# Texture and colour descriptors for visual recognition: an overview of methods applications

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Perugia, 23 June 2021

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# Outline

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# About the speaker

# About the speaker (1/2)

- **Contacts**
  - Department of Engineering, Università degli Studi di Perugia
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  - e-mail: bianco@ieee.org
- **Position**: *Professore Associato* (eqv. UK = Senior Lecturer)
  - Currently *Academic Visitor* in the School of Mathematics, Computer Science & Engineering at City, University of London
- **Background** in Industrial Engineering (MEng Mechanical Engineering, PhD Computer-aided Design)

# About the speaker (2/2)

- **Research interests** in the area of image processing, with particular focus on:
  - Colour and texture analysis
    - Theory (*mathematics of textures*)
    - Industrial applications (*surface sorting* and *grading*, *defect detection*)
    - Biomedical applications (*histology*, *radiomics*)

# The University of Perugia

- Established in 1308;
- About 26,000 students;
- Sixteen departments:
  - Agricultural Sciences; Ancient and Modern Literatures, Languages and Cultures; Chemistry, Biology and Biotechnologies; Civil and Environmental Engineering; Economics; Engineering; Experimental Medicine; Law; Mathematics and Computer Science; Medicine; Philosophy, Human and Social Sciences; Pharmacy; Physics and Geology; Political Sciences; Surgery and Biomedicine; Veterinary.
- Ranked 1st for the fifth year in a row among the Italian universities with a student population between 20,000 and 40,000[1]

[1] CENSIS. *Le classifiche degli atenei statali (2018/2019)*. Available online at `http://www.censis.it/17?shadow_pubblicazione=120579`. Last accessed on sep.. 4, 2018. 2018.

# The city of Perugia

- A well-preserved medieval town
- Population of about 160,000
- Quiet and safe but culturally active
- Good environment for students

# Umbria: ‘The green heart of Italy’

# What is ‘visual recognition’?

# What is 'visual recognition'?

*Visual recognition*:[2]

- The capacity to identify an item visually
- The ability to recognize items in their visual environment

*Visual*:[3]

- Related to seeing or sight

[2] M.S. Pam. *Visual recognition*. In PsychologyDictionary.org, April 29, 2013, `https://psychologydictionary.org/visual-recognition/`. Visited on 20 May 2021. 2013.

[3] Various authors. *Visual*. In Oxford English Dictionary, online version. Visited on 20 May 2021. 2020.

# Applications

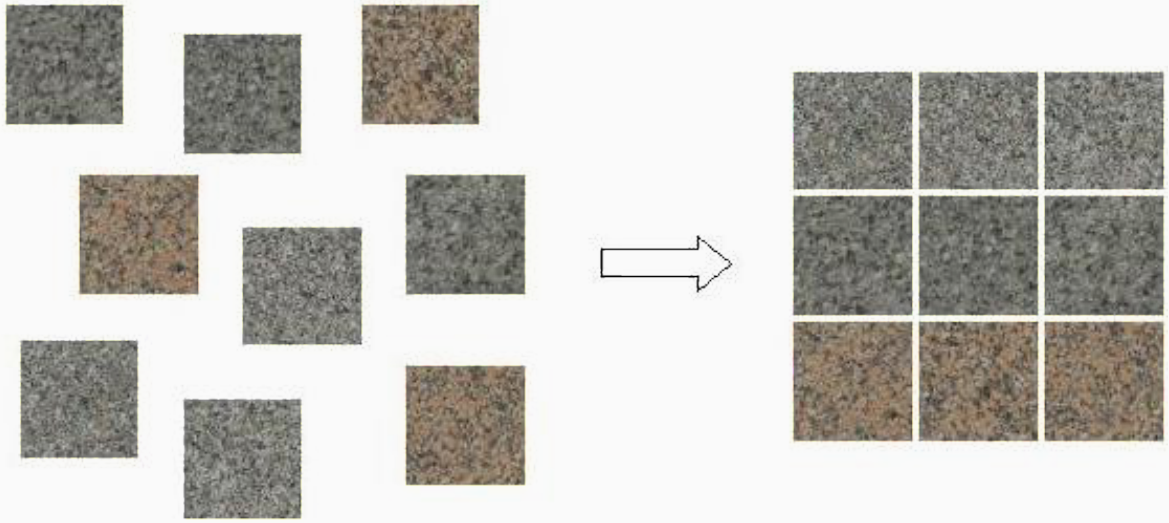
# Industrial: sorting and grading (food)

Grouping products into lots based on the criterion of *maximum similarity*.

Application: separating green apples from red

# Industrial: sorting and grading (marble and granite)

Sorting granite and marble tiles into lots of similar visual appearance[4]



[4] F. Bianconi et al. "Automatic classification of granite tiles through colour and texture features". In: *Expert Systems with Applications* 39.12 (Sept. 2012), pp. 11212–11218.

# Industrial: sorting and grading (wood)

Grouping wood planks into batches of same tone (for flooring and cladding – *parquet*)[5]

Grade '1' Grade '2' Grade '3'

[5] F. Bianconi et al. "Performance analysis of colour descriptors for parquet sorting". In: *Expert Systems with Applications* 40.5 (Apr. 2013), pp. 1636–1644.

# Industrial: defect detection (wood)

Detection and classification of wood defects (e.g. knots, splits and stains)[6]


[6] M. Niskanen et al. "Color and texture based wood inspection with non-supervised clustering". In: *Proceedings of the 12th Scandivanian Conference on Image Analysis (SCIA 2001)*. Bergen, Norway, 2001, pp. 336–342.

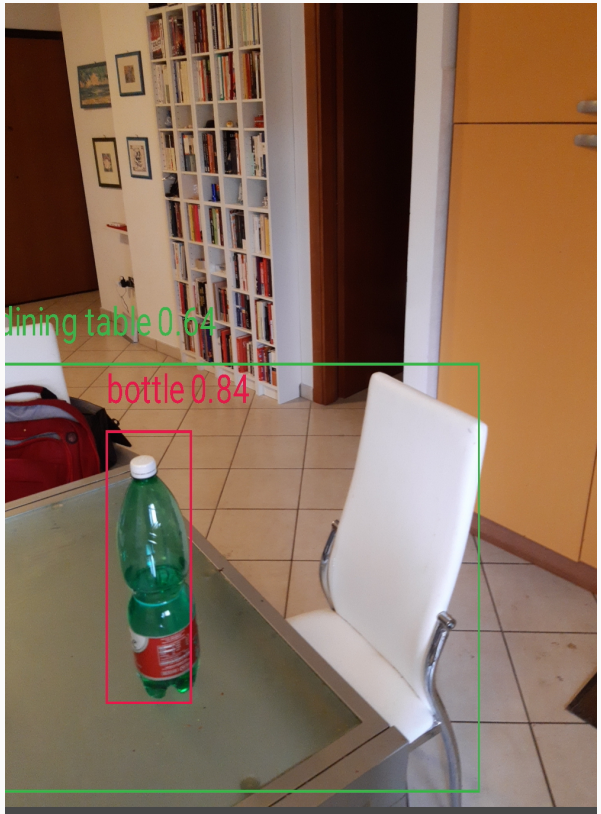
# Industrial: defect detection (paper)

Detection and classification of paper impurities[7]

[7] F. Bianconi et al. "A sequential machine vision procedure for assessing paper impurities". In: *Computers in Industry* 65.2 (Feb. 2014), pp. 325–332.

# Industrial: object detection and recognition (1/1)


Time elapsed: 642 ms
Class: bowl | Confidence: 0.84
Class: tv | Confidence: 0.80
Class: book | Confidence: 0.70




Time elapsed: 607 ms
Class: bottle | Confidence: 0.84
Class: dining table | Confidence: 0.64

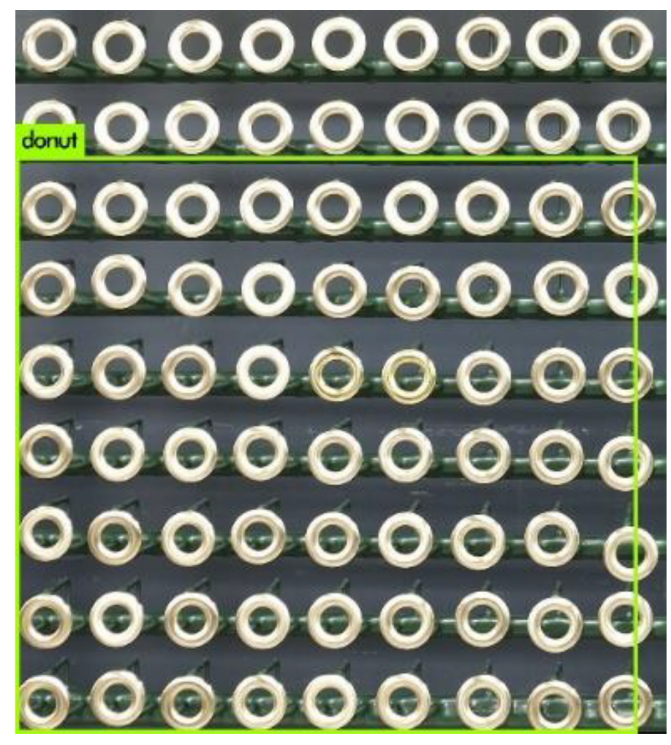
# Industrial: recognition of mechanical parts

Recognition of aircraft mechanical parts for smart maintenance[8]


[8] C. Cusano and P. Napoletano. "Visual recognition of aircraft mechanical parts for smart maintenance". In: *Computers in Industry* 86 (2017), pp. 26–33.

# Industrial: counting mechanical parts

Automated counting of small metal parts in the electro-deposition industry[9]

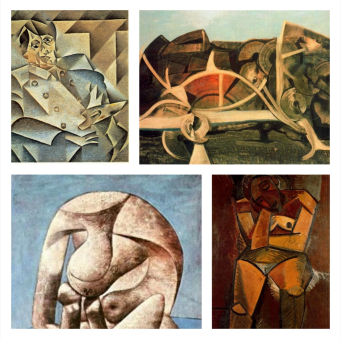



[9] R. Furferi et al. "Machine vision system for counting small metal parts in electro-deposition industry". In: *Applied Sciences* 9.12 (2019). Art. no. 418.

# Cultural heritage: art style and/or author recognition

Painting style classification[10]

Baroque



Cubism

Fauvism

[10] F. Bianconi and R. Bello-Cerezo. "Evaluation of visual descriptors for painting categorisation". In: *Florence Heri-Tech – The Future of Heritage Science and Technologies*. Vol. 364. IOP Conference Series: Materials Science and Engineering. Art. no. 012037. Florence, Italy: IOPScience, May 2018.

# Food: recognition and classification

Food recognition for monitoring dietary behaviour, keeping track of food consumption and estimating leftovers[11]

[11] G. Ciocca et al. "Food Recognition: A New Dataset, Experiments, and Results". In: *IEEE Journal of Biomedical and Health Informatics* 21.3 (May 2017). Art. no. 7776769, pp. 588–598.

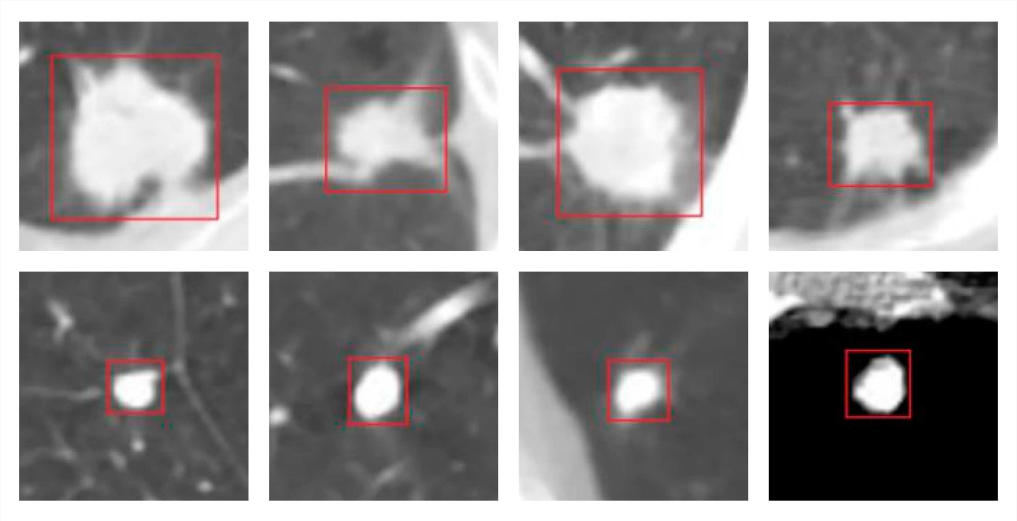
# Food: monitoring ripening of fruits & veggies

Automatic recognition of ripening tomatoes[12]

[12] J. Wu et al. "Automatic recognition of ripening tomatoes by combining multi-feature fusion with a bi-layer classification strategy for harvesting robots". In: *Sensors* 19.3 (2019). Art. no. 612.

# Biomedical: computer-assisted diagnosis

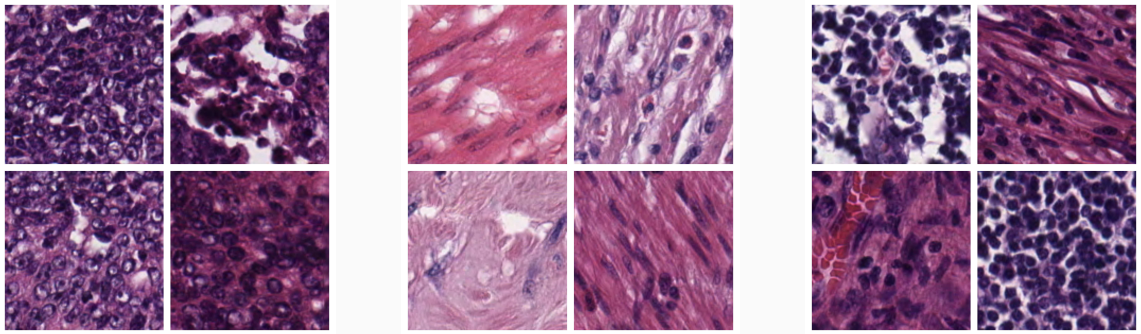
Predicting benignity/malignancy of lung nodules from CT[13]



[13] X. Wang et al. "An appraisal of lung nodules automatic classification algorithms for CT images". In: *Sensors* 19.1 (2019). Art. no. 194.

# Biomedical: computer-assisted diagnosis

Automated classification of tissue type and subtype from histological images[14]



Epithelium Stroma Lymphocytes

[14] J.N. Kather et al. "Multi-class texture analysis in colorectal cancer histology". In: *Scientific Reports* 6 (2016). art. no. 27988.

# Biomedical: computer-assisted diagnosis

Automated classification of naevi from dermoscopy images[15]

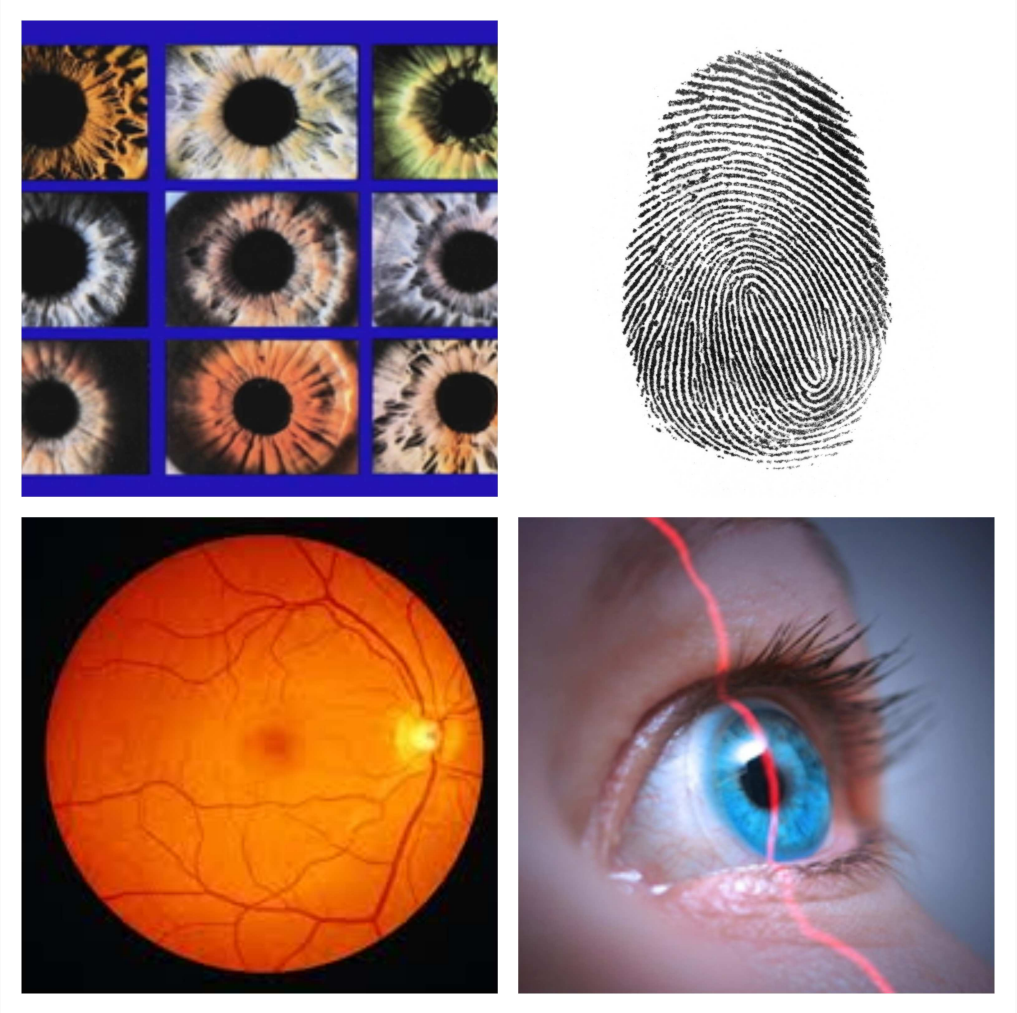
Benign

Malignant

[15] L.-M. Sánchez-Reyes et al. "A high-accuracy mathematical morphology and multilayer perceptron-based approach for melanoma detection". In: *Applied Sciences* 10.3 (2020). Art. no. 1098.

# Biometric identification

Personal identification based on fingerprints, iris, retina, etc.



# Remote sensing

Automated classification of urban/rural areas[16]

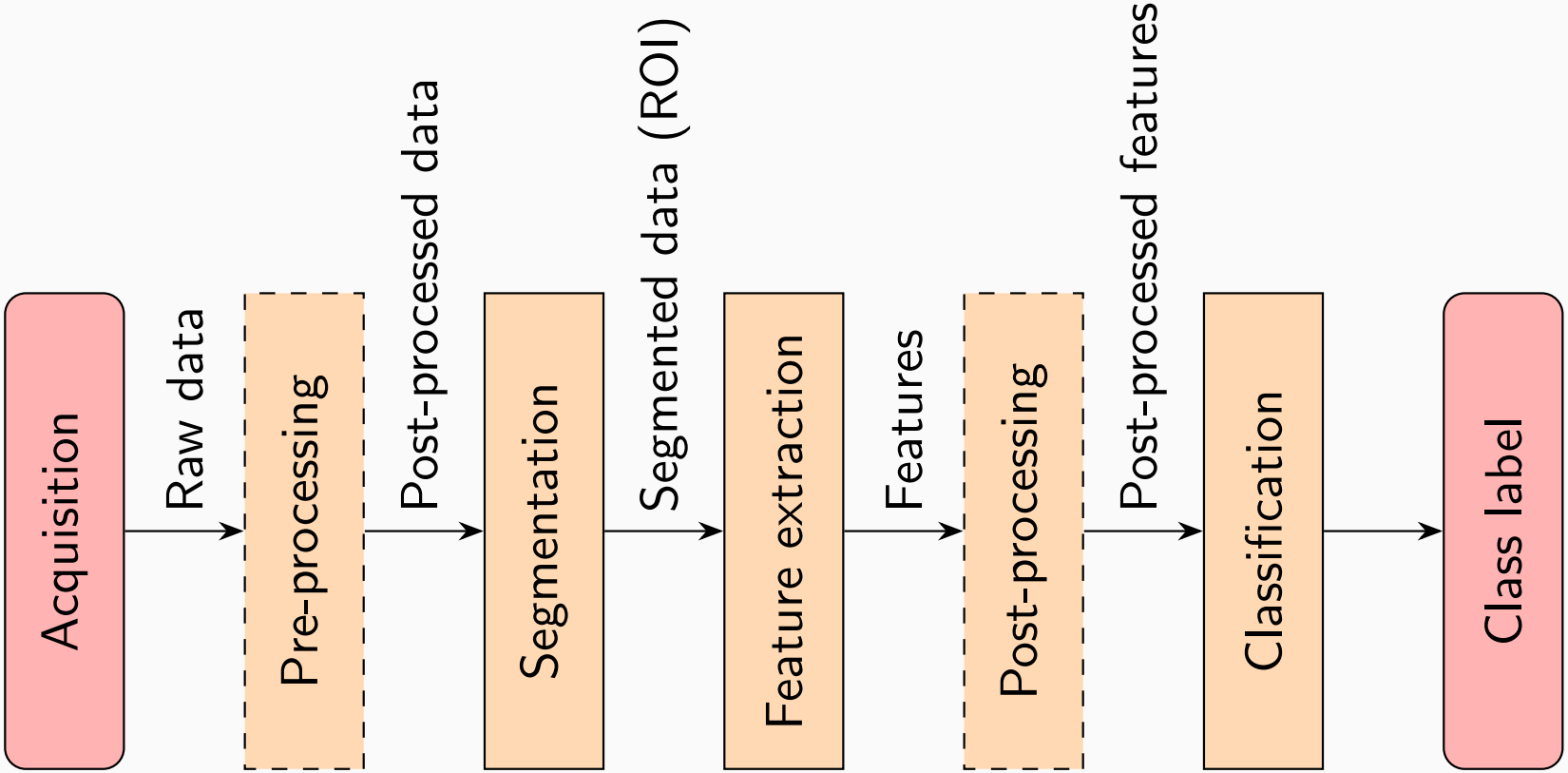

Satellite image


Segmented image

[16] M.A. Aguilar et al. "Classification of urban areas from geoeye-1 imagery through texture features based on histograms of equivalent patterns". In: *European Journal of Remote Sensing* 49 (Mar. 2016), pp. 93–120.

# Pipeline

# The overall pipeline

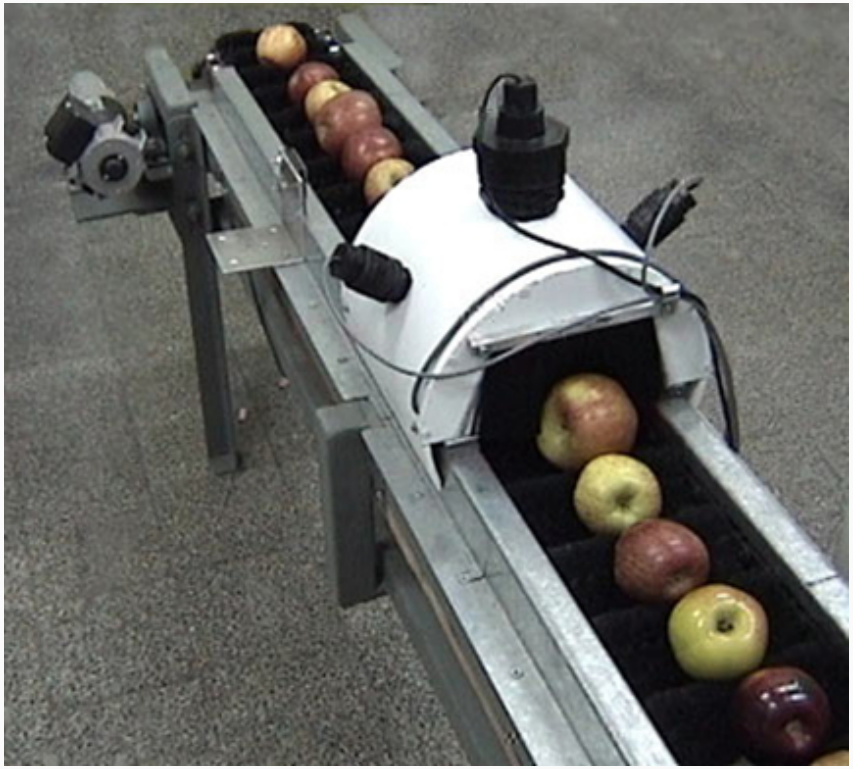


# Acquisition (1/2)

Image and/or video acquisition through any suitable device as for instance:

- Standard (RGB) colour camera
- Multi-spectral camera
- Light and/or electron microscopy
- Medical imaging systems
  - Computed Tomography (CT)
  - Magnetic Resonance Imaging (MRI)
  - Optical Coherence Tomography (OCT)
  - Positron Emission Tomography (PET)
  - Ultrasonography (US)
  - X-rays

# Acquisition (2/2)



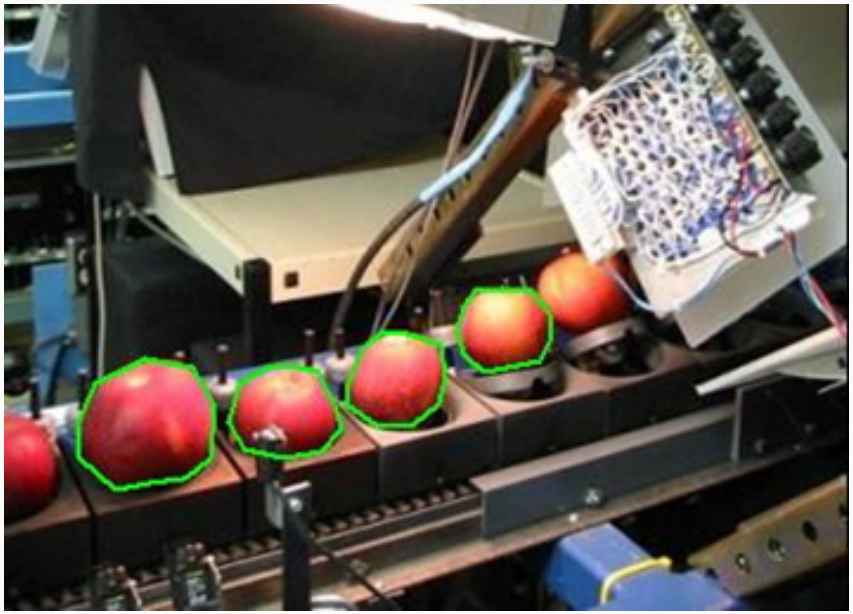
# Pre-processing

An optional step which may involve one or more operations such as:

- Colour-preprocessing (e.g. colour constancy, colour augmentation, histogram equalisation)
- Resampling/rescaling
- Spatial and/or frequency filtering (e.g. smoothing, sharpening, edge detection)
- Noise reduction
- Restoration and de-blurring

# Segmentation

Identification of the part of the image that is relevant for the task



# Feature extraction (1/2)

Computation of discriminative visual parameters from the input images – e.g.:

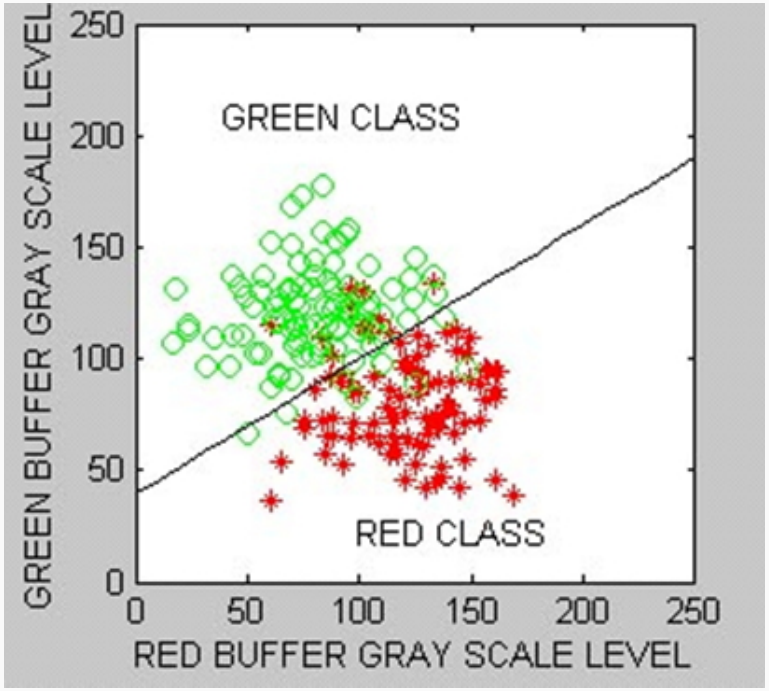
- Colour
- Shape
- Texture

# Feature extraction (2/2)

Ideally the features should be:

- Few
- Easy to compute
- Discriminative
- Interpretable

We'll come to features in detail later



# Post-processing

Features can be further processed with the aim of reducing their number and/or increasing the discrimination capability. Most common strategies are:

- Feature selection[17]
  - Filter methods
  - Wrapper methods
  - Embedded methods
- Feature generation[18]
  - Principal component analysis (PCA)
  - Independent component analysis (ICA)

[17] G. Chandrashekar and F. Sahin. "A survey on feature selection methods". In: *Computers and Electrical Engineering* 40 (2014), pp. 16–28.

[18] S. Theodoridis and K. Koutroumbas. *Pattern Recognition. Third edition.* Academic Press, 2006.

# Classification

**Unsupervised**

Input:

- A set of elements (features)
- The number of classes $n$

Output:

- A partition of the set into $n$ classes

**Supervised**

Input:

- A set of pre-classified elements (features + class labels)
- An unknown element (features)

Output:

- The class label of the unknown element

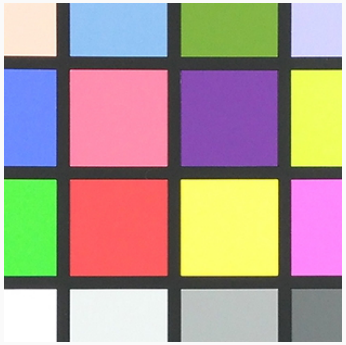
# Visual descriptors

# What is a visual descriptor?

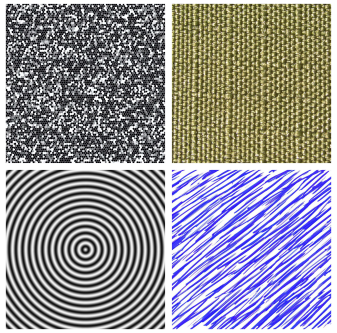
A visual descriptor is a *function* $F$ that extracts a set of quantitative parameters $v_i$ (*features*) from an input image I:

$$\{v_0, \ldots, v_{n-1}\} = F(\mathrm{I}) \tag{1}$$

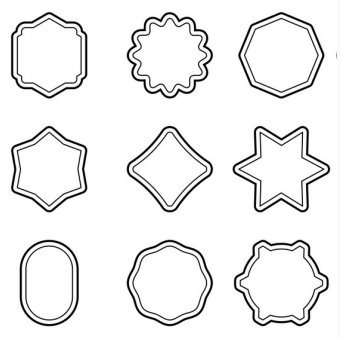
The features are related to some visual characteristics of the image, in particular:



Colour

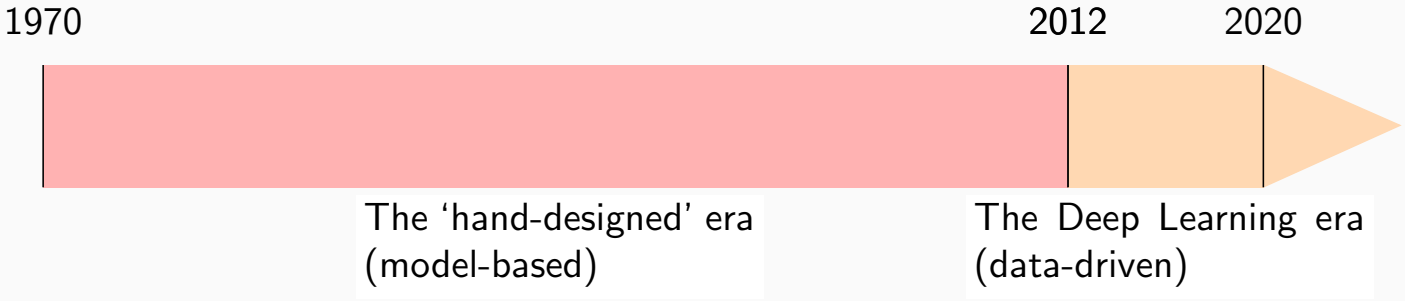


Texture



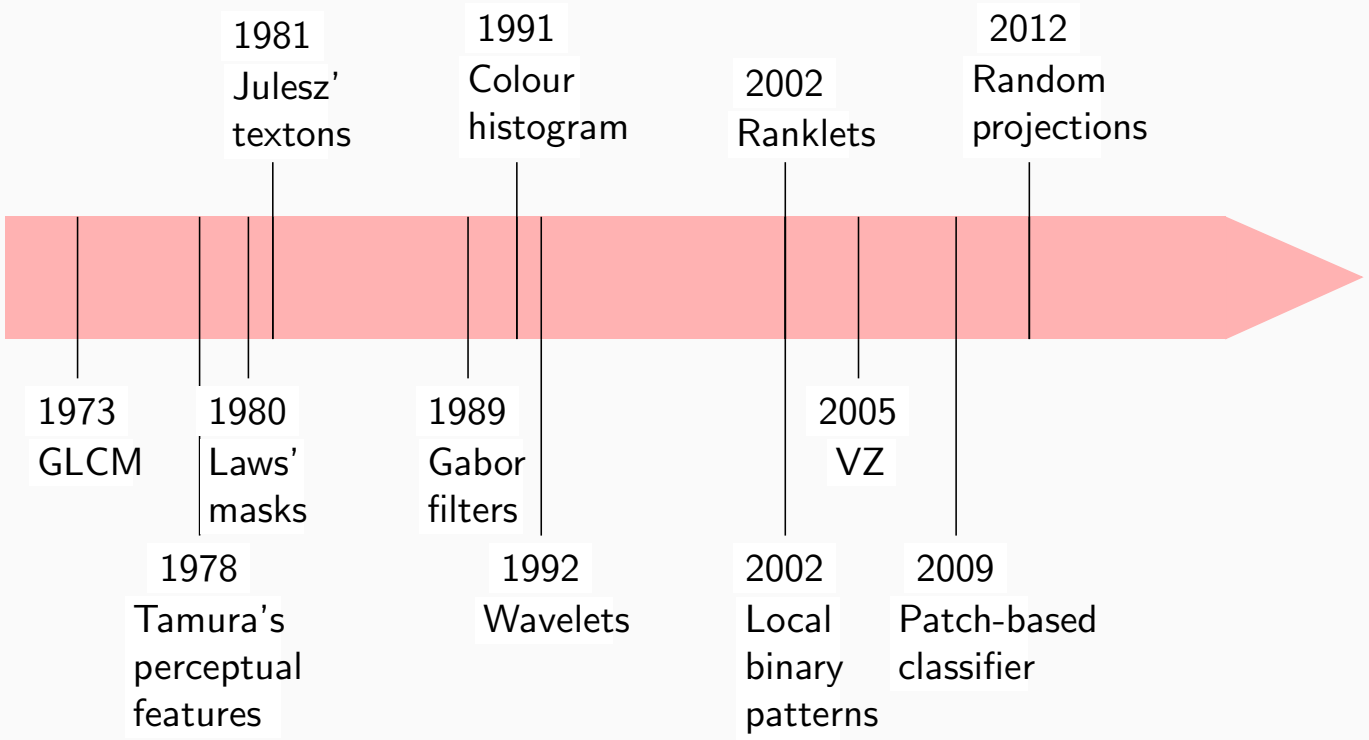
Shape

# Visual descriptors: a chronology (1/3)



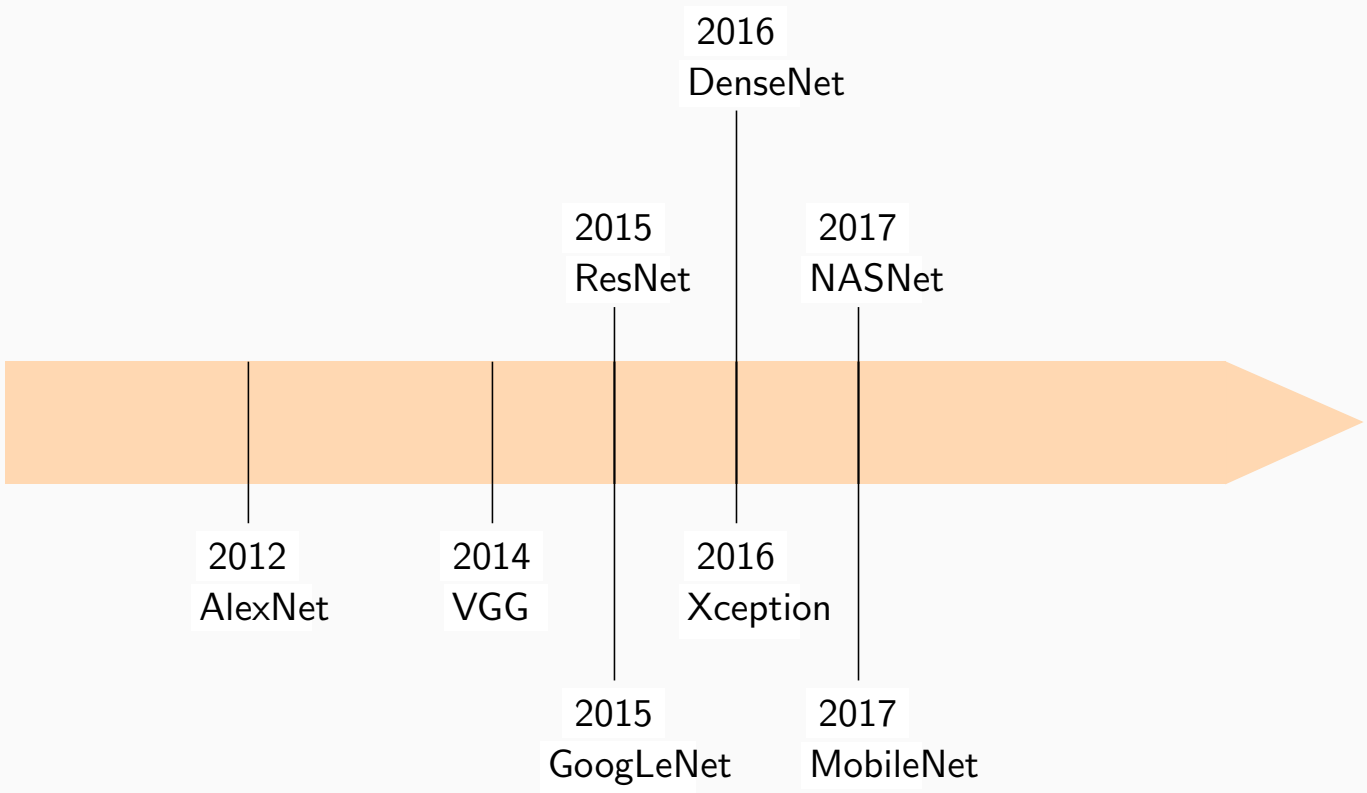
# Visual descriptors: a chronology (2/3)

## Hand-designed methods



# Visual descriptors: a chronology (3/3)

Methods based on deep learning (convolutional networks)



# Visual descriptors: Hand-designed vs. Deep Learning

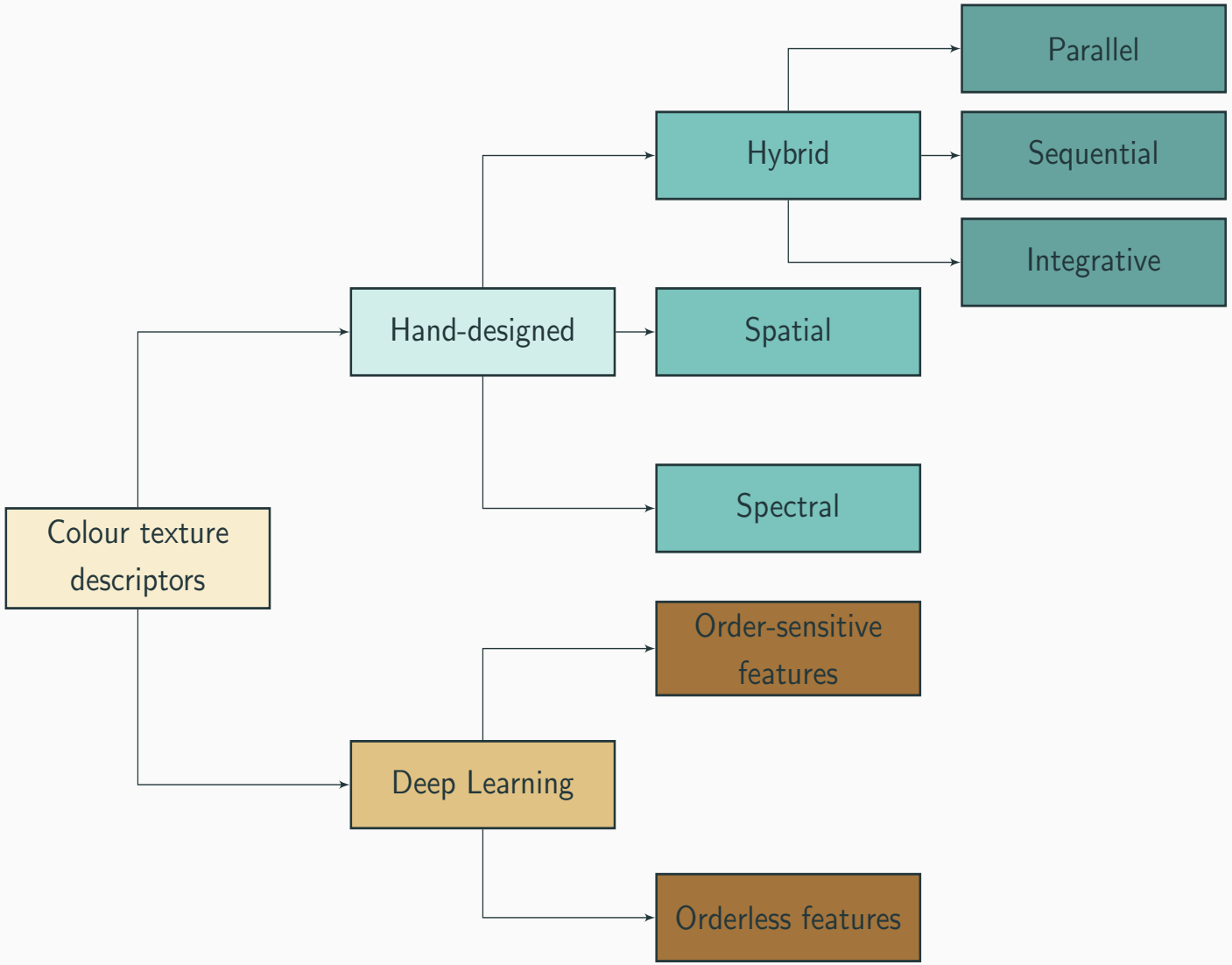
| Hand-designed | Deep learning |
| --- | --- |
| Mostly defined **a priori** (little or no training needed) | Based on **modules** and sets of **free parameters** (to be determined by training) |
| Relatively **intuitive** / **interpretable** features | Features **difficult to interpret** |
| Low computational demand | Require **large datasets** for training and dedicated hardware |
| **Unconstrained** input field | **Constrained** (fixed) input field |
| Accuracy can be very **dataset-dependent** | **Unprecedented accuracy** in many tasks |
| Need to **find the right method** for any specific task | **Generalizable** results |

# Colour and texture

# Colour and texture

- Colour and texture are two fundamental **visual stimuli** that determine most of the appearance of materials, objects and scenes
  - **Colour**: property of **a point** or **an area**
  - **Texture**: property of **an area**, related to the spatial variation of the visual appearance
- The ability to describe colour and texture plays a fundamental role in many computer-vision tasks, e.g.:
  - **Classification**
  - **Segmentation**
  - **Content-Based Image Retrieval**

# A taxonomy of colour and texture descriptors for visual recognition

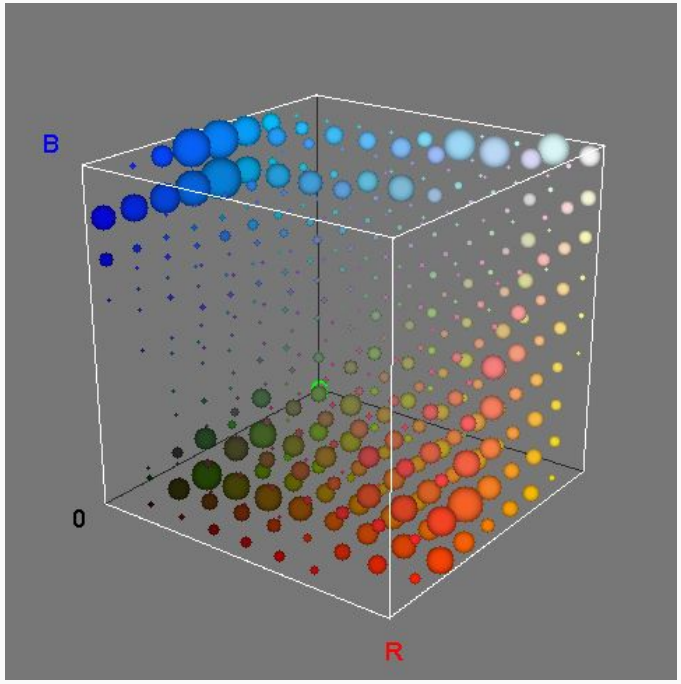


# Spectral methods (colour descriptors – 1/4)

- Statistical distribution of **colour only – no spatial information**
  - Computationally inexpensive and easy to implement 👍
  - Rather resilient to rotation, changes in scale and/or viewpoint 👍
  - Surprisingly good under invariable illumination conditions 👍
  - Sensitive to illumination changes 👎

# Spectral methods (colour descriptors – 2/4)

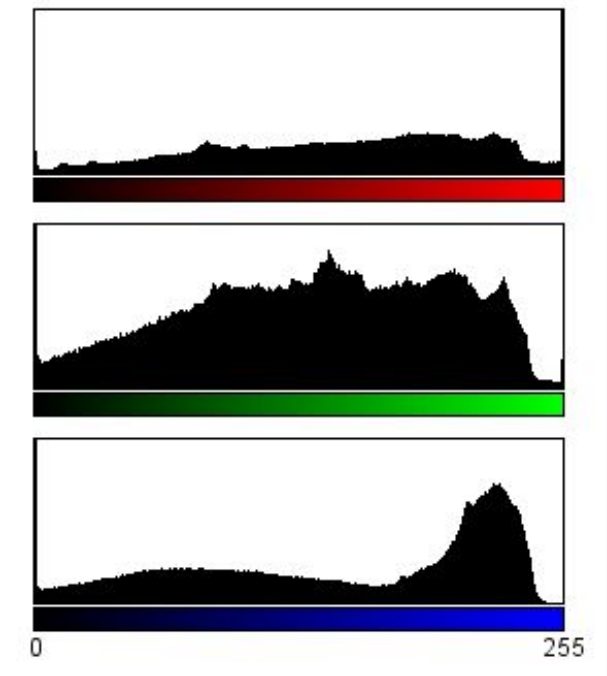
Full colour histogram[19]




[19] M.J. Swain and D.H. Ballard. "Color indexing". In: *International Journal of Computer Vision* 7.1 (1991), pp. 11–32.

# Spectral methods (colour descriptors – 3/4)

Marginal colour histograms[20]




[20] M. Pietikainen et al. "Accurate color discrimination with classification based on feature distributions". In: *Proceedings of the International Conference on Pattern Recognition (ICPR)*. vol. 3. Art. no. 547285. Vienna, Austria, 1996, pp. 833–838.

# Spectral methods (colour descriptors – 4/4)

*Soft* colour descriptors:

- Colour percentiles[21]
- Mean, standard deviation and higher-order moments of each colour channel[22]

[21] M. Niskanen et al. "Color and texture based wood inspection with non-supervised clustering". In: *Proceedings of the 12th Scandivanian Conference on Image Analysis (SCIA 2001)*. Bergen, Norway, 2001, pp. 336–342.

[22] S. Kukkonen et al. "Color features for quality control in ceramic tile industry". In: *Optical Engineering* 40.2 (Feb. 2001), pp. 170–177; F. López et al. "Performance evaluation of soft color texture descriptors for surface grading using experimental design and logistic regression". In: *Pattern Recognition* 41.5 (2008), pp. 1761–1772.

# Spatial methods (texture descriptors)

Computed on the **luminance** channel – **colour is discarded**

- Rather resilient to illumination changes 👍
- Sensitive to rotation, changes in scale and/or viewpoint 👎(but some degree of invariance can be achieved)

# Texture descriptors: an overview

There is a huge amount of descriptors available in the literature[23]

Although a classification is difficult, there are two recurrent ideas behind most of them:

- Filtering
- The bag-of-visual-words (BoVW) model

[23] X. Xie and M. Mirmehdi. "A Galaxy of Texture Features". In: *Handbook of texture analysis*. Ed. by M. Mirmehdi et al. Imperial College Press, 2008, pp. 375–406.

# Texture descriptors: filtering

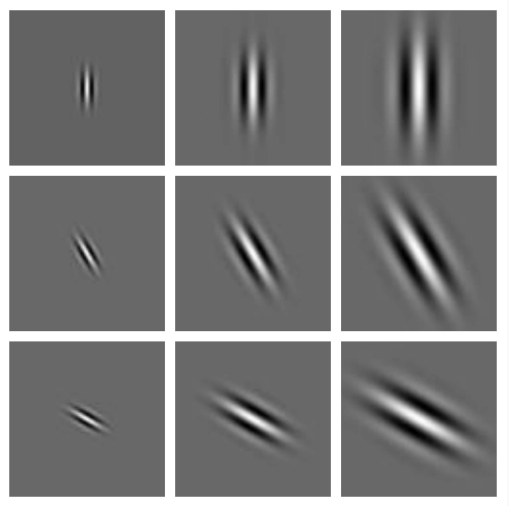
Involves the following steps:

1. Defining a set of filters (Gabor, Gaussian, wavelet, etc.)
2. Filtering the input image and obtain a set of transformed images
3. Extracting global statistical parameters from the transformed images (mean, std. dev., moments, etc.)

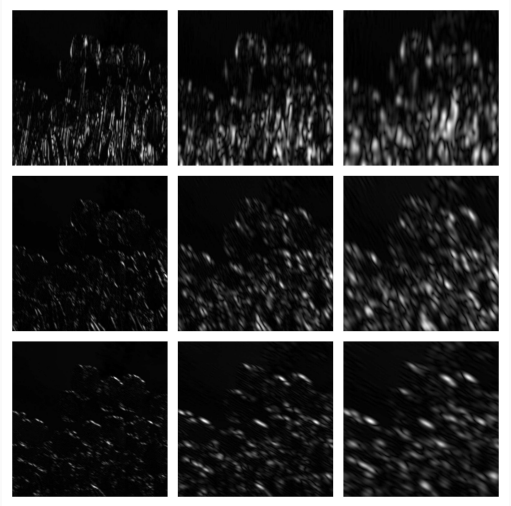
# Texture descriptors based on filtering: Gabor filters

Set of filters at different frequencies and orientations[24]

Input image



Filters



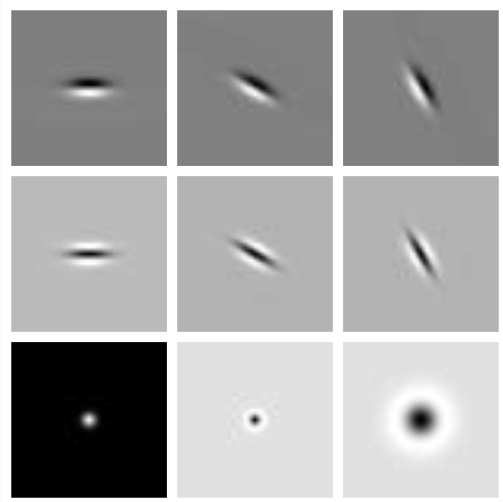
Transformed images

[24] B.S. Manjunath. "Texture features for browsing and retrieval of image data". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 18.8 (1996), pp. 837–842.

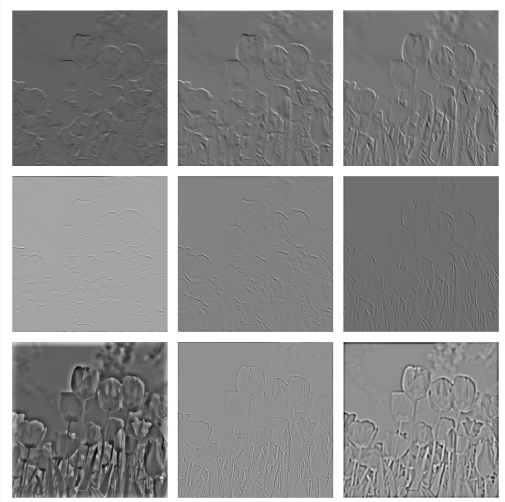
# Texture descriptors based on filtering: 'LM' filters

The Leung-Malik (LM) filter bank: first and second derivatives of Gaussian (three scales, six orientations), eight Laplacian of Gaussian (LOG) and four Gaussian filters (48 filters)[25]

Input image



Filters



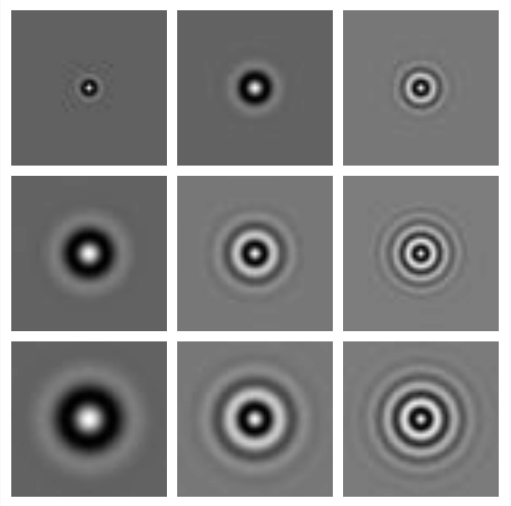
Transformed images

[25] T. Leung and J. Malik. "Representing and recognizing the visual appearance of materials using three-dimensional textons". In: *International Journal of Computer Vision* 43.1 (2001), pp. 29–44.

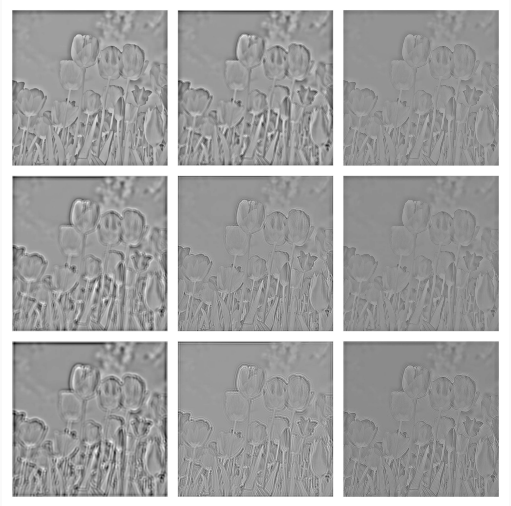
# Texture descriptors based on filtering: 'S' filters

The Schmid (S) filter bank: 13 rotationally invariant filters[26]

Input image



Filters



Transformed images

[26] C. Schmid. "Constructing models for content-based image retrieval". In: *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. Vol. 2. Kauai, HI, United States, 2001, pp. II39–II45.

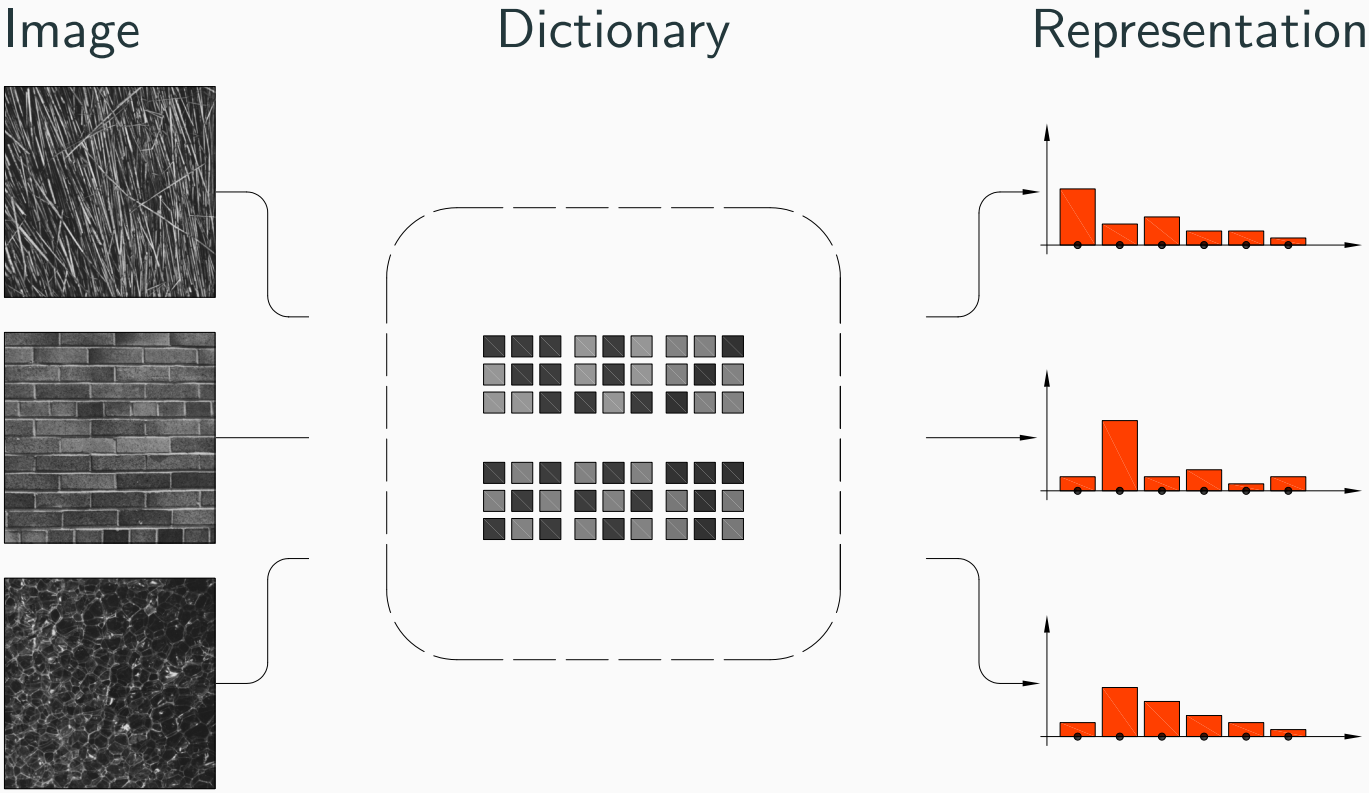
# Texture descriptors: the 'bag of visual words' model (1/2)

**Strategy**: to describe an image through the statistical distribution of a set of local primitives (*visual words*)

**Steps**:

1. Define the primitives (*dictionary*)
2. Analyse the occurrence of the primitives within the input image (e.g. through histogram or other statistics)

# Texture descriptors: the 'bag of visual words' model (2/2)



# An analogy: the 'bag of words' model for text analysis

He lay flat on the brown, pine-needled floor of the forest, his chin on his folded arms, and high overhead the wind blew in the tops of the pine trees. The mountainside sloped gently where he lay; but below it was steep and he could see the dark of the oiled road winding through the pass. There was a stream alongside the road and far down the pass he saw a mill beside the stream and the falling water of the dam, white in the summer sunlight.[27]

Dictionary: he, the, his and summer (dimension = four)

Total number of words = 87

Occurrences: he = 4, the = 13, his = 2 and summer = 1

Bag-of-words representation: $\{4/87, 13/87, 2/87, 1/87\}$;

[27] E. Hemingway. *For whom the bell tolls*. First published in Great Britain in 1941. Arrow books, 2004, p. 3.

# BoVW methods: Rank transform (RT)

Number of pixels in the periphery of the window whose grey-values are less than that of the central pixel[28]

For a 3×3 window there are nine possible visual words

| | | |
|---|---|---|
| 0.39 | 0.52 | 0.65 |
| 0.75 | 0.65 | 0.85 |
| 0.35 | 0.81 | 0.61 |

$\longrightarrow$

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 0 | | 0 |
| 1 | 0 | 1 |

$\sum = 4$

[28] R. Zabih and J. Woodfill. "Non-parametric local transforms for computing visual correspondence". In: *Proceedings of the 3rd European Conference on Computer Vision*. Vol. 801. Lecture Notes in Computer Science. Stockholm, Sweden: Springer, 1994, pp. 151–158.

# BoVW methods: Local binary patterns (LBP)

The grey-levels of the peripheral pixels are compared with that of the central pixel[29]

A unique code is obtained by multiplication by a predefined mask. For a 3×3 window there are $2^8 = 256$ possible visual words

| | | |
|---|---|---|
| 0.39 | 0.52 | 0.65 |
| 0.75 | 0.65 | 0.85 |
| 0.35 | 0.81 | 0.61 |

$\longrightarrow$

| | | |
|---|---|---|
| 0 | 0 | 1 |
| 1 | | 1 |
| 0 | 1 | 0 |

$\times$

| | | |
|---|---|---|
| $2^7$ | $2^6$ | $2^5$ |
| $2^0$ | | $2^4$ |
| $2^1$ | $2^2$ | $2^3$ |

$\sum = 53$

[29] T. Ojala et al. "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 24.7 (2002), pp. 971–987.

# Hybrid methods (colour texture descriptors)

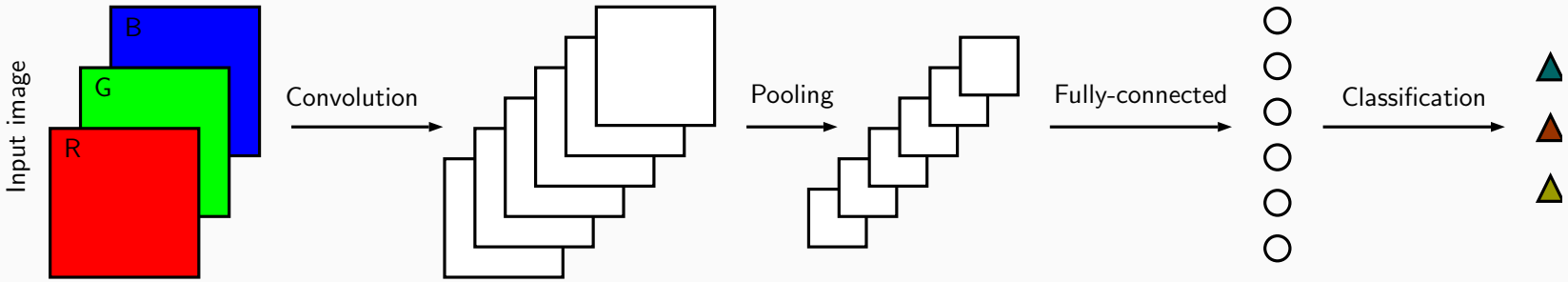
Different ways to combine of colour and texture descriptors[30]

- **Parallel**: extract colour and texture separately then concatenate
- **Sequential**: convert to single-channel then extract texture features
- **Integrative**: extract texture features from each colour channel and/or couples of channels

[30] C. Palm. "Color texture classification by integrative Co-occurrence matrices". In: *Pattern Recognition* 37.5 (2004), pp. 965–976.

# Convolutional Neural Networks: overall architecture

- Based on sets of modules that can be combined together, e.g.: **convolutional layers**, **pooling layers**, **rectifying units**, and **fully-connected layers**
- Some modules (**learnable layers**) include parameters that need to be set by training



# Convolutional layers

- Banks of linear filters
  - Structure of the kernel defined a priori (e.g. 3px $\times$ 3px)
  - Weights learned by training

Input field

| | | | | |
|---|---|---|---|---|
| 0 | 3 | 1 | 0 | 0 |
| 5 | 2 | 2 | 4 | 4 |
| 5 | 0 | 3 | 2 | 0 |
| 2 | 2 | 0 | 1 | 1 |
| 2 | 3 | 4 | 0 | 3 |

Kernel

| | | |
|---|---|---|
| 0 | 2 | 0 |
| 1 | 3 | 1 |
| 0 | 0 | 2 |

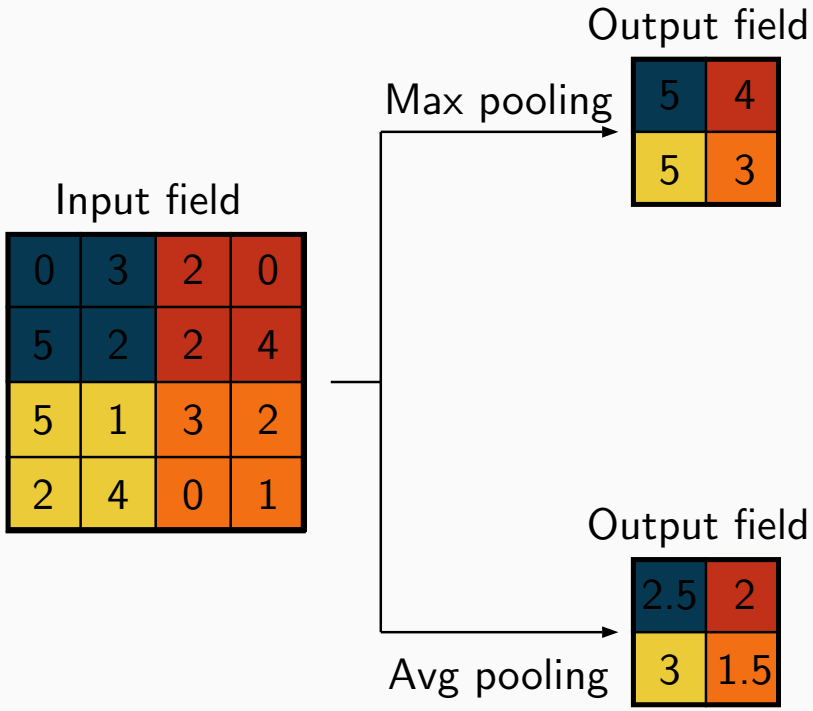
Convolution

Output field

| | | |
|---|---|---|
| 13 | 24 | 24 |
| 22 | 15 | 15 |
| 24 | 11 | 10 |

# Pooling layers

- Reduce the spatial size of the representation



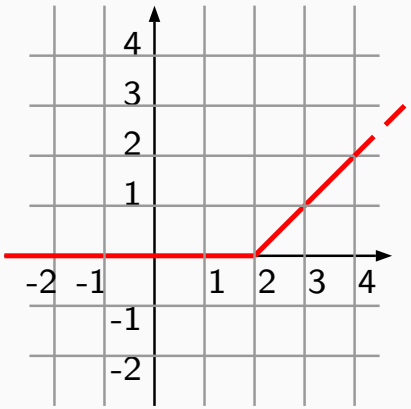
# Rectifying units

- Implement some kind of activation function (e.g.: piecewise linear, hyperbolic tangent or sigmoidal)

Input field

| | | | |
|---|---|---|---|
| 0 | 3 | 2 | 0 |
| 5 | 2 | 2 | 4 |
| 5 | 1 | 3 | 2 |
| 2 | 4 | 0 | 1 |

Activation function

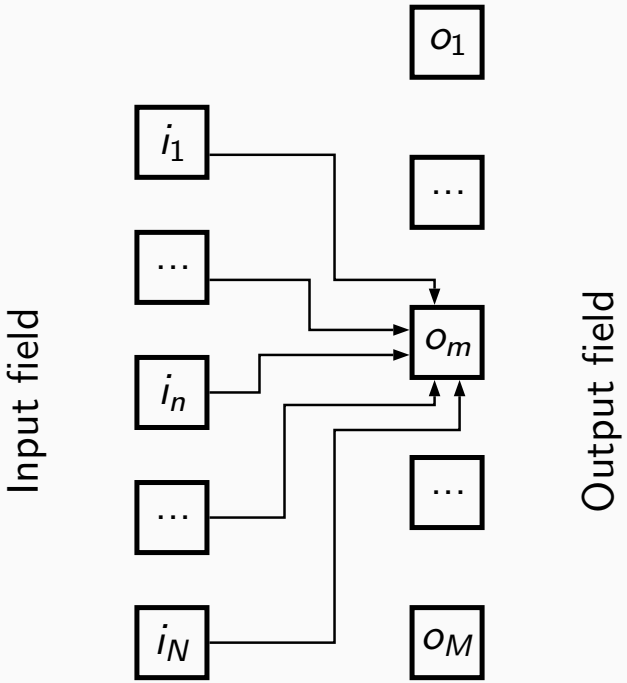



Output field

| | | | |
|---|---|---|---|
| 0 | 1 | 0 | 0 |
| 3 | 0 | 0 | 2 |
| 3 | 0 | 1 | 0 |
| 0 | 2 | 0 | 0 |

# Fully-connected layers

- Each value of the output field depends on all the values of the input field
  - Can be implemented as convolutional layer where the kernel is the same size as the input field



# Approaches to convolutional networks

- **Full training**: the network is trained from scratch, all the parameters need to be 'learned'
  - Requires large datasets of images
  - Computationally expensive
- **Transfer learning**: take a network trained for one task (e.g. face recognition) and use it *as is* for another task (e.g. texture classification)
  - No training, little overhead
  - Computationally cheap
- **Fine tuning**: take a network trained for one task and optimise some of its parameters for another task
  - Requires medium-sized datasets
  - Computationally not so expensive

# Hand-designed methods vs. Deep Learning: object recognition (1/2)

ImageNet classification: recognition of the image class[31]

Artichoke

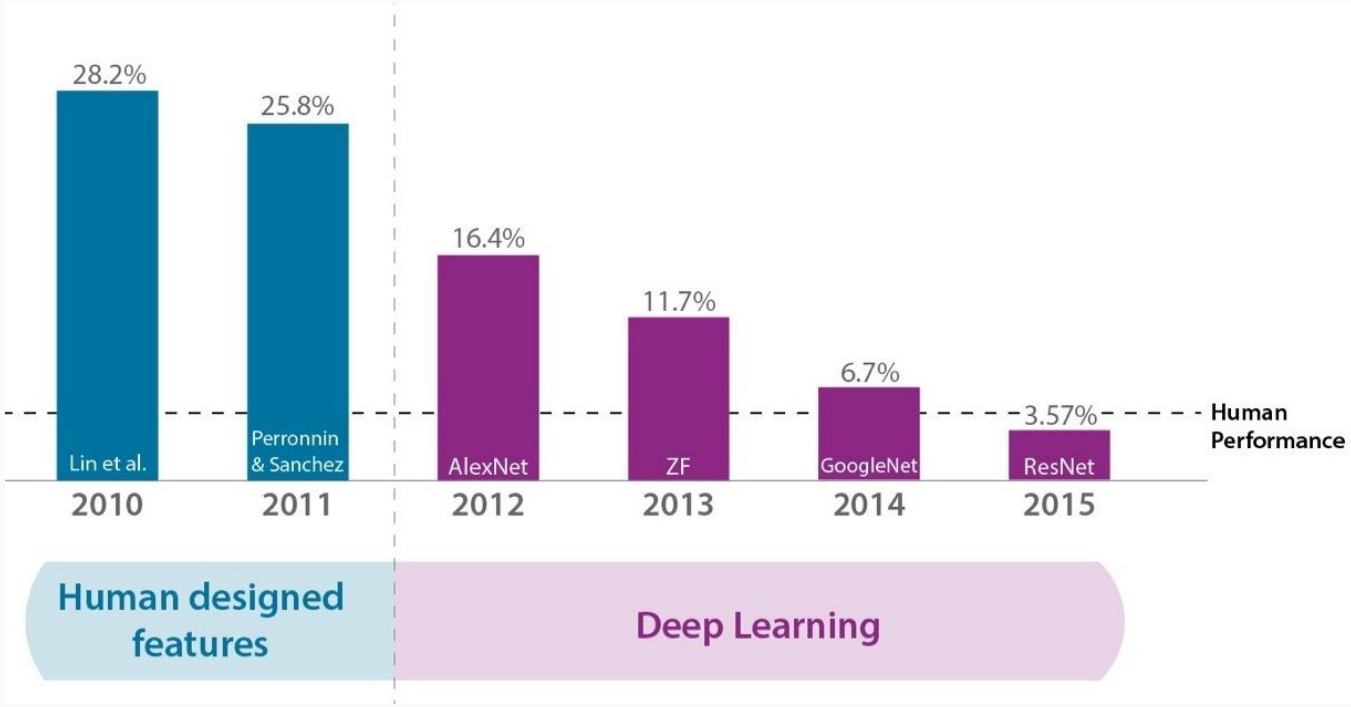
Bridge

Goldfish

[31] *ImageNet*. Available online at `http://www.image-net.org`. Visited on 23 February 2018.

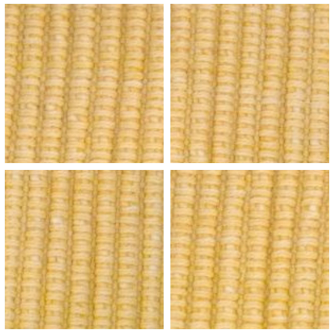
# Hand-designed methods vs. Deep Learning: object recognition (2/2)

Evolution of the top-five error rate on ImageNet classification[32]



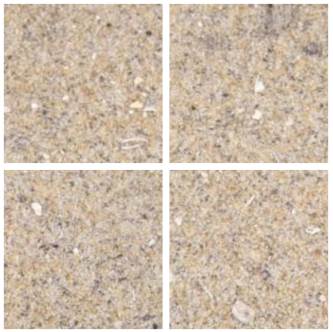

[32] S. Welch. *Deep Learning vs Traditional Machine Vision*. Available online at `https://mariner-usa.com/deep-learning-vs-traditional-machine-vision/`. Visited on 3 August 2020. 2019.

# Hand-designed methods vs. Deep Learning: materials recognition (steady imaging conditions)



Cardboard

Rice



Sand

Best accuracy[33]: Hand-designed = 96.7% (Improved Opp.-colour Local Binary Patterns – IOCLBP); Deep Learning = **98.7**% (ResNet 50)

[33] R. Bello-Cerezo et al. "Comparative Evaluation of Hand-Crafted Image Descriptors vs. Off-the-Shelf CNN-Based Features for Colour Texture Classification under Ideal and Realistic Conditions". In: *Applied Sciences* 9.4 (Feb. 2019). Article number: 738.

# Hand-designed methods vs. Deep Learning: materials recognition (variable imaging conditions)

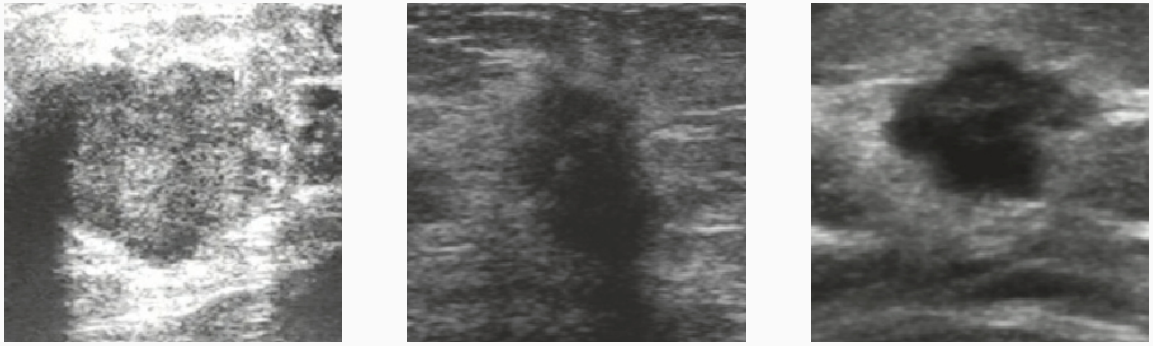
Chocolate

Flour

Pineapple

Best accuracy: Hand-designed = 41.9% (IOCLBP); Deep Learning = **75.7**% (ResNet 152)

# Hand-designed methods vs. Deep Learning: discrimination of benign vs. malignant masses from ultrasound images

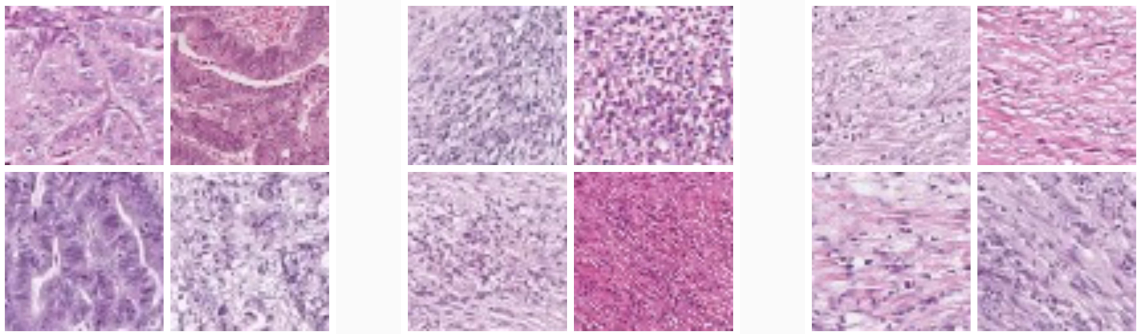


Benign Malignant Malignant

Best accuracy[34]: hand-designed = 71.8% (combination of texture and shape features); Deep Learning = **74.4**% (custom CNN)

[34] T. Xiao et al. "Comparison of Transferred Deep Neural Networks in Ultrasonic Breast Masses Discrimination". In: *BioMed Research International* (2018). Art. no. 4605191.

# Hand-designed methods vs. Deep Learning: tissue sub-typing from histology images



Epithelium Lymphocytes Stroma

Best accuracy[35]: hand-designed = **94.8**% (Improved Opp.-colour Local Binary Patterns); Deep Learning = 93.4% (ResNet 50)

[35] J.N. Kather et al. "Classification of tissue regions in histopathological images: Comparison between pre-trained convolutional neural networks and local binary patterns variants". In: *Deep learners and deep learner descriptors for medical applications*. Ed. by L. Nanni et al. Vol. 186. Intelligent Systems Reference Library. Springer, 2020. Chap. 3, pp. 95–115.

# Hand-designed methods vs. Deep Learning: recognition of art movement

Impressionism

Realism

Surrealism

Best accuracy[36]: hand-designed = 45.7% (colour histogram); Deep Learning = **67.2%** (ResNet 50)

[36] F. Bianconi and R. Bello-Cerezo. "Evaluation of visual descriptors for painting categorisation". In: *Florence Heri-Tech – The Future of Heritage Science and Technologies*. Vol. 364. IOP Conference Series: Materials Science and Engineering. Art. no. 012037. Florence, Italy: IOPScience, May 2018.

# Discussion

# Deep Learning vs. traditional methods (1/1)

Computer vision has undergone major and rapid changes in recent years

Are the methods invented before Deep Learning still relevant today?[37]

[37] N. O'Mahony et al. "Deep Learning vs. Traditional Computer Vision". In: *Proceedings of the Computer Vision Conference*. Ed. by K. Arai and S. Kapoor. Vol. 943. Advances in Intelligent Systems and Computing. Las Vegas, United States: Springer, 2019, pp. 128–144.

# The reasons behind Deep Learning's success

- Increasing computing power
- Availability of Big Data
- Improved imaging systems

# Advantages and disadvantages of Deep Learning

- Can solve closed-end classification problems with **super-human accuracy** 👍
- Often requires **less analysis** and **domain specific knowledge** than traditional methods 👍
- Models can be **retrained** on custom datasets for specific problems 👍
- Models can be **transferred** and used *off-the-shelf* for other tasks 👍
- Requires **computational power** and **large amount of data** 👎
- Is a sort of *black-box* where it is hard to intervene, therefore it is difficult to detect and correct mistakes 👎
- Some tasks are more easily and effectively treated with traditional methods (risk of *overkilling*) 👎

# Advantages and disadvantages of traditional methods

- Usually **transparent** (produce **human-interpretable** features) 👍
- Computationally cheap 👍
- Do not require large amounts of data for training 👍
- Suitable when the problem is contained within a **well defined domain** (e.g. invariable imaging conditions)... 👍
- ...but generally non-competitive otherwise 👎

# Pushing things a bit further: data-driven vs. model-based methods

Can data replace models?

Has the scientific method become obsolete?[38,39,40]

[38] H. Hosni and A. Vulpiani. "Data science and the art of modelling". In: *Lettera Matematica* 6 (June 2018), pp. 121–129.

[39] C. Anderson. "The End of Theory: The Data Deluge Makes the ScientificMethod Obsolete". In: *Wired Magazine* (June 2008). Available online at `https://www.wired.com/2008/06/pb-theory/`. Visted on 26 August 2020.

[40] F. Mazzocchi. "Could Big Data be the end of theory in science?: A few remarks on the epistemology of data-driven science". In: *EMBO Reports* 16.10 (Oct. 2015), pp. 1250–1255.

# Arguments in favour of the data-driven approach

- 'All models are wrong – some are useful'[41]
- With enough data the numbers speak for themselves
- Correlation is *enough*; causation is not needed.
- Correlations may not tell us why things happen, but alert us that they are happening. This is just enough in most situations.

[41] Attributed to Bristish statistician George E.P. Box (1919–2013)

# Arguments in favour of the model-based approach

- The observations that generate data are *made*, not just *found*
- It is difficult to think of data without responding to a model hypothesis
- Giving up models could mean giving up the chance to detect mistakes and correcting them ('What I cannot create I cannot understand'[42])

[42] Reportedly written by American physicist Richard Feynman (1918–1988) on a blackboard shortly before his death

# Conclusions

- Research on visual descriptors has undergone major changes in recent years
- Data-driven approaches have been gaining ground at the expenses of traditional, model-based methods
- The new methods tend to be very effective but also difficult to understand and control ('black box')

Thank you for your attention

Any questions?