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Tutorial for Computer Vision Technical Project

03/02/2025

Chengliang Dai

Key Tasks in Medical Image Analysis

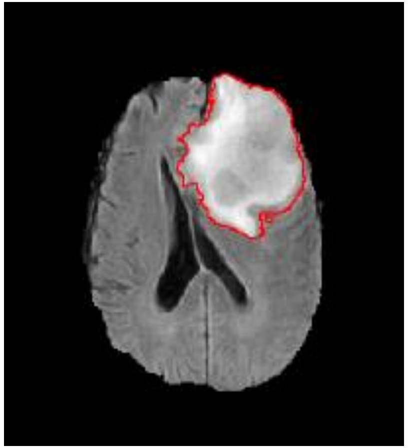
Localisation

Output: bounding boxes

Classification

Output: tumour/no tumour

Semantic Segmentation



Output: segmentation map

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Other Tasks in Computer Vision

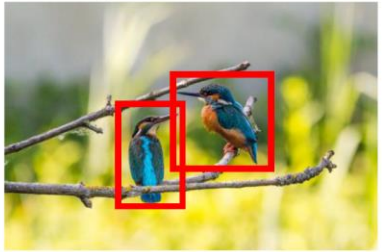
Image Classification

Output: Category (e.g., “bird”)

Object Detection

Output: Coordinates (e.g., centroid)

Object Localisation

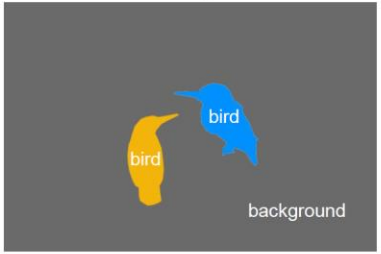


Output: Coordinates (e.g., bounding box)

Object Recognition

Output: Category (e.g., “kingfisher”)

Semantic Segmentation



Output: Labelmap

Image Captioning

Output: Text
(e.g., “two birds sitting on a branch”)

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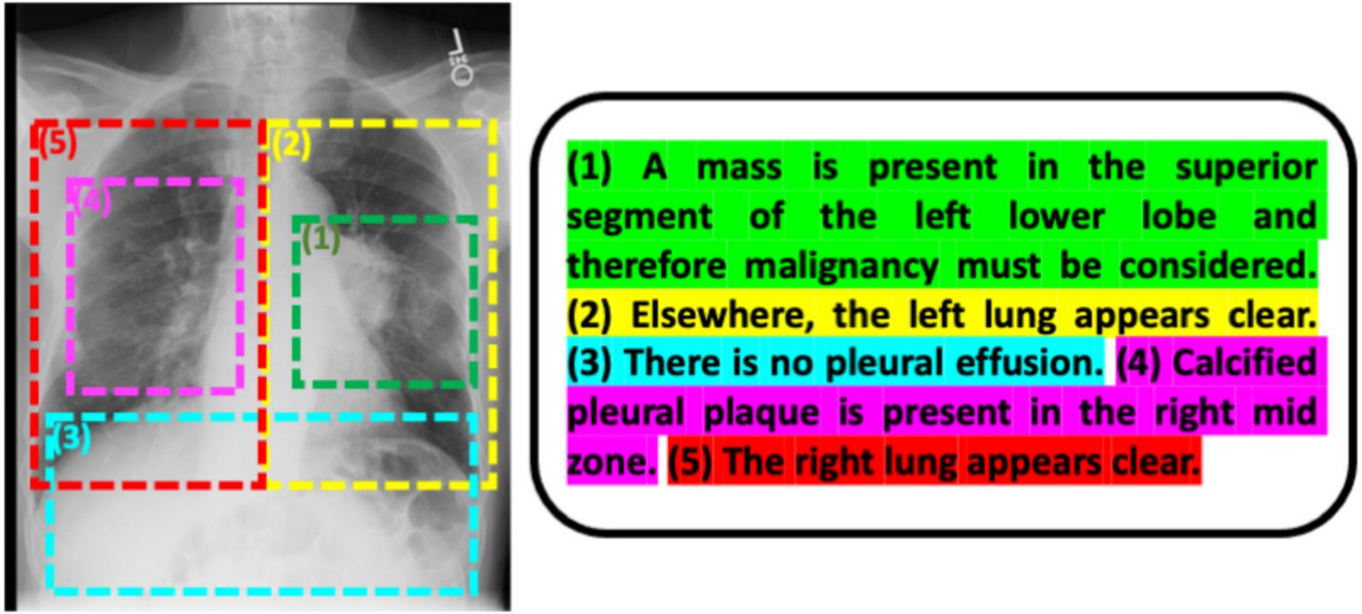
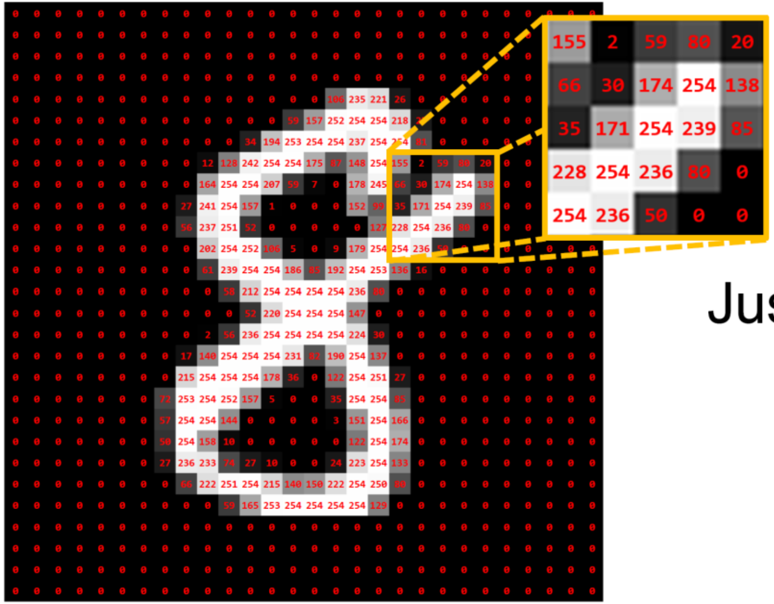


Liao, R., Moyer, D., Cha, M., Quigley, K., Berkowitz, S., Horng, S., Golland, P. and Wells, W.M., 2021. Multimodal representation learning via maximization of local mutual information. In *Medical Image Computing and Computer Assisted Intervention–MICCAI 2021: 24th International Conference, Strasbourg, France, September 27–October 1, 2021, Proceedings, Part II 24* (pp. 273-283). Springer International Publishing.

Example: Image Classification Algorithms

→ Image Classification Algorithms → With/without tumour



Just an array of numbers

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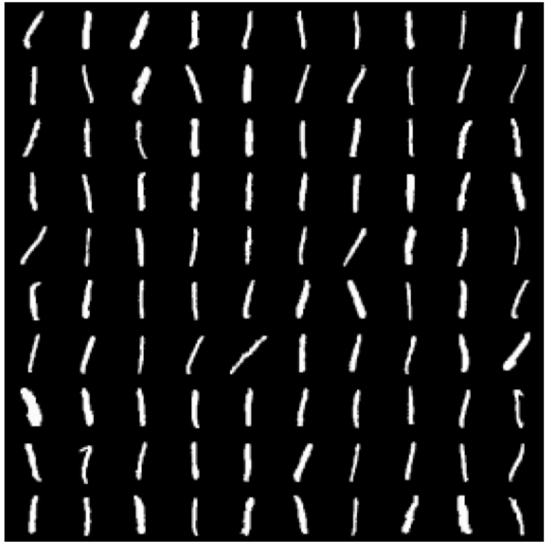
Classification Example : Digit Recognition



ones

eights

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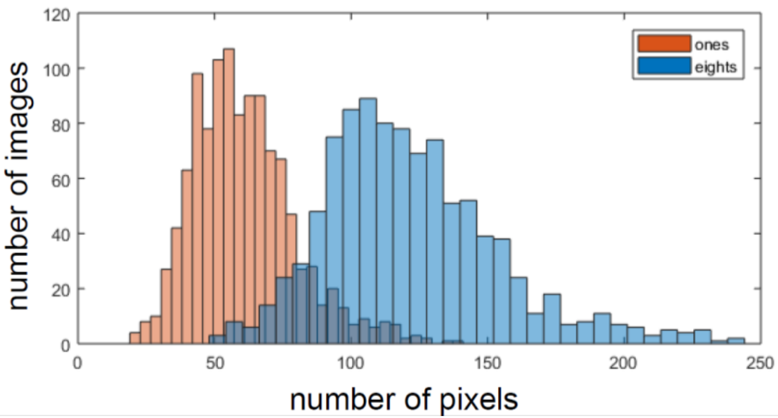
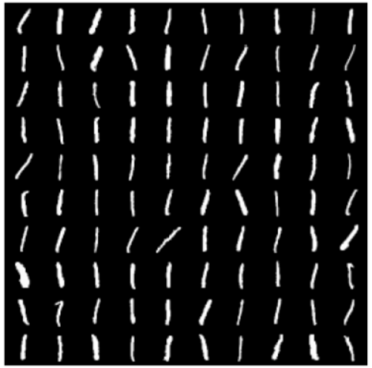
Classification Example : Digit Recognition





ones

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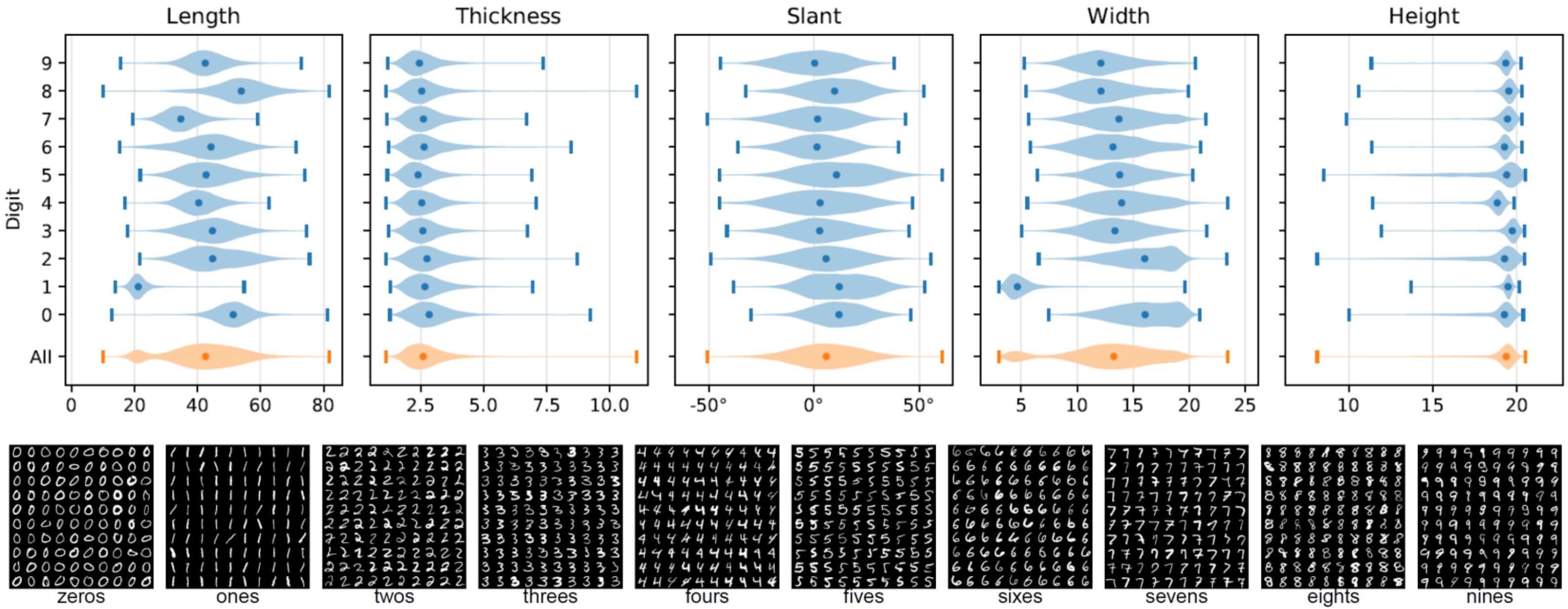
Classification Example : Digit Recognition



Source: Castro et al. 2018. https://arxiv.org/abs/1809.10780

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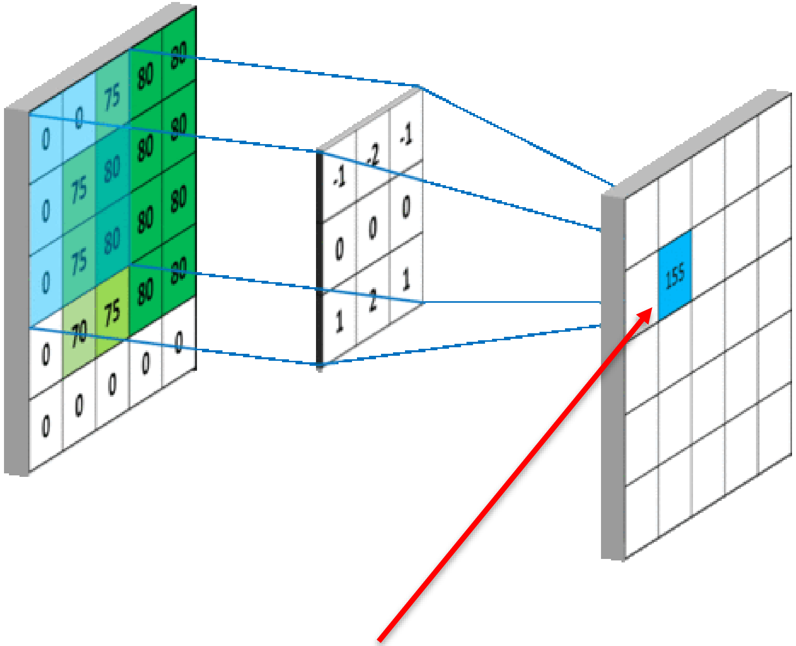
Convolutional Operations in Image Processing



$$-1 * 0 + (-2) * 0 + (-1) * 75 + 0 * 0 + 0 * 75 + 0 * 80 + 1 * 0 + 2 * 75 + 1 * 80 = 155$$

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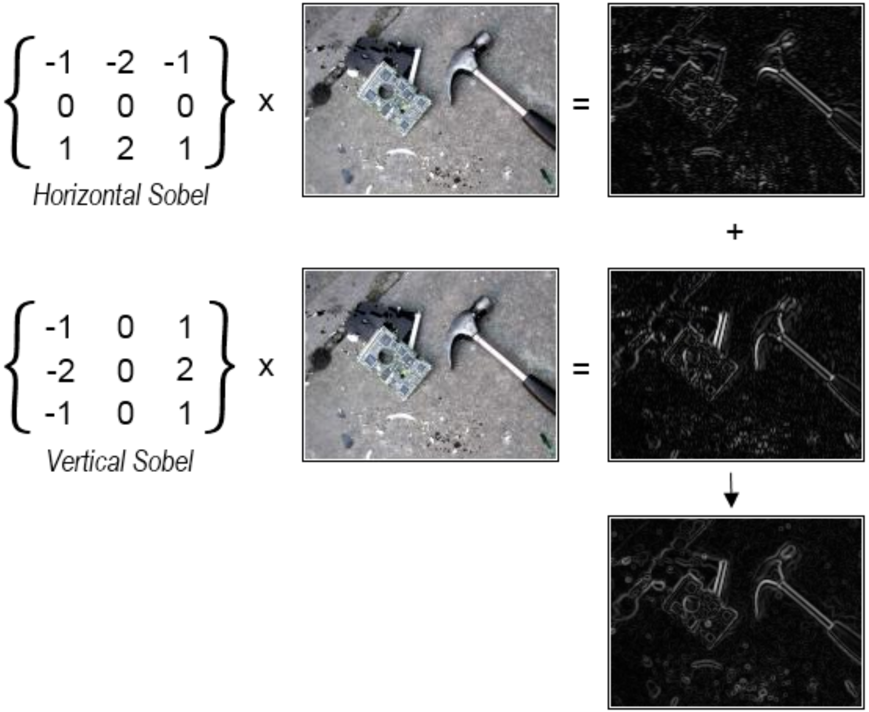
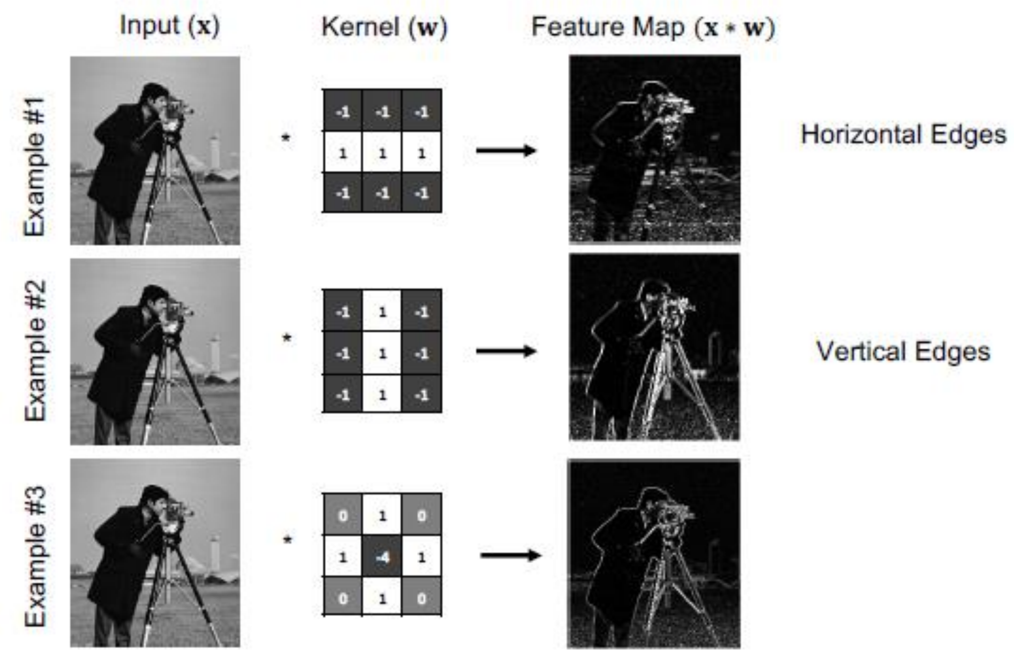
Convolutional Operations with a Sobel Filter



Applying Convolutional Operations



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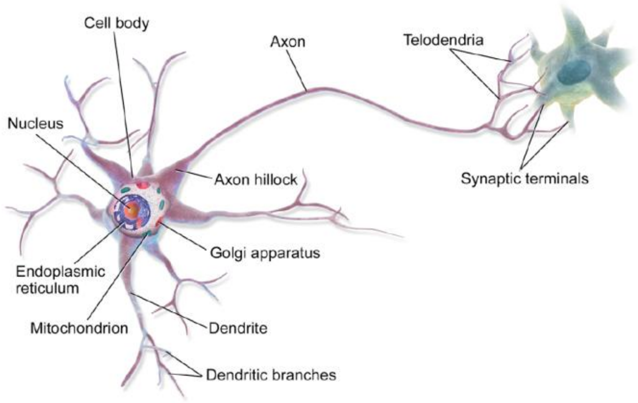
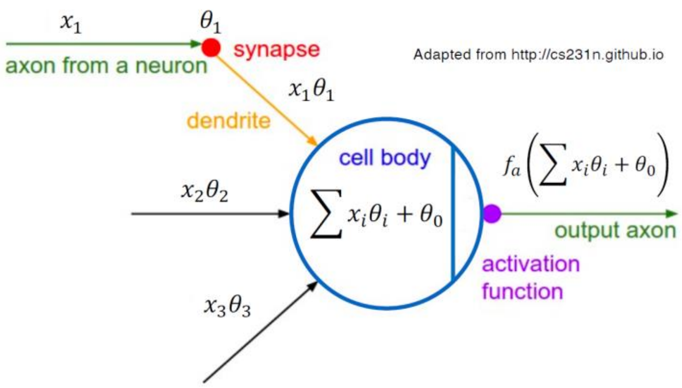
Neural Network

- First machine learning methods were inspired by how the brain works:



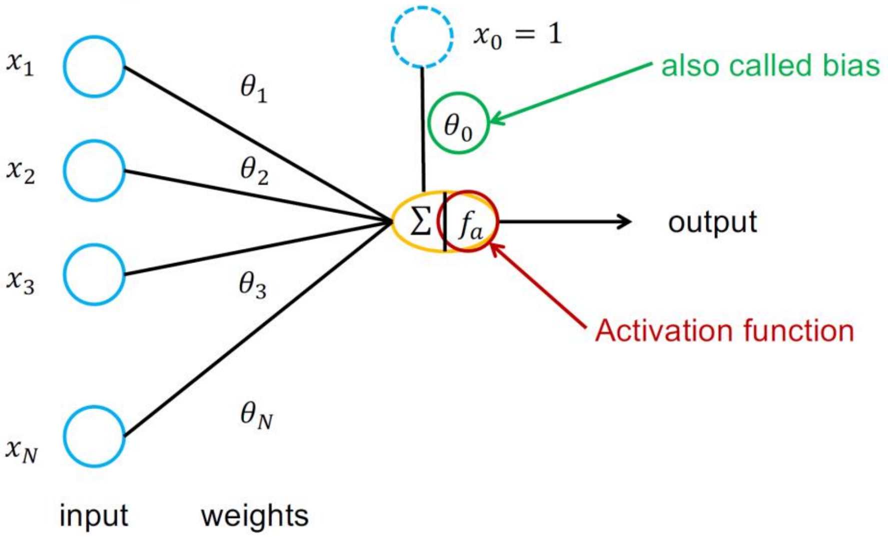
Biological neuron



Artificial neuron

Single-layer Perceptron

- A single-layer perceptron looks as follows:



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Single-layer Perceptron

- Training a perceptron means to iteratively updating the weights associated with each of its inputs
- This allows to progressively approximate the underlying relationship in the given training dataset
- Once properly trained, it can be used to classify entirely new samples

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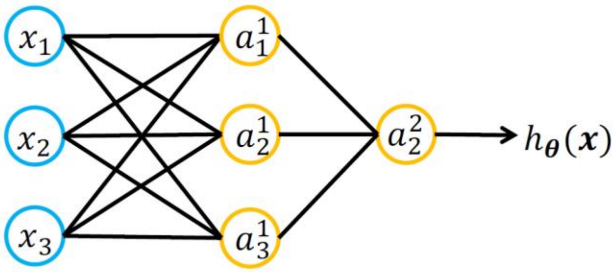
Neural Network



$\mathbf{a}_j^i$ activation of neuron j in layer i

$\boldsymbol{\Theta}^i$ matrix of weights controlling mapping from layer $i-1$ to i

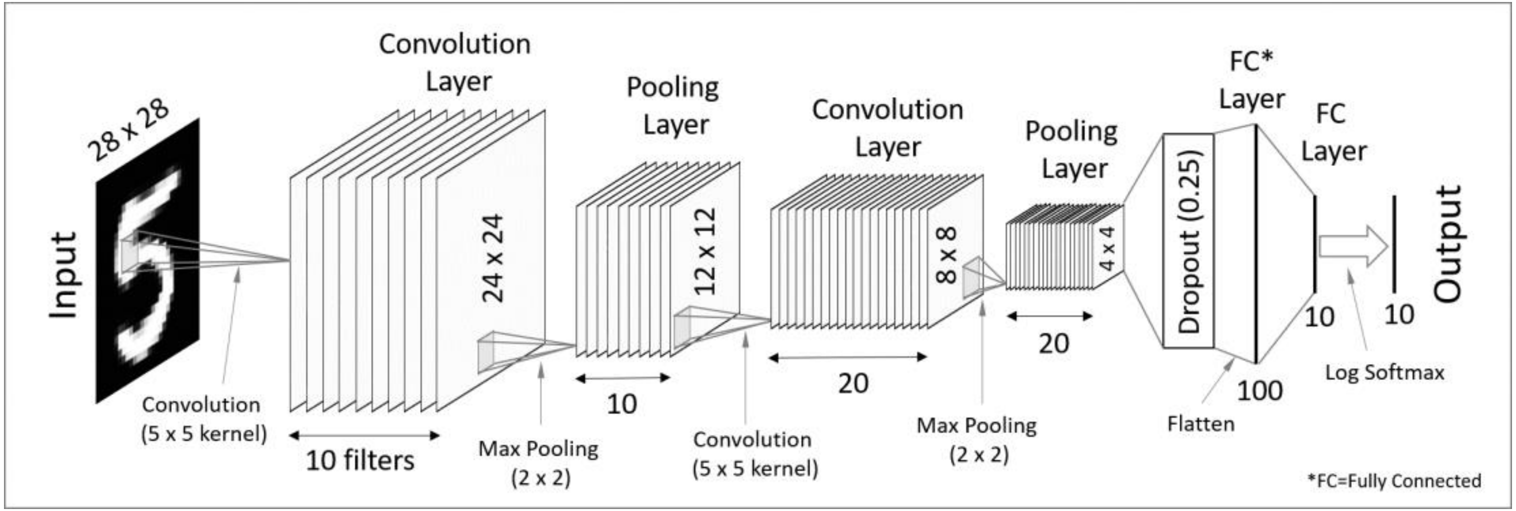
$$a_1^1 = f_a(\theta_{0,0}^1 + \theta_{1,0}^1 x_1 + \theta_{2,0}^1 x_2 + \theta_{3,0}^1 x_3)$$

$$a_2^2 = f_a(\theta_{0,1}^1 + \theta_{1,1}^1 x_1 + \theta_{2,1}^1 x_2 + \theta_{3,1}^1 x_3)$$

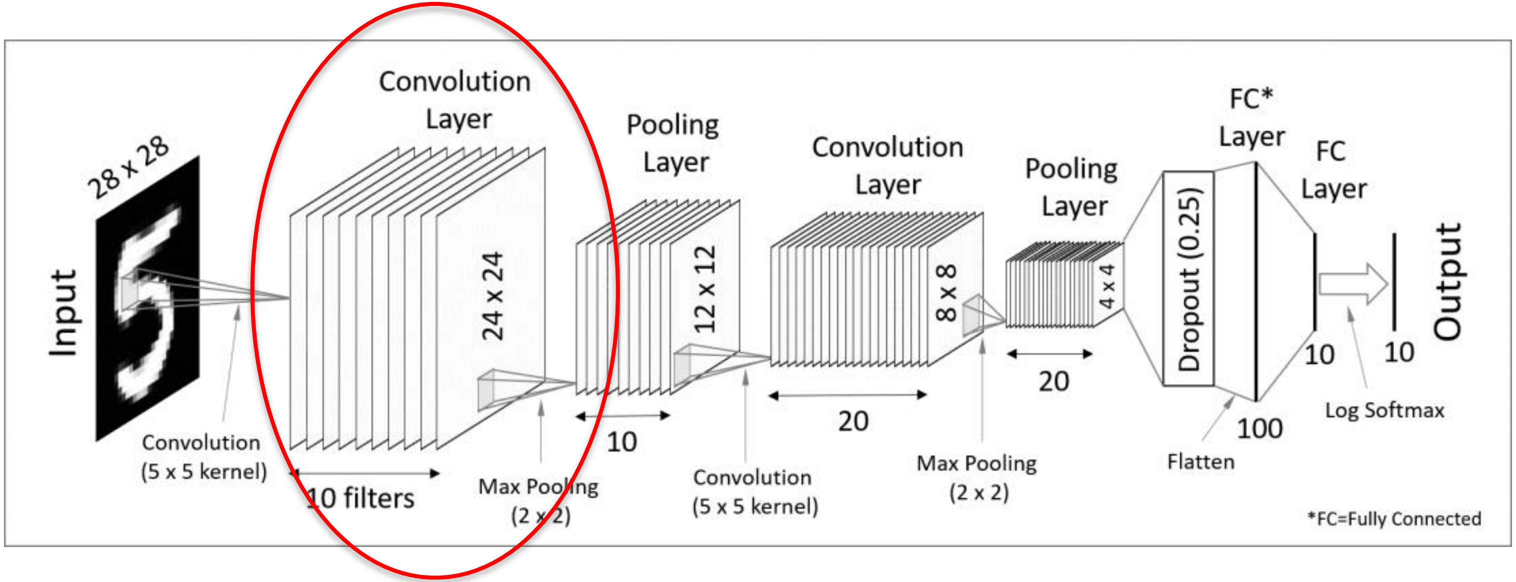
$$a_3^1 = f_a(\theta_{0,2}^1 + \theta_{1,2}^1 x_1 + \theta_{2,2}^1 x_2 + \theta_{3,2}^1 x_3)$$

$$h_{\boldsymbol{\theta}} = a_1^2 = f_a(\theta_{0,0}^2 + \theta_{1,0}^2 a_1 + \theta_{2,0}^2 a_2 + \theta_{3,0}^3 a_3)$$

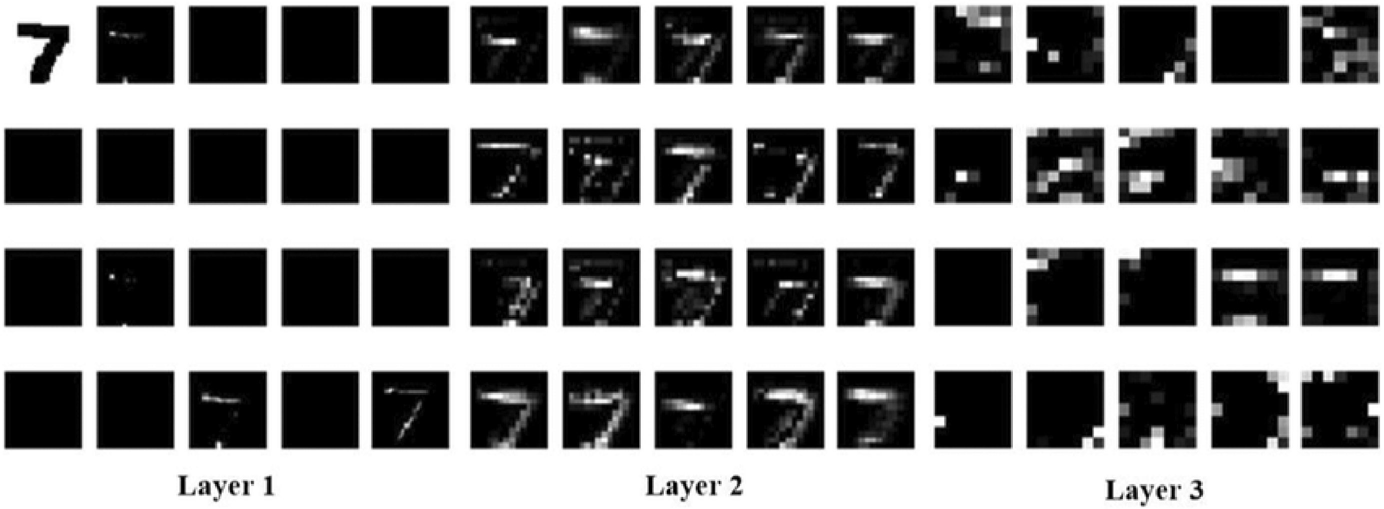
Convolutional Neural Network (CNN) Model



Convolution Layer

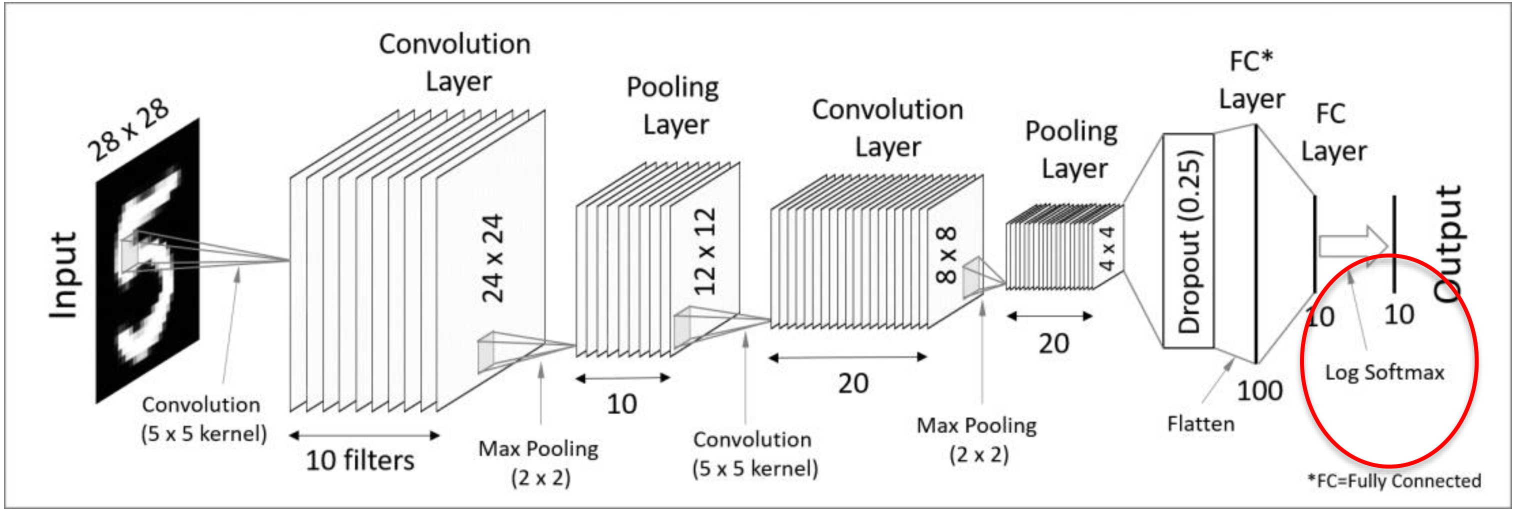


Feature maps



Liu, J., Shao, H., Jiang, Y. and Deng, X., 2022. CNN-based hidden-layer topological structure design and optimization methods for image classification. Neural Processing Letters, 54(4), pp.2831-2842.

Activation Functions



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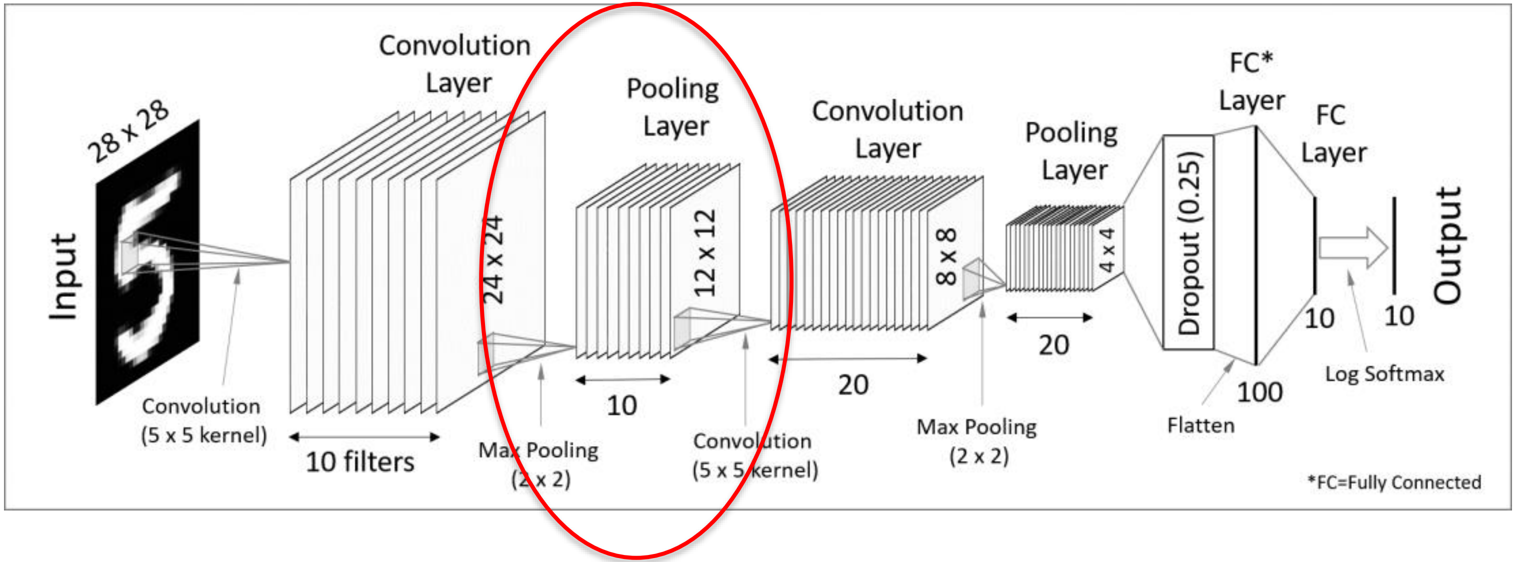
Pooling Layer



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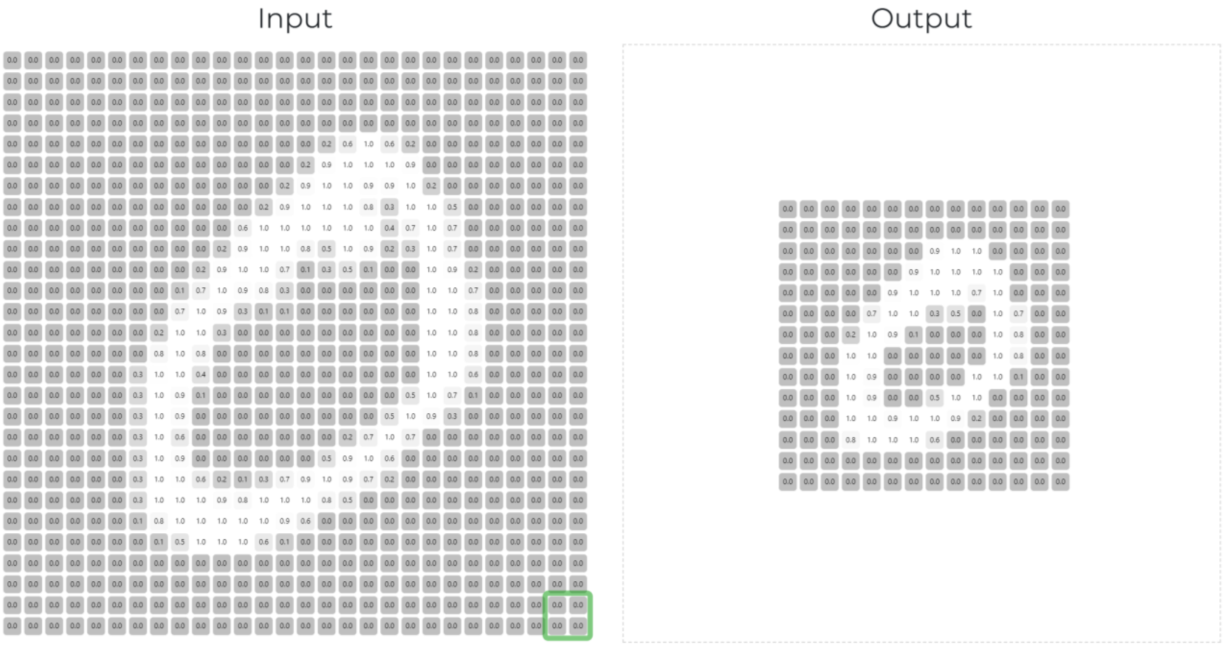
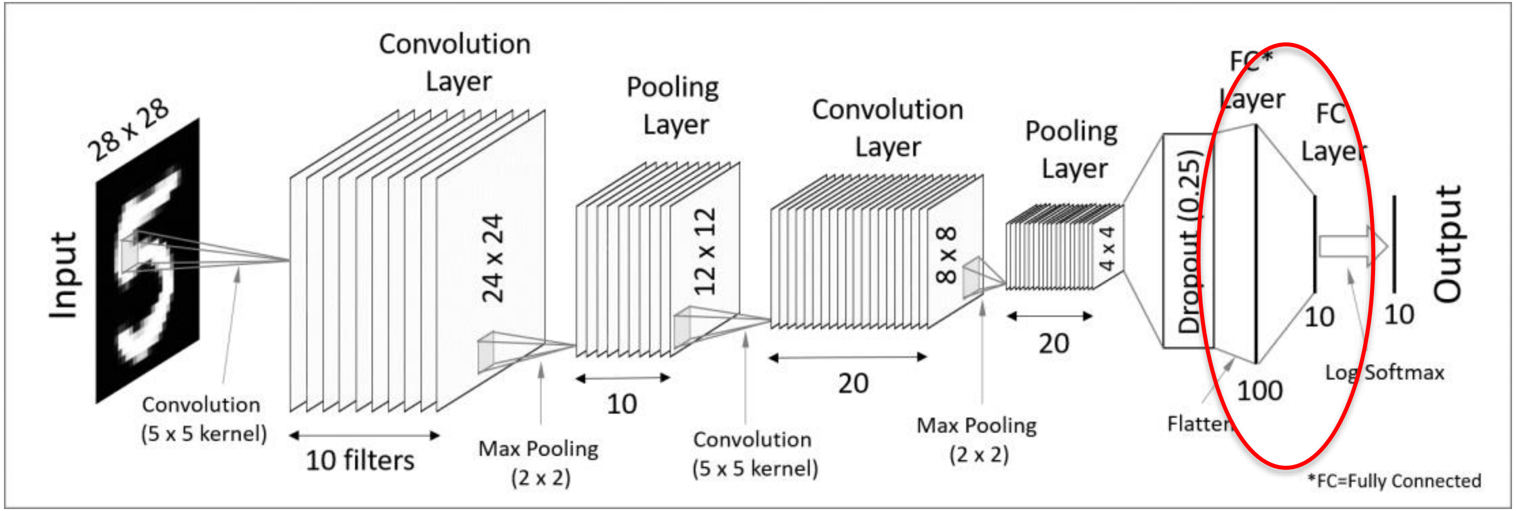
Max Pooling



https://deeplizard.com/resource/pavq7noze3

Fully Connected Layer



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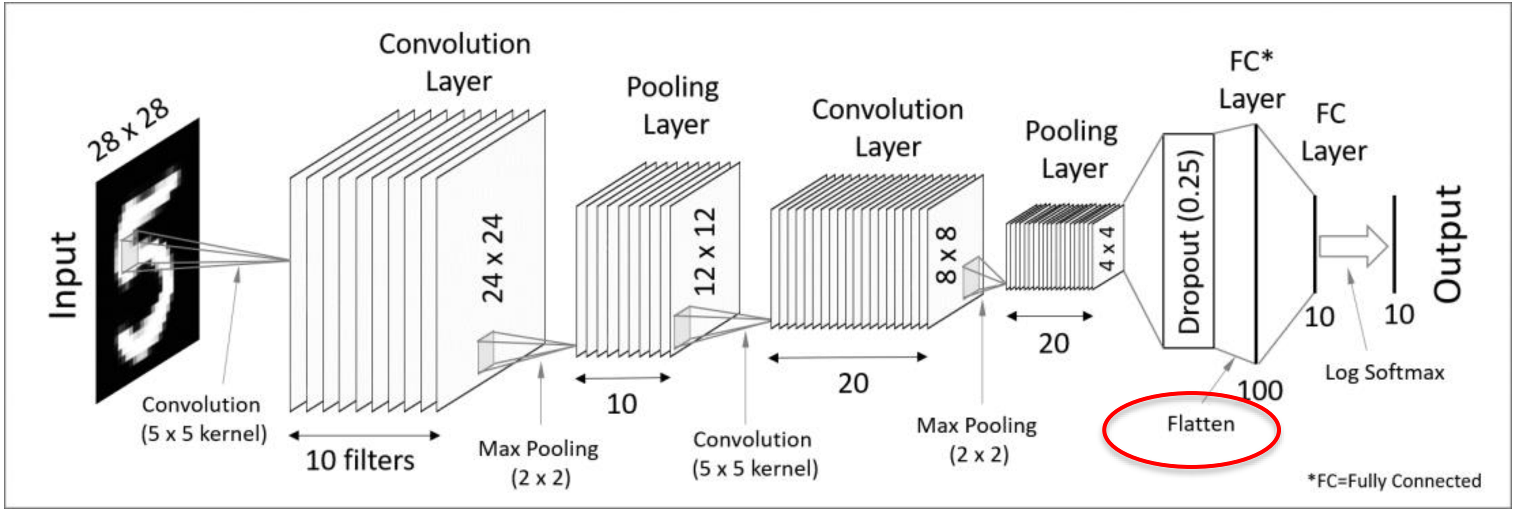
Flattening



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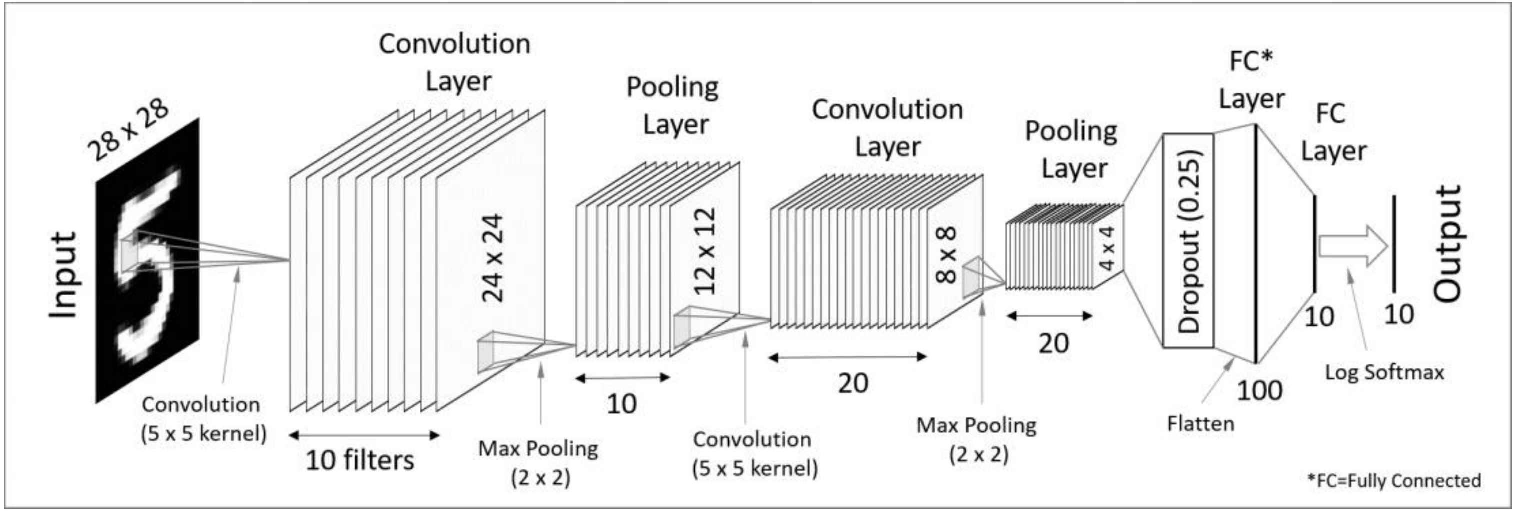
Dropout Layer



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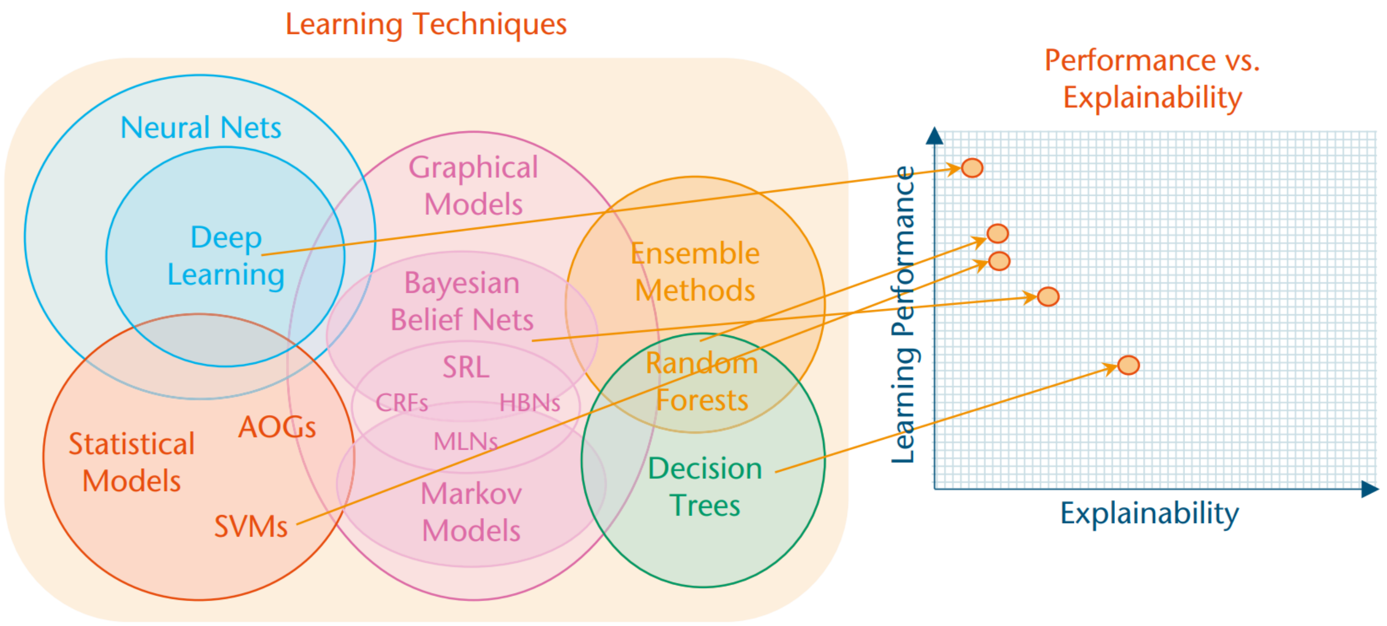
Performance vs Explainability



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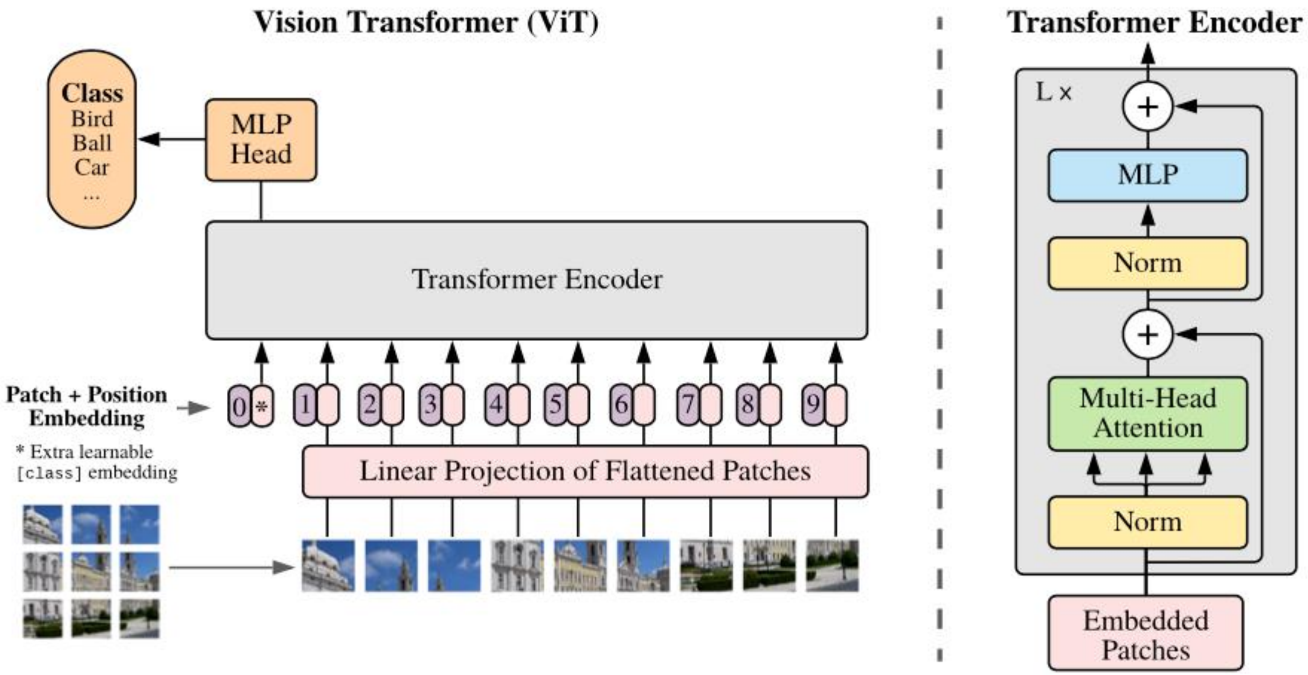
Vision Transformer (ViT)



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Project Workflow

- Understanding and Preprocessing Your Dataset
- Building and Training the Model
- Optimising Hyperparameters
- Evaluating Performance
- Testing the Model

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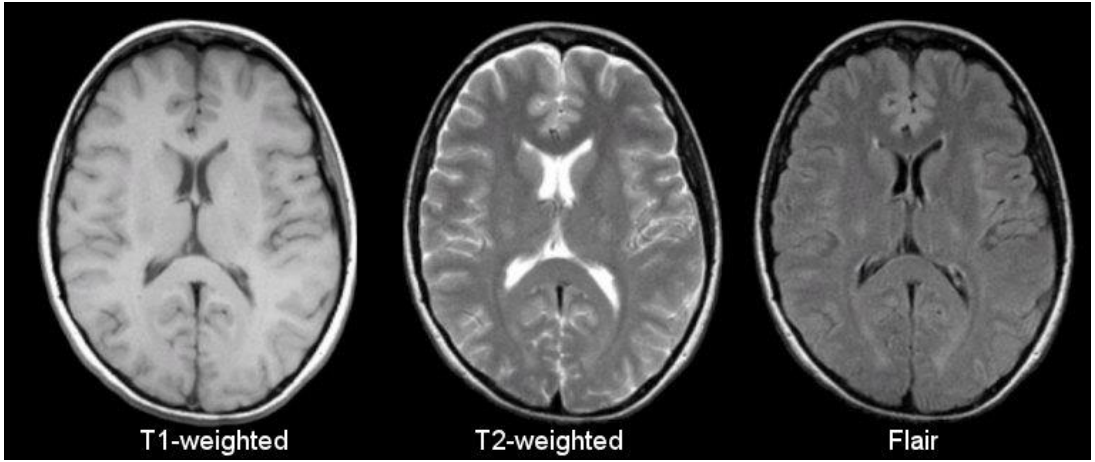
Brain MRI

- Non-invasive imaging technology
- Providing three dimensional detailed anatomical images
- Used for disease detection, diagnosis, and treatment monitoring

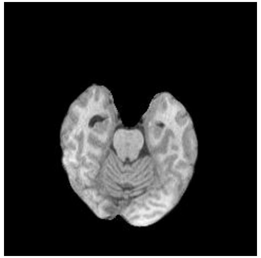
Different Sequences of Brain MR Images



Different MRI sequences

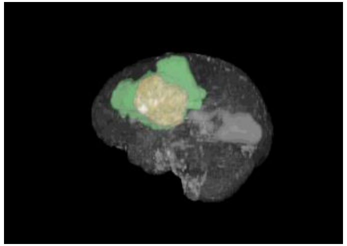
Dataset

- 210 MRI volumes will be given to you for training and evaluating the segmentation model.



Brain image with tumour

Brain image w/o tumour



Brain tumour in 3D

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Data preprocessing

- Denoising
- Image Standardisation (Resizing , Normalisation, etc.)
- Data Augmentation (Rotation, Shearing, Scaling, etc.)

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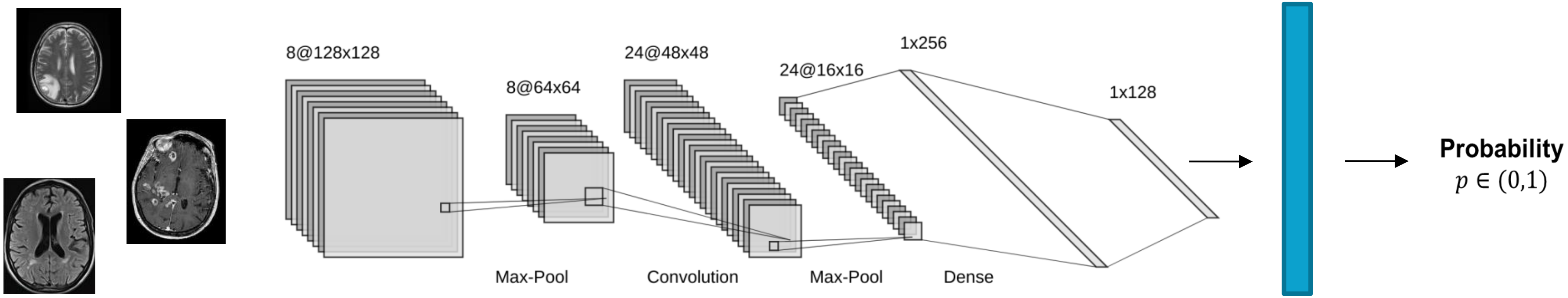
Building the Classification Model



Preprocessed dataset

CNN-based backbone model for feature extraction (VGG16, AlexNet, ResNet, etc)

Classifier

Output

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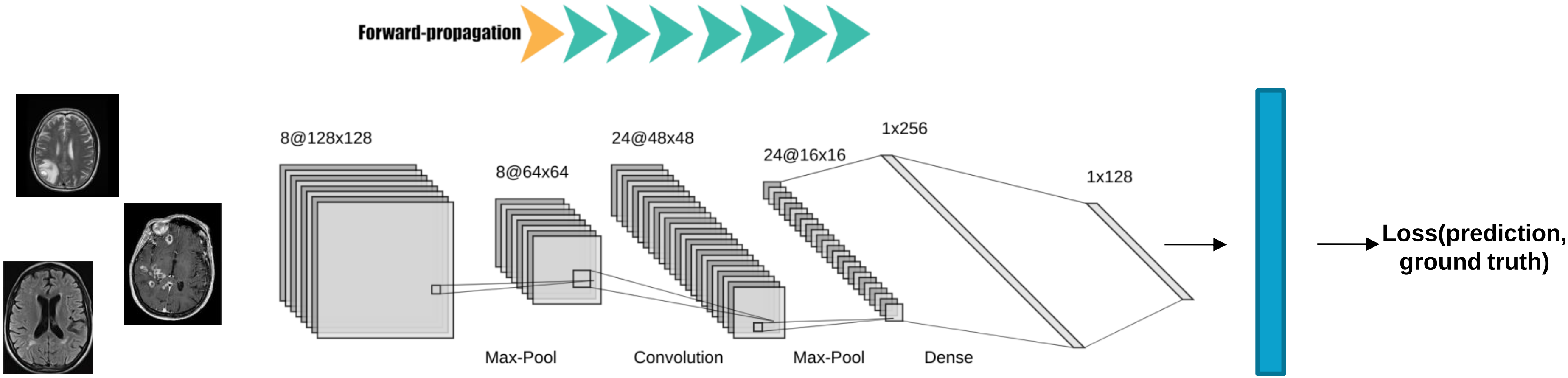
Training the Classification Model



Preprocessed dataset

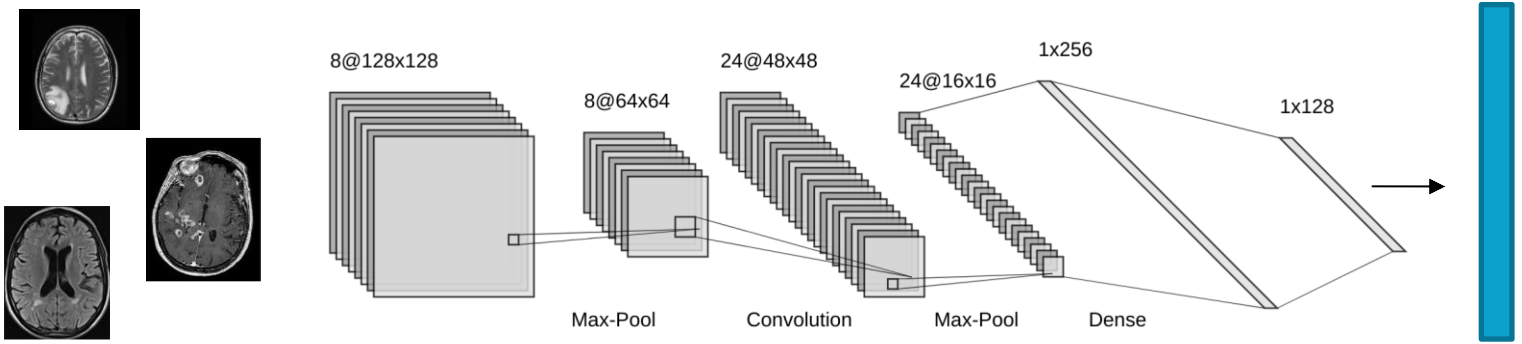
CNN-based backbone model for feature extraction (VGG16, AlexNet, ResNet, etc)

Classifier

Improving Prediction Accuracy

- Choose the right data augmentation methods;
- Find the optimal backbone model;
- Choose to finetune the model or train it from the scratch;
- Set the number of epochs to train the model and early stopping criteria;
- Tune other hyperparameters to achieve the best performance.

Test/Evaluate the Classification Model



Presence (1) or Absence (0) of Tumour

Preprocessed dataset

CNN-based backbone model for feature extraction (VGG16, AlexNet, ResNet, etc)

Classifier

Result

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Result Evaluation

Accuracy is used to evaluate the performance of your classification model, which is defined as

$$Accuracy = \frac{Number\ of\ correctly\ classified\ images}{Number\ of\ total\ images} \times 100\%$$

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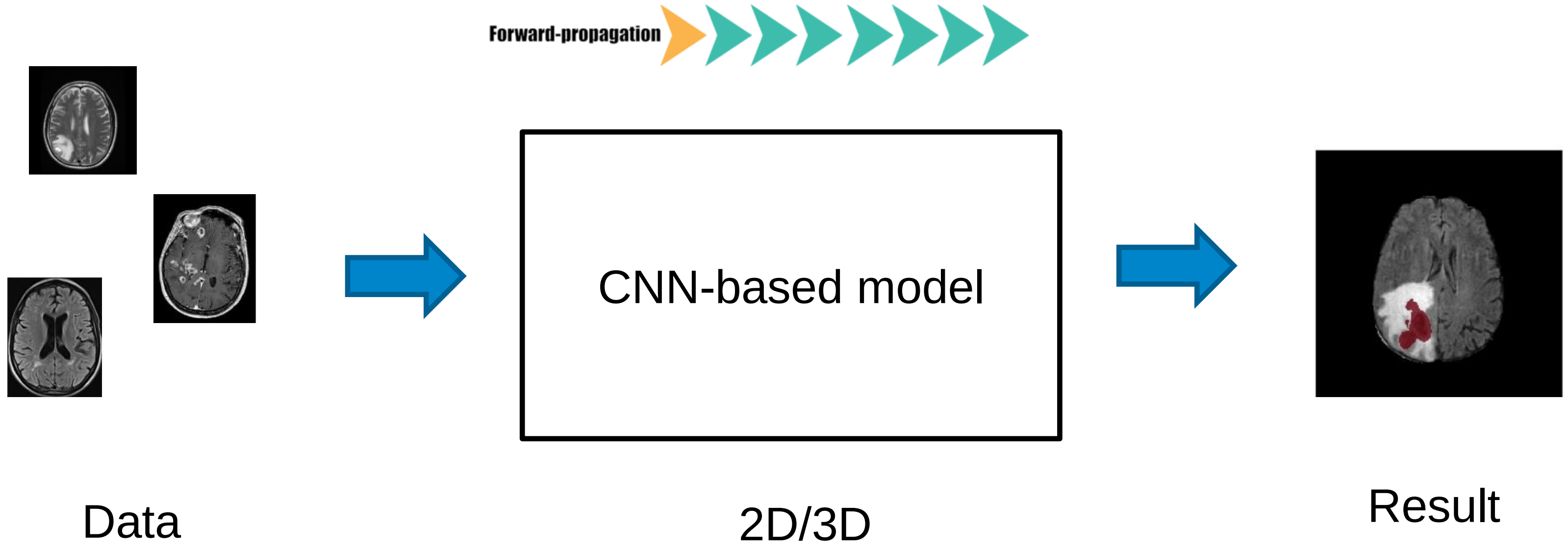
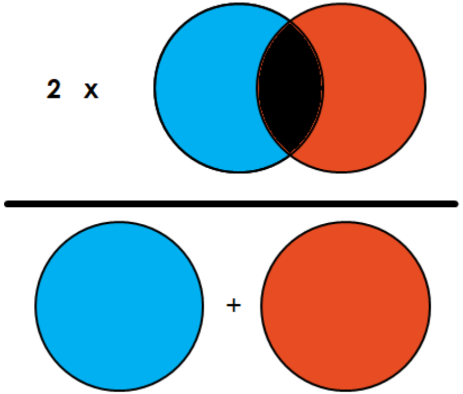
Building/Training Segmentation Model



Result evaluation

Dice score and 95% Hausdorff Distance are used to evaluate the performance of your segmentation model. Dice score is defined as

*Dice score = (2 * Area of Overlap)/(total pixels combined)*



Blue: Ground Truth
Red: Prediction

Source: https://towardsdatascience.com/metrics-to-evaluate-your-semantic-segmentation-model-6bcb99639aa2

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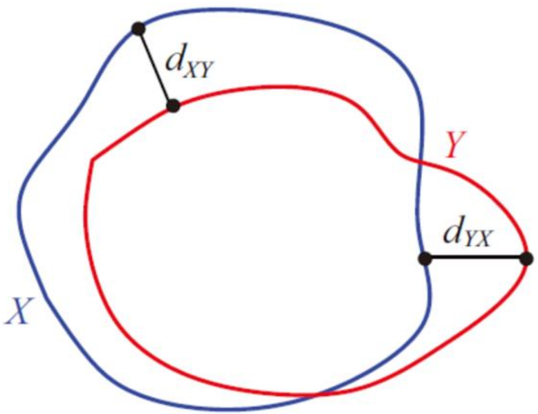
Result evaluation

The maximum Hausdorff Distance is defined as:

$$d_H(X,Y)=\max\{d_{XY},d_{YX}\}=\max\left\{\max_{x\in X}\min_{y\in Y}d(x,y),\max_{y\in Y}\min_{x\in X}d(x,y)\right\}$$



95% Hausdorff Distance it is based on the calculation of the 95th percentile of the distances between boundary points in X and Y.

Choice Considerations

- Model architecture: depth, width, scales, residuals,…
- Loss function: (weighted) cross-entropy, IoU, Dice,...
- Sampling strategy: equally per class, fore/background, uniform,...
- Optimization: optimizer, learning rate, momentum, regularization,…
- Data normalization/standardisation: z-score, bias field correction, histogram matching,...
- Post-processing: conditional random fields (CRF), smoothing,…

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Setting Up Python Development Environment

Anaconda and Tensorflow Installation (2020.02)
https://www.h2kinfosys.com/blog/how-to-download-and-setup-tensorflow-with-anaconda/
https://repo.anaconda.com/archive/

For using Nvidia GPU
https://saturncloud.io/blog/how-to-install-tensorflow-with-anaconda-on-windows/

Key Packages:
numpy>=1.19.2
tensorflow>=2.4.0
matplotlib>=3.3.2
scikit-learn>=0.24.0
tqdm>=4.50.2