Thermografische assistentie bij huidkanker screening

Masterproef – 17 juni

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Table of content

Introduction

Post-processing & data collection

Classification algorithms

Classification in Matlab

Classification evaluation

Conclusion and future work

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Introduction

Objective: Investigate to what extent it is possible to distinguish from each other different types of skin spots, based on statically and dynamically obtained thermal images, using machine learning.

Hypothesis:
- Different temperature profiles (steady-state analysis)
- Different thermal recovery process (dynamic analysis)

Has been demonstrated in multiple studies.

Malignant skin tumors	Benign skin tumors
Melanoma	Melanomacytic nevi
Basal cell carcinoma (BCC)	Actinic keratoses
Squamous cell carcinoma (SCC)	Seborrheic keratoses

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Data collection

- **Statically obtained data**
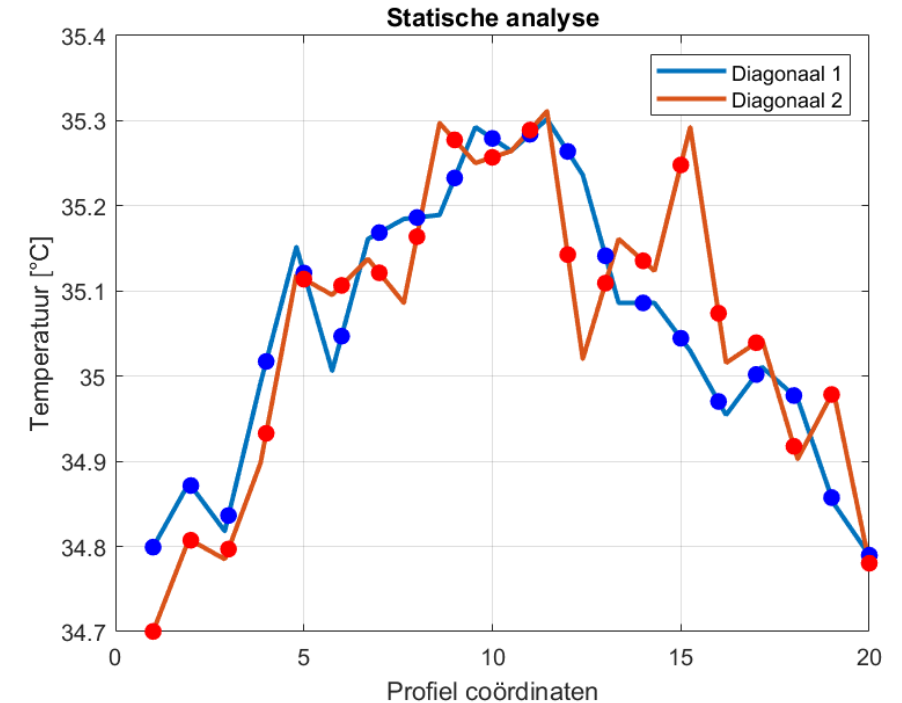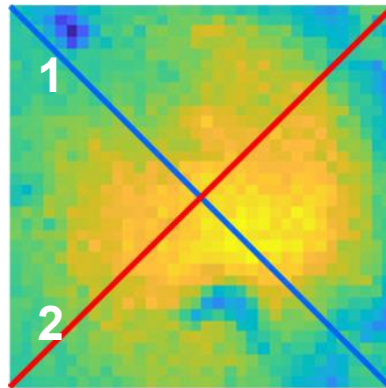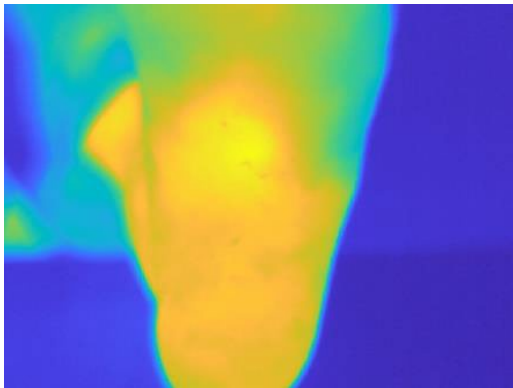
20 datapoints are stored in array:

Data = {a1,a2,a3,…,a20} → Mean of diagonal 1 & 2

Serves as input for machine learning classifier.

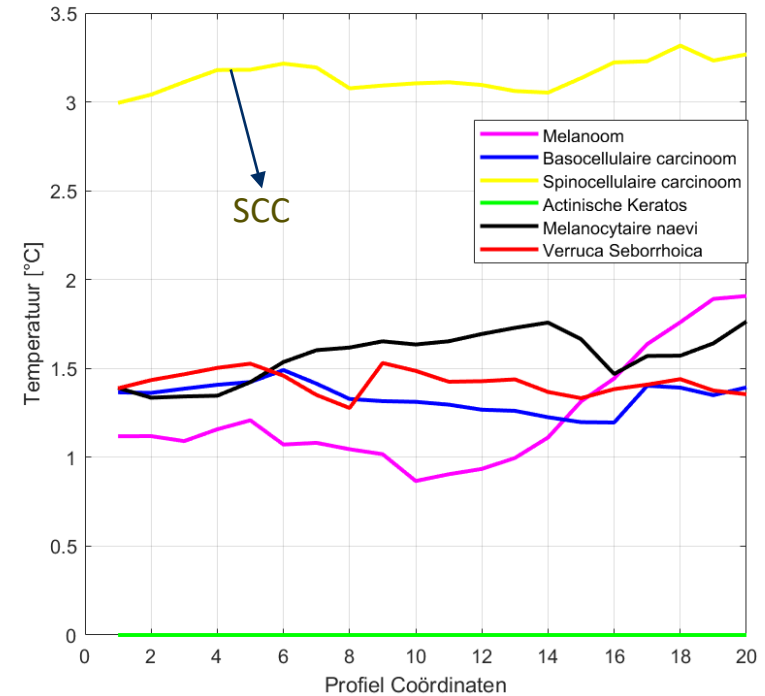University of Antwerp

Data collection

- **Statically obtained data**

Temperature profiles
(average value for each type)
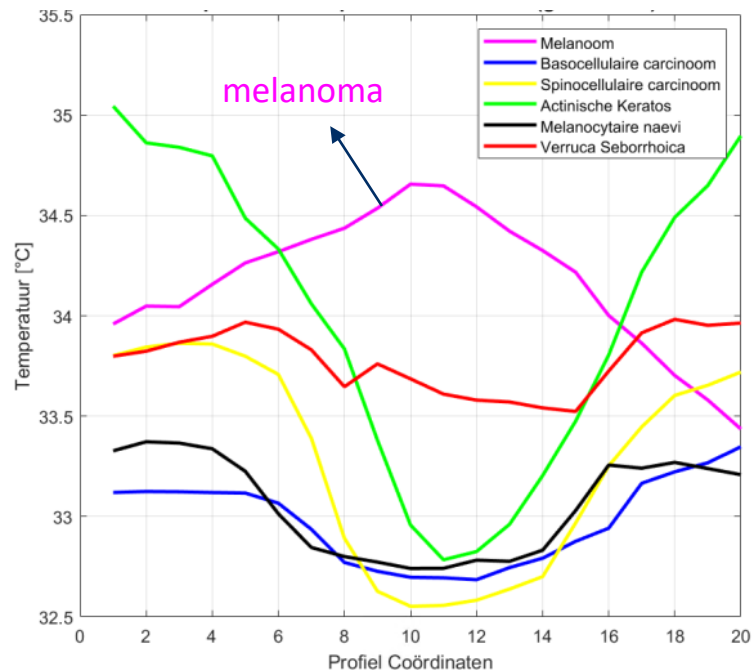
- Different curve for melanoma
  (higher temperatures in the center)
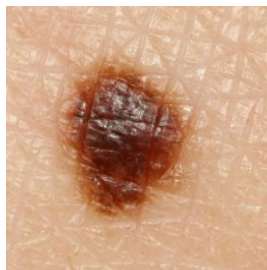

Standard deviation
(average value for each type)
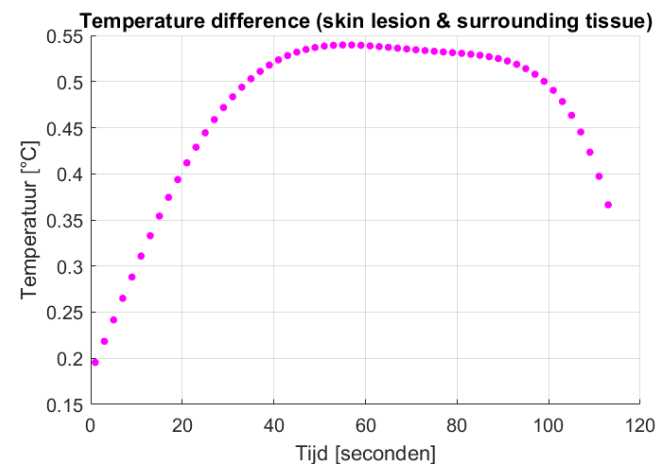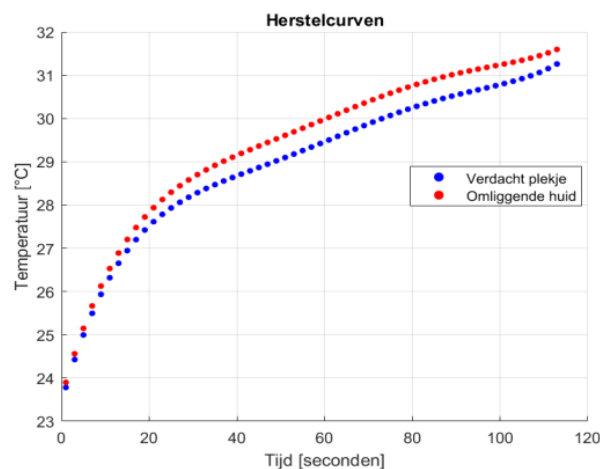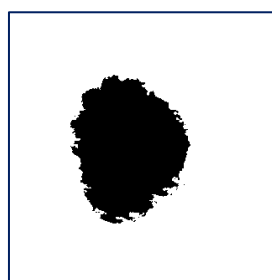
- Different curve for SCC
  (more dispersed)

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Data collection

- **Dynamically obtained data – Measurement setup labo**

Alignment & crop
using square marker

Visual image
sequence

Mask projected
on IR-images

Herstelcurven

- Verdacht plekje
- Omliggende huid

Temperature difference (skin lesion & surrounding tissue)

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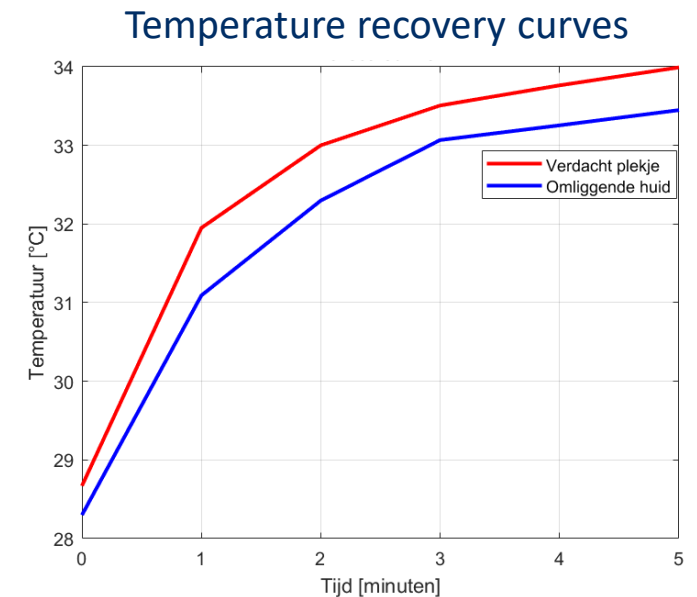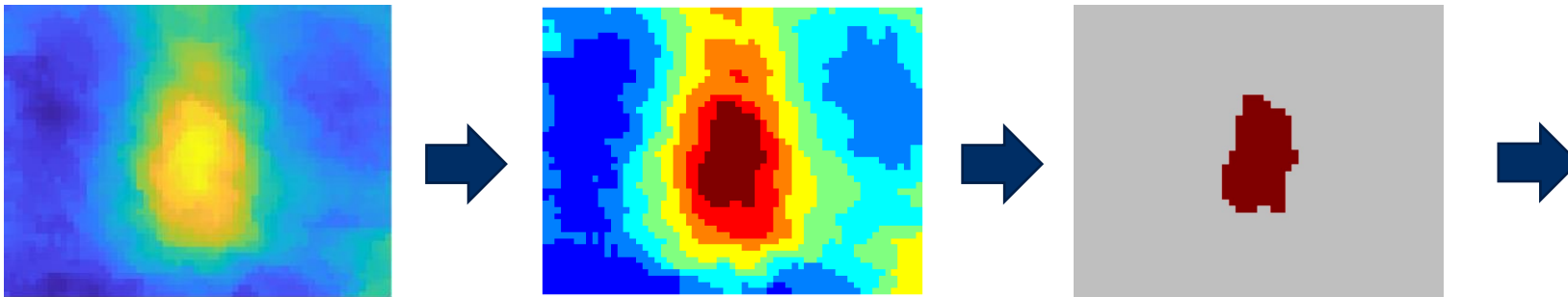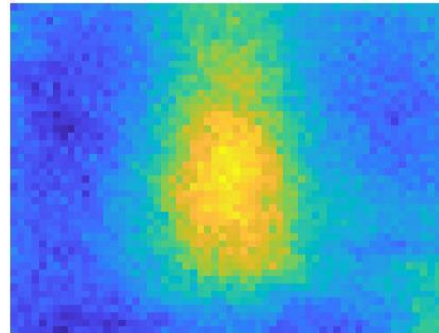
Data collection

- **Dynamically obtained data – Dataset from Porto**

  - No reference in image & no visual image

  - Image segmentation

  - Less accurate than previous method

Temperature recovery curves

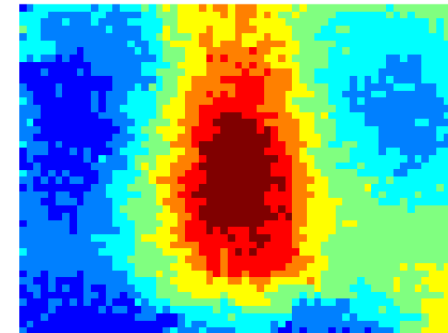# Data collection

- **Dynamische data – Dataset from Porto**

Otsu's segmentation method

Without Gaussian filter

With Gaussian filter

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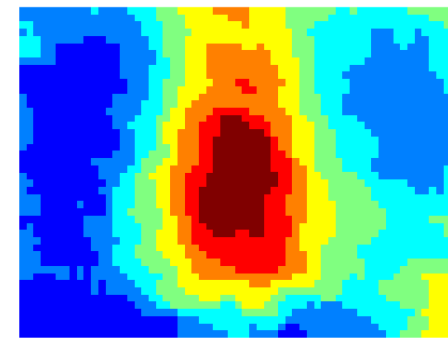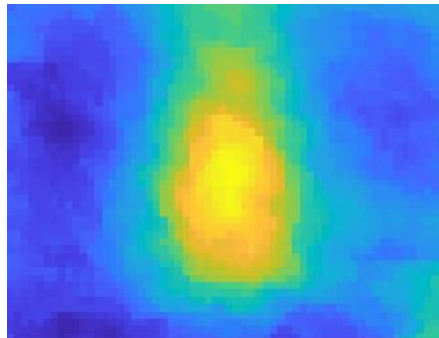
Data collection

- **Dynamische data – Dataset from Porto**

Melanoma vs. melanocytic nevi
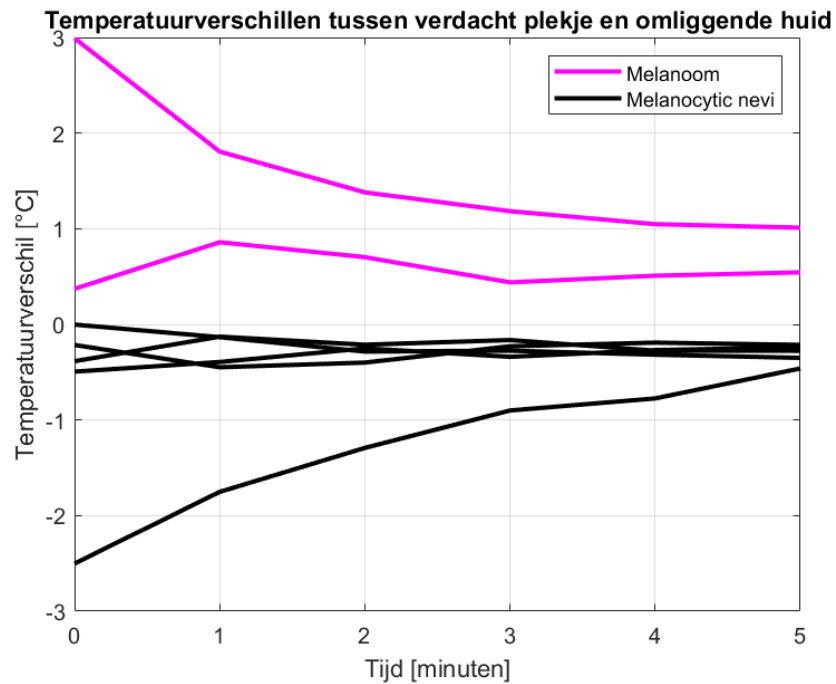
Melanoma vs. melanocytic nevi vs. BCC vs.SCC

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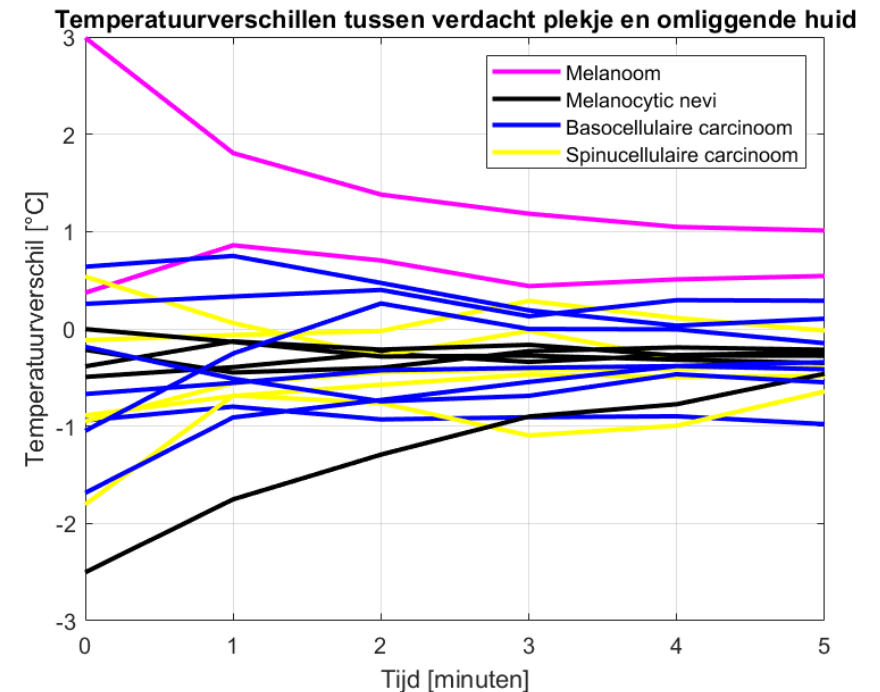
Classification

Supervised learning:

- Input data has been labeled for a particular output

- Trained until it can detect the underlying patterns and relationships

  between the input data and the output labels

- Good for classification of never-before-seen data

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Classification algorithms

Ensemble

k-Nearest Neighbors

Algorithms

Convolutional Neural Network

Decision tree

Support Vector Machine

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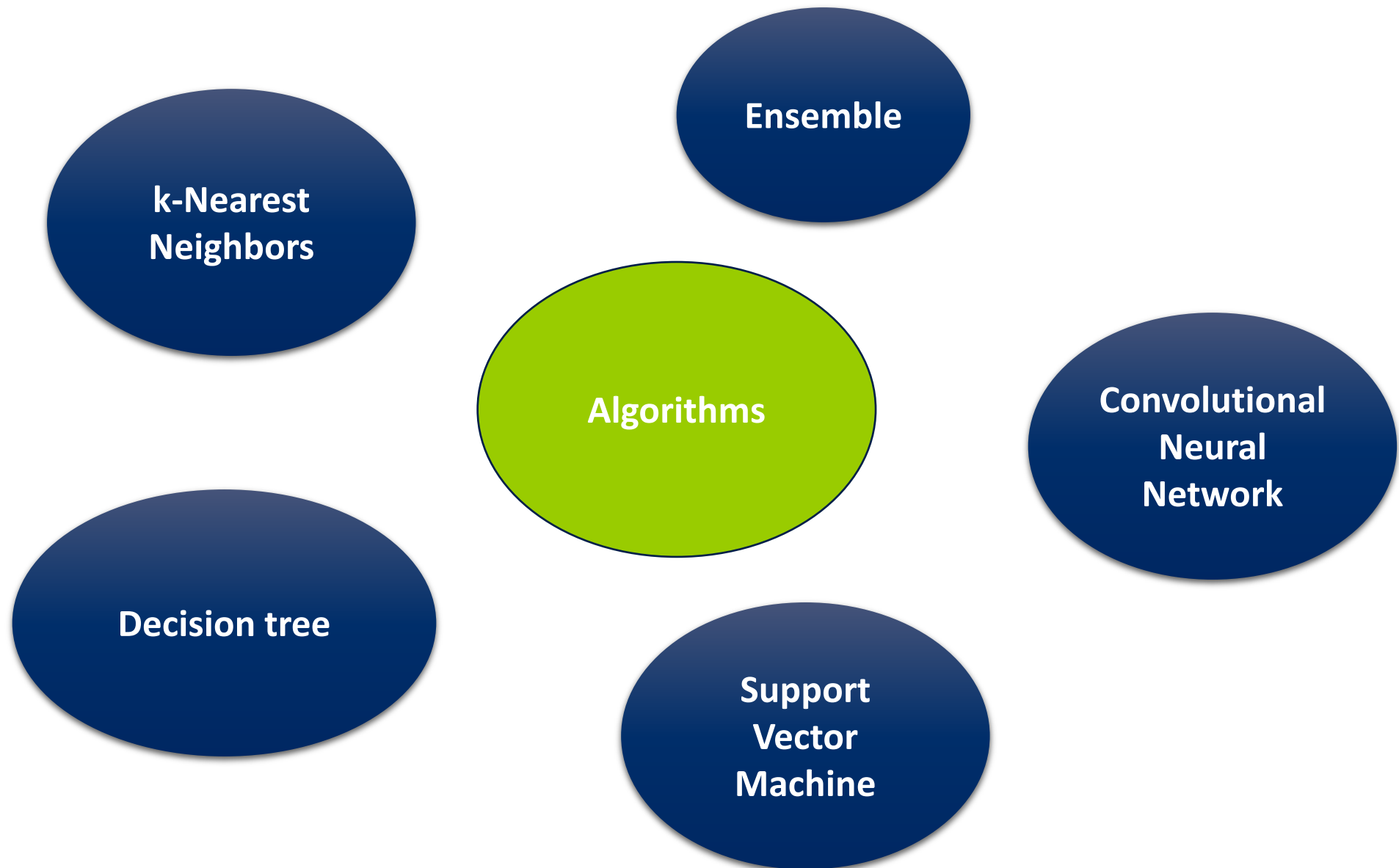
k-Nearest Neighbors (k-NN)

CLASS A
CLASS B

K= 3
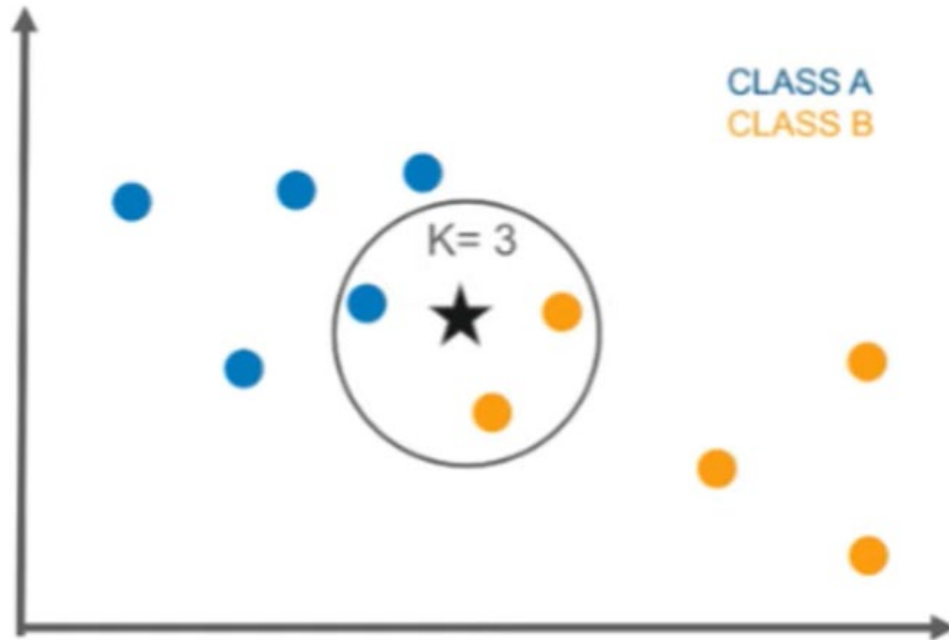
$$d_{Euclidisch}(x_1, x_2) = \frac{1}{2}\sqrt{\sum_{j=1}^{N}(x_{1j} - x_{2j})^2}$$

- Assumes that similar things exist in close proximity

- 'k' is the number of closest objects that the algorithm looks at to determine the class of a new object.

- Several distance metrics can be used (e.g. Euclidean distance function)

- Long execution time

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Decision tree
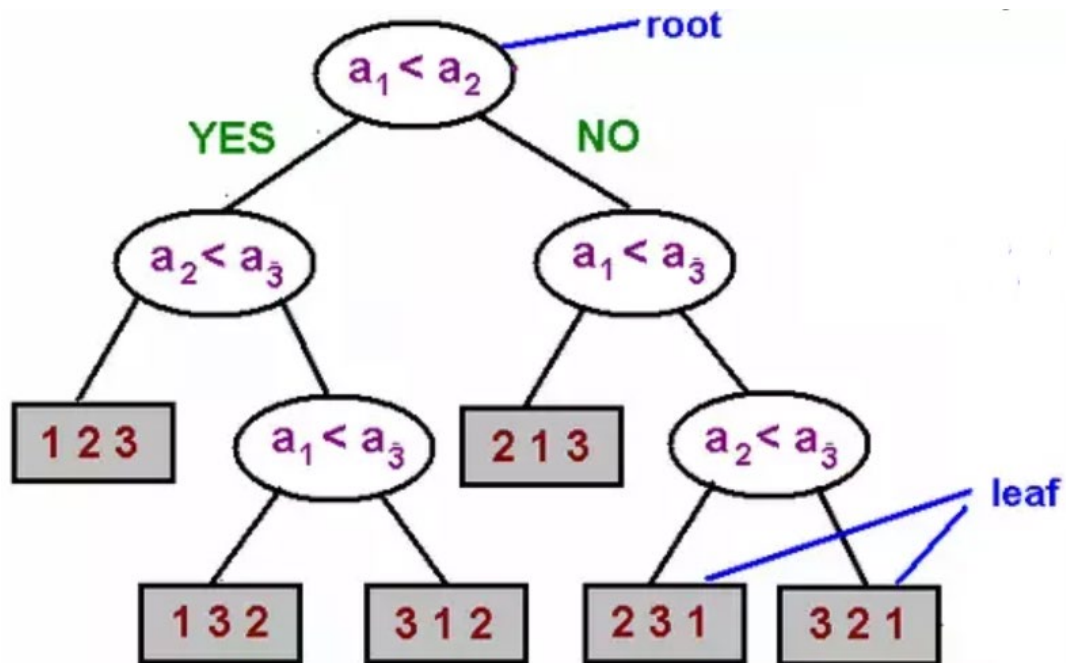
- Binary classification in Matlab

- Unstable learning algorithm

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Support vector machine (SVM)

Margin

Hyperplane

Support Vectors
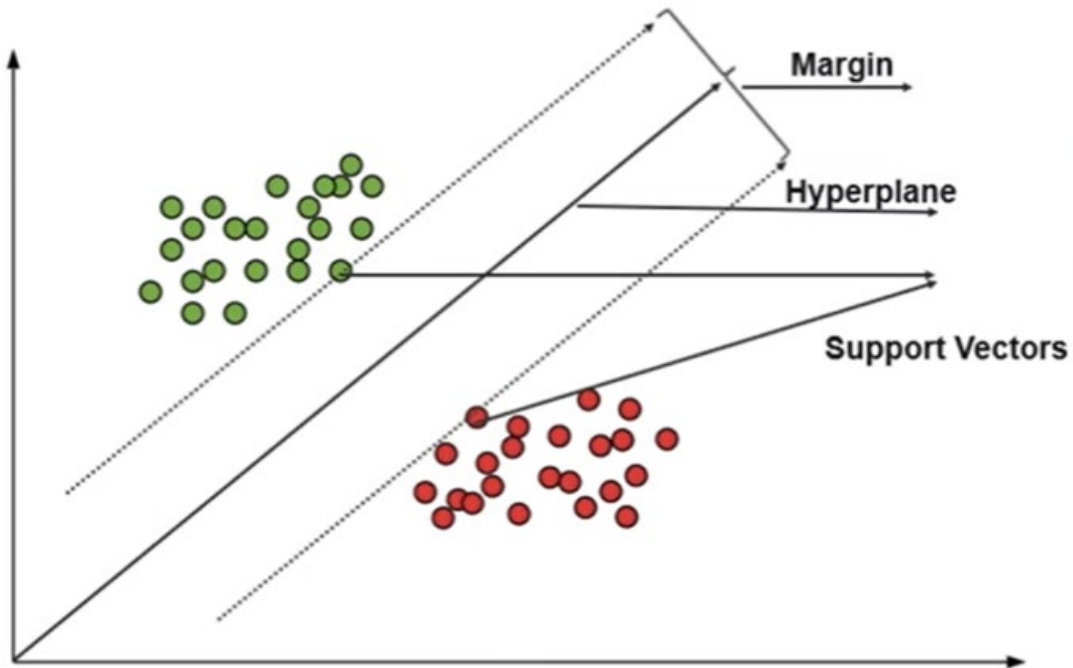
- Line or hyperplane between separates the data into two classes

- Unstable learning algorithm

- Originally designed for binary classification, but extended for multi-class-problems

- Sensitive to noise

- Accurate with small dataset, not suitable for large datasets

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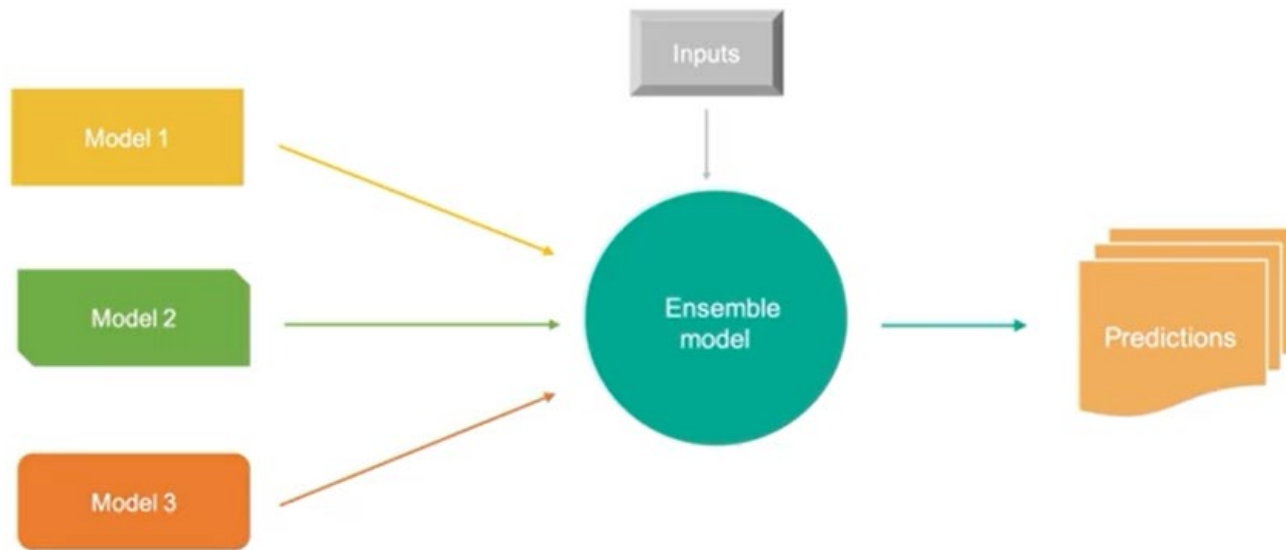
Ensemble

- Combining several models

- Many ensemble techniques available

Convolutional neural network (CNN)
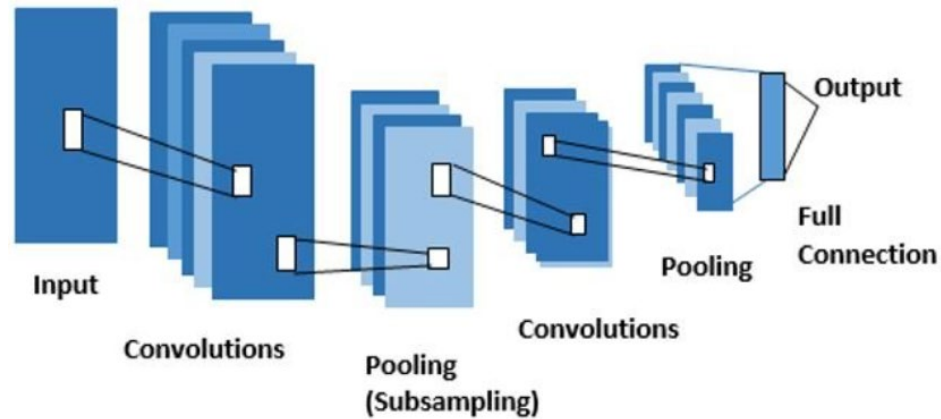
- Large amount of data needed for training

- Other studies did not show good results using CNN for melanoma detection.

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Classification in Matlab

- k-fold cross validation   (k=5)

- Run 5 times

- Choose algorithm with best results for each case

- Choose average result of this algorithm for each case

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Cases

Case 1   Melanocytic nevi vs. melanoma

Case 2   Benign vs. melanoma

Case 3   Classifying all 6 types of tumors

Case 4   Benign vs. malignant

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Resultaten

Static analysis

Task	Algorithm	Accuracy	Sensitivity	Specificity
Melanocytic nevi vs. Melanoma	Ensemble	87,5%	50%	100%
Benign vs. Melanoma	Ensemble	58,3%	50%	100%
All types of skin tumors	SVM	46,2%	56,3%	60%
Benign vs. Malignant	Ensemble	57,7%	68,8%	40%

Dynamic analysis

Task	Algorithm	Accuracy	Sensitivity	Specificity
Melanocytic nevi vs. Melanoma	Ensemble	100%	100%	100%
Benign vs. Melanoma	k-NN	63,6%	100%	100%
All types of skin tumors	k-NN	47,8%	85,7%	66,7%
Benign vs. Malignant	Beslissingsboom	82,6%	85,7%	77,8%

$$Sensitivity = \frac{\Sigma true\ positive}{\Sigma malignant\ tumors}$$

$$Specificity = \frac{\Sigma true\ negative}{\Sigma benign\ tumors}$$

Better classification results for dynamically obtained data.

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Reliability & validity

- Limited number of skin lesions

- Measurement procedure

  o Uneven cooling (in ear, on eyelid, …)

  o Only one image per minute

  o No visual images & no square marker
  (less accurate temperature determination)

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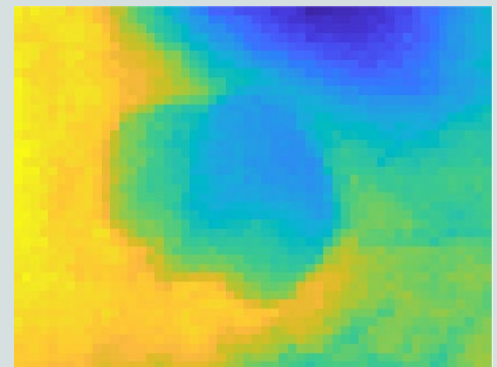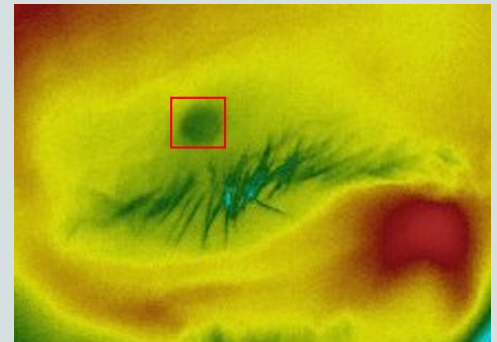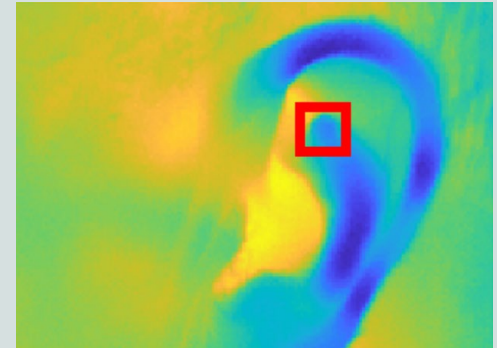
Conclusion & future work

- Melanoma and melanocytic nevi seems to be distinguishable from each other

- BCC and SCC are more difficult to classify correctly

- More accurate measurement results with alignment algorithm and visual images → probably better classification results

- Examine a larger number of skin tumors → = more accurate classification

- Research into relationship between size of the tumor and the recovery temperature (use the size of the tumor as an extra input parameter for the ML classifier?)

- Combine with multispectral measurements

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Q/A

Thank you for your attention!