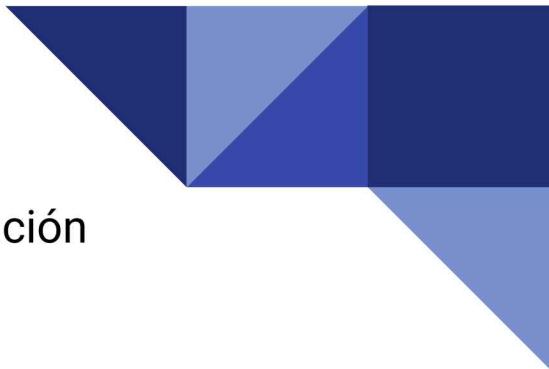
[17] <https://doi.org/10.1016/j.ecolind.2020.107316>

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Gracias

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