BEYOND CONVENTIONAL METHODS: THE ROLE OF ARTIFICIAL NEURAL NETWORKS IN NUCLEAR WASTE MANAGEMENT

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European Joint Programme on Radioactive Waste Management

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SUMMARY

- **Introduction to Artificial Neural Networks**

- **Applications:**
  - Classification of diversion scenarios for safeguards applications
  - Anomaly detection in camera data for IAEA surveillance
  - Prediction of safety parameters for canister loading optimization

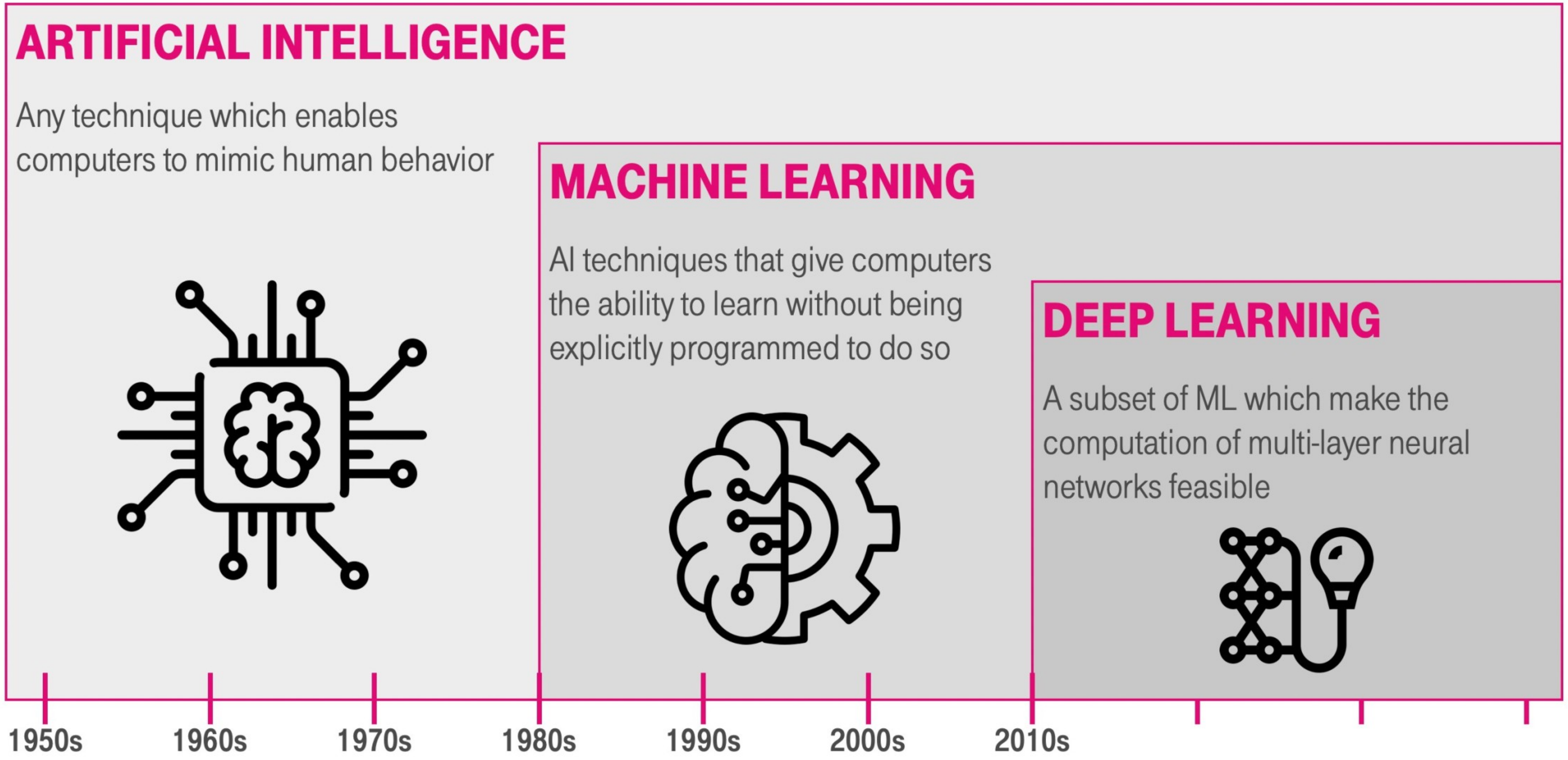
- **Advantages/Disadvantages of using ANN**

- **For the future**

ARTIFICIAL INTELLIGENCE vs MACHINE LEARNING vs ARTIFICIAL NEURAL NETWORKS vs DEEP LEARNING ?

Do you know the difference?

ARTIFICIAL INTELLIGENCE vs MACHINE LEARNING vs ARTIFICIAL NEURAL NETWORKS vs DEEP LEARNING ?



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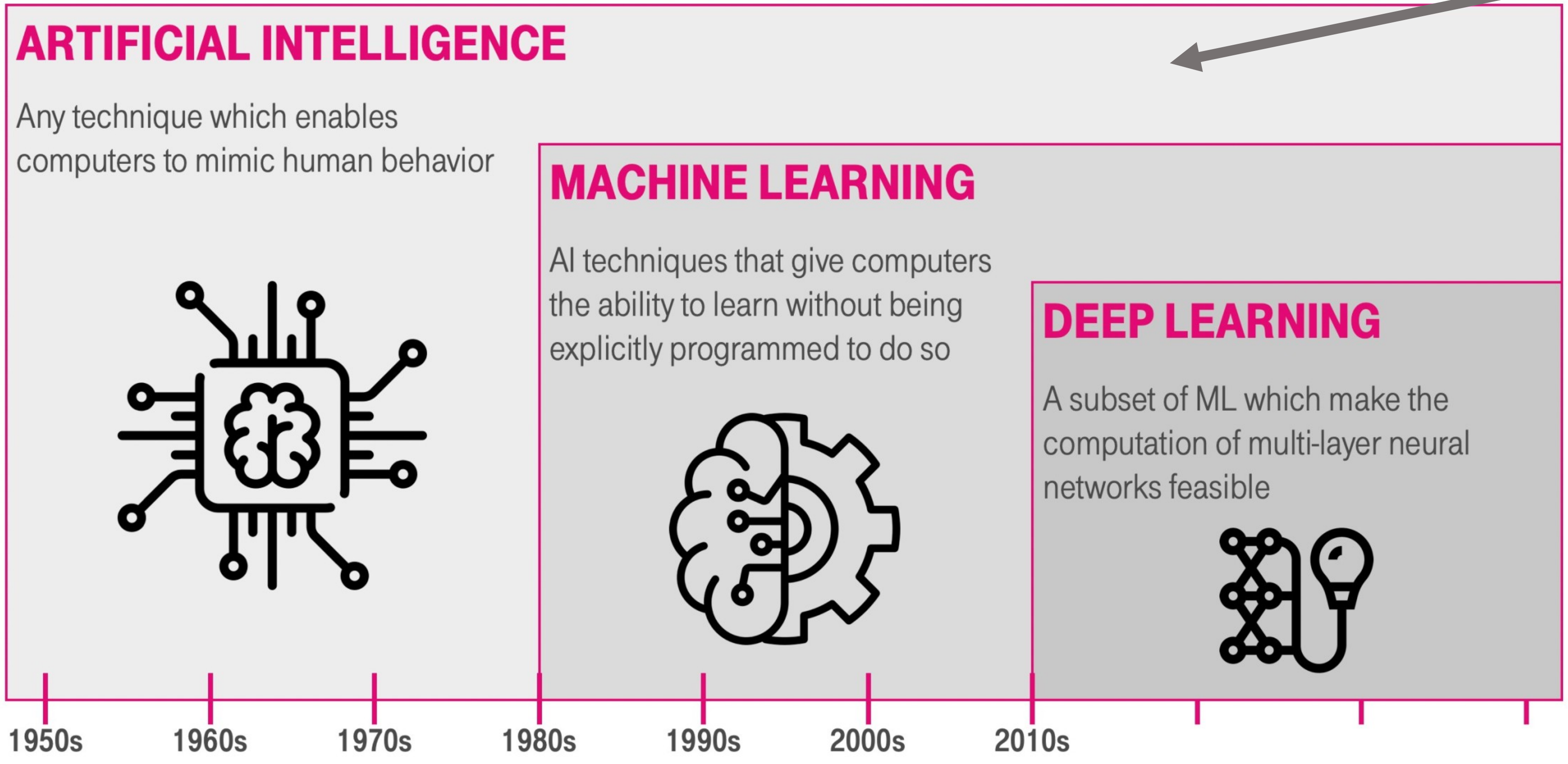

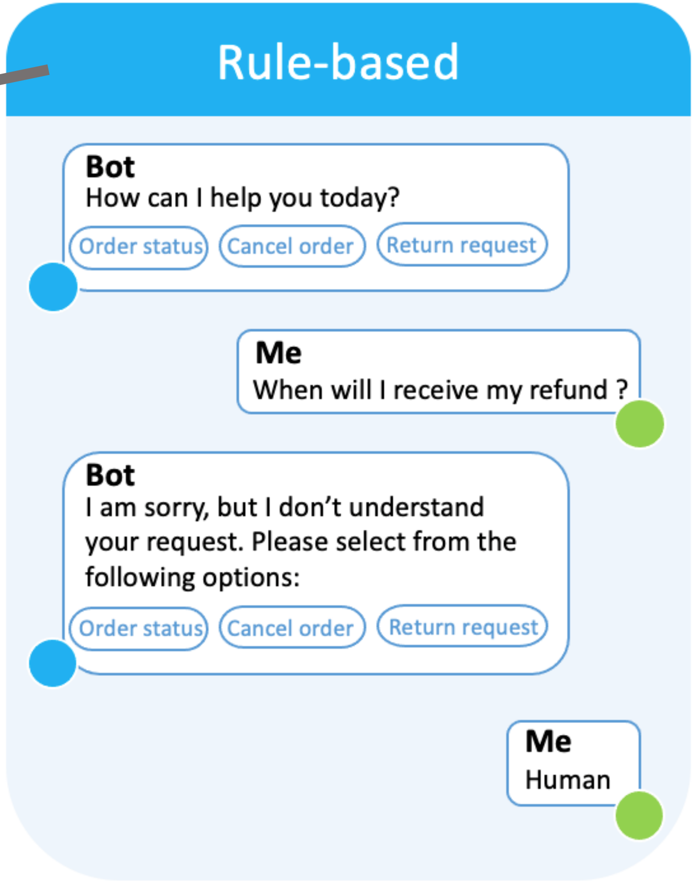

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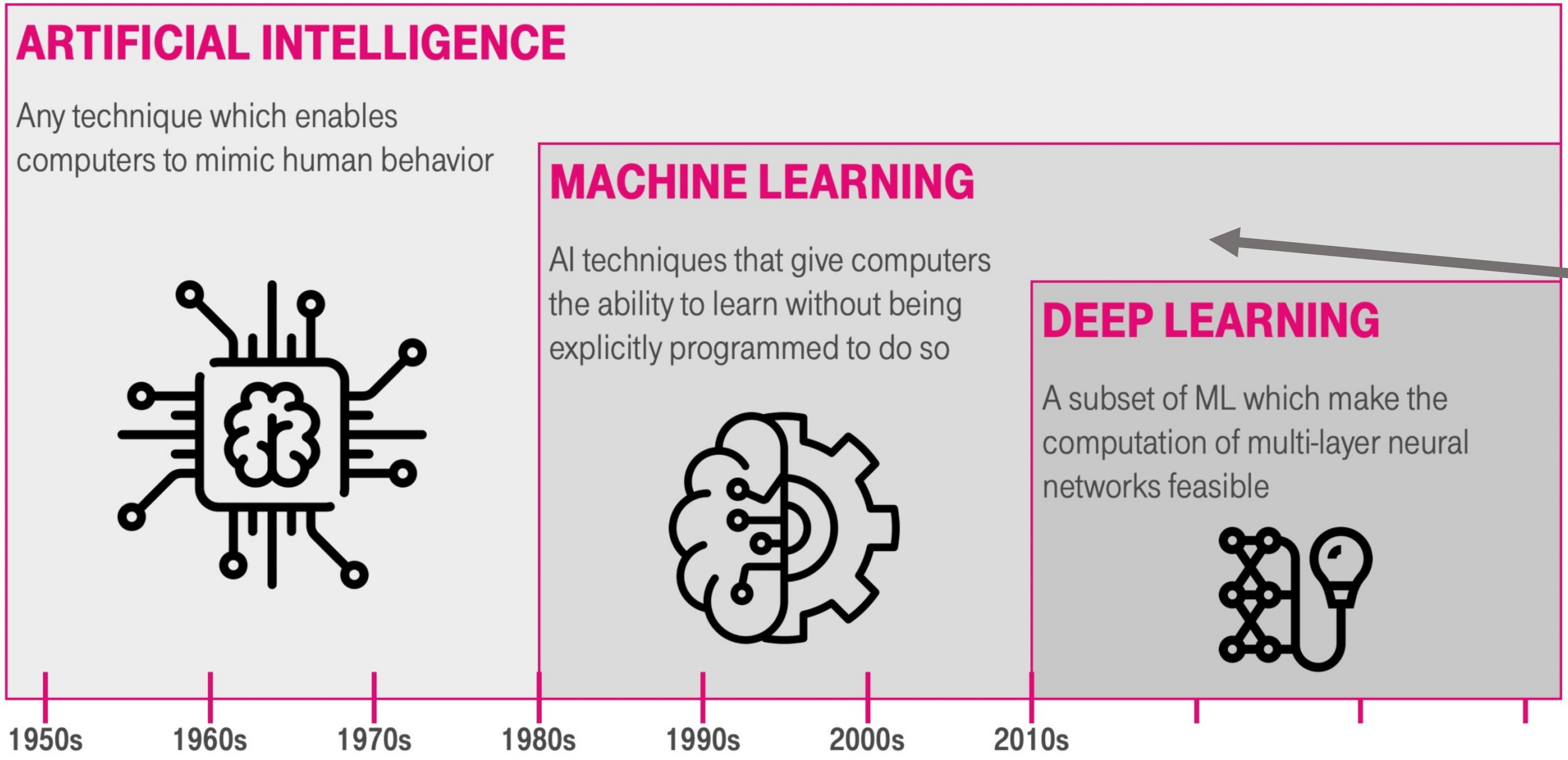

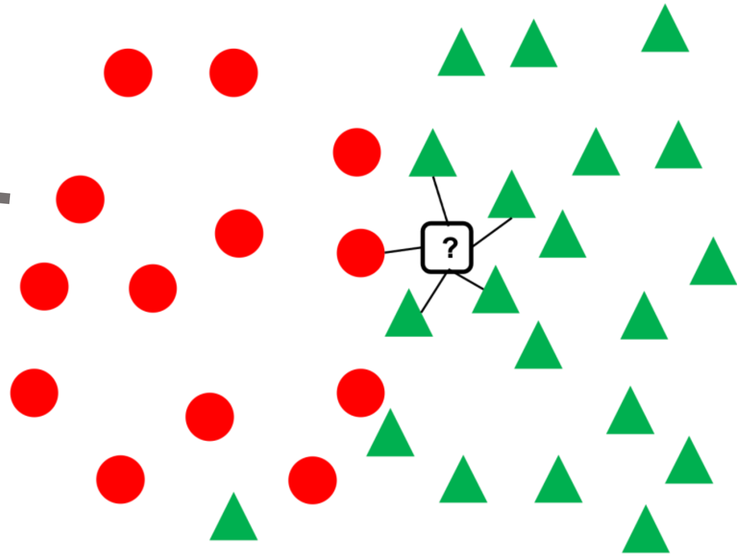

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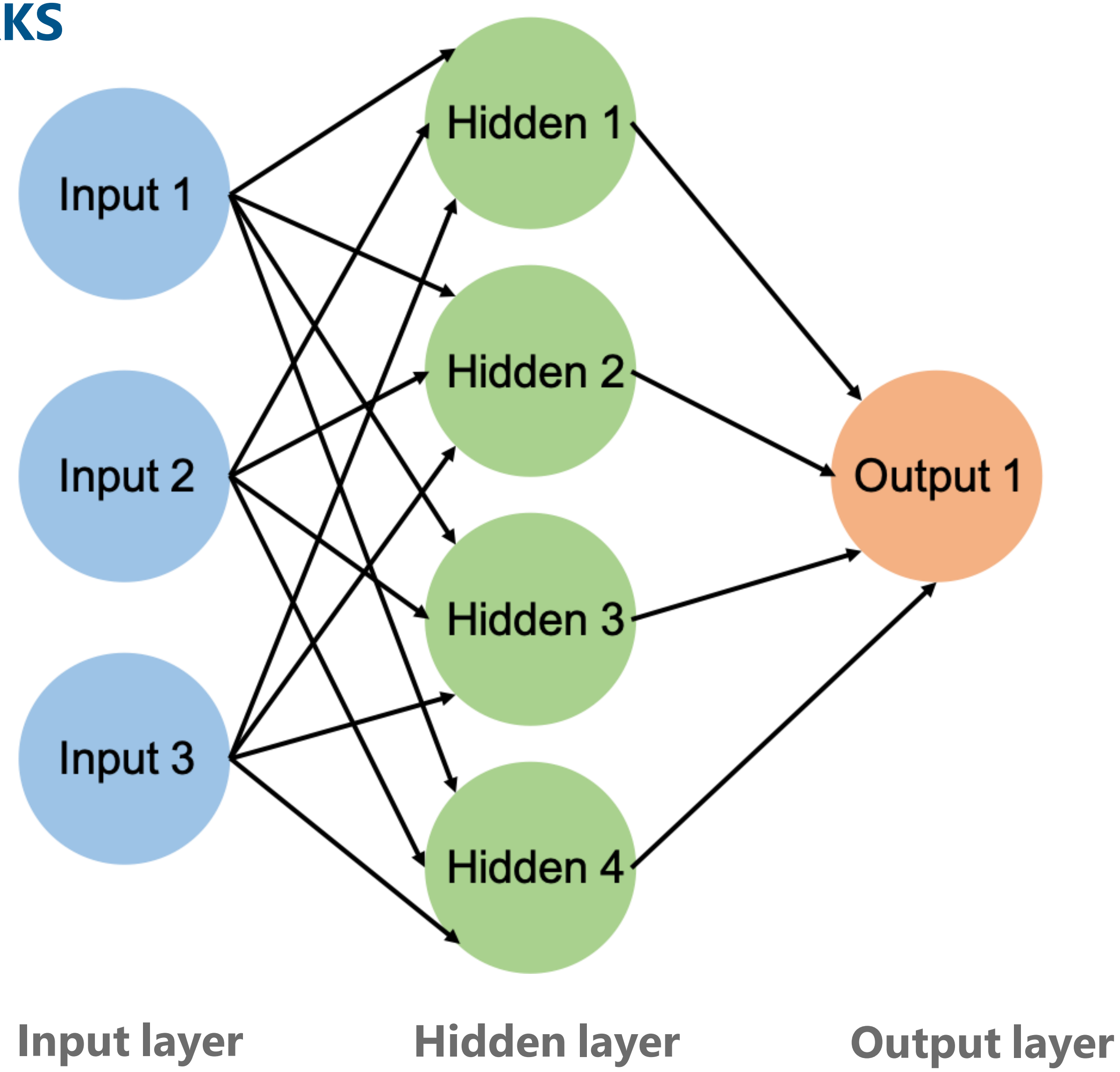
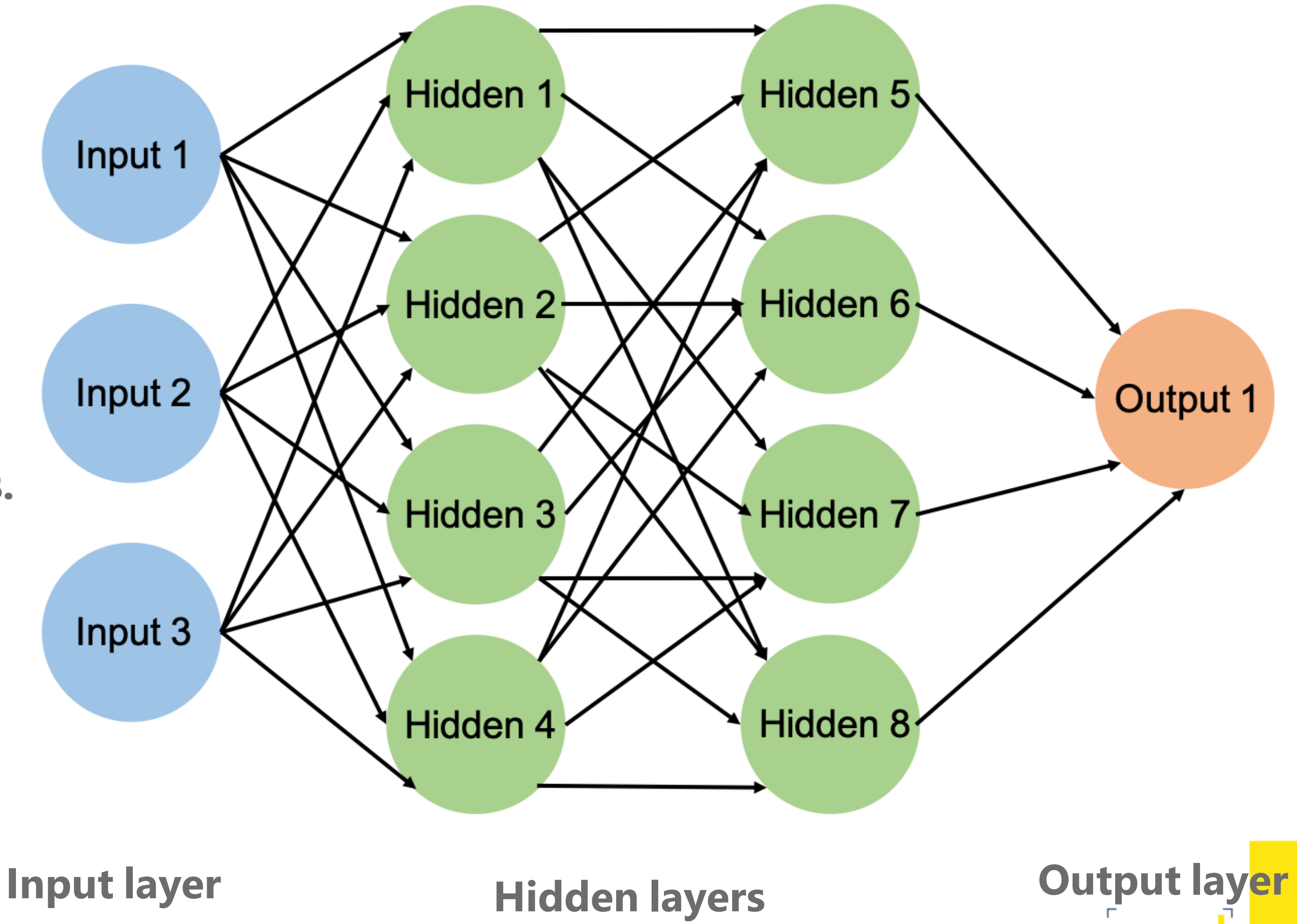
ARTIFICAL NEURAL NETWORKS

- Inspiration from the human brain's structure.



DEEP LEARNING

- Deep learning is a category of ANN with several hidden layers.
- Can handle more complex problems.
- Needed for image recognition (Convolutional Neural Network).

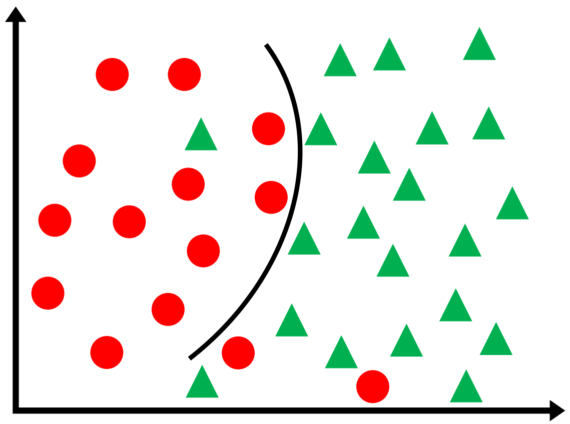


ANN APPLICATIONS

The ANN applications are usually divided into two types:

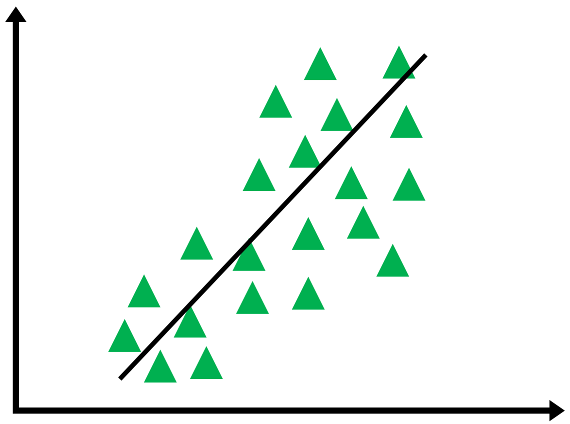
1) CLASSIFICATION

Classify into different classes (expected/abnormal)



2) REGRESSION

Try to predict a continuous value



DIFFERENT APPLICATIONS

- **Classification of diversion scenarios for safeguards applications**
  - Al-dbissi et al. Identification of diversions in spent PWR fuel assemblies by PDET signatures using Artificial Neural Networks (ANNs). Annals of nuclear energy (2023).

- **Anomaly detection in camera data for IAEA surveillance**
  - Smith et al. A Deep Learning Workflow for Spatio-Temporal Anomaly Detection in NGSS Camera Data. Proceedings from INMM & ESARDA Joint Virtual Annual Meeting (2021).

- **Prediction of safety parameters before encapsulation**
  - Solans et al. Optimisation of used nuclear fuel canister loading using a neural network and genetic algorithm. Neural Computing and Applications (2021).
  - Current EURAD work

APPLICATION 1:
CLASSIFICATION OF DIVERSION SCENARIOS FOR SAFEGUARDS APPLICATIONS

Identification of diversions in spent PWR fuel assemblies by PDET signatures using Artificial Neural Networks (ANNs). Al-dbissi et al. Annals of nuclear energy (2023).

SAFEGUARDS

- **The aim of safeguards:**
  - No nuclear material missing from SNF
  - Detection of partial defect: Search for missing or replaced fuel pins in SNF
  - After encapsulation, any verifications will be challenging/impossible

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PARTIAL DEFECT TESTER (PDET)

- Inspection technique developed by Lawrence Livermore National Laboratory
- **Gamma and neutron** detector inserted in the Guide tubes of PWR SNFs

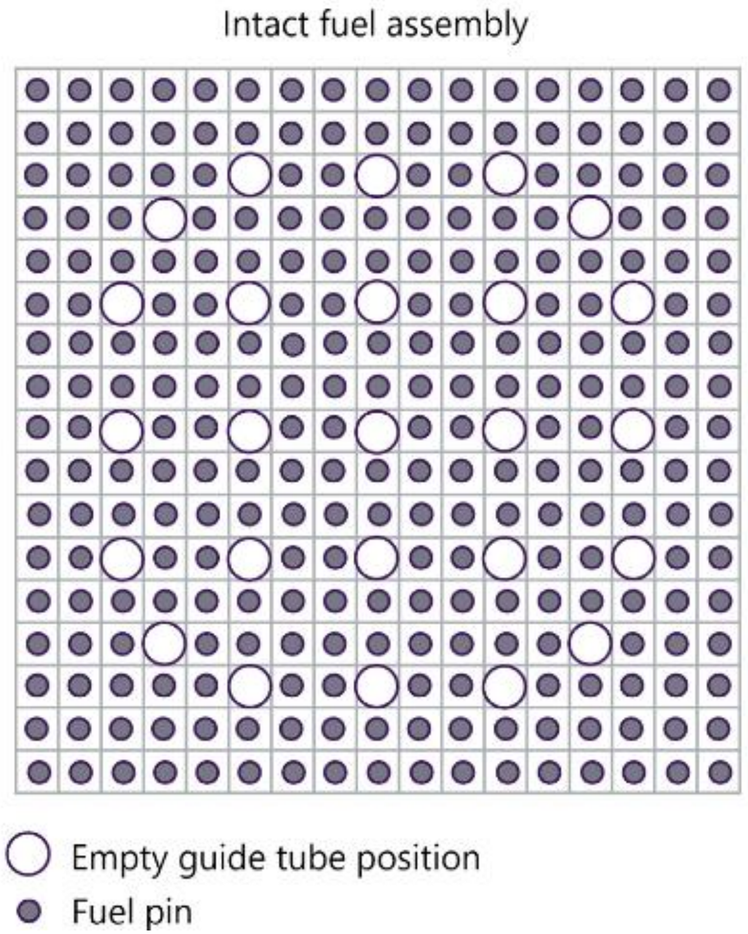

Figure from Al-dbissi et al.

DATA AND MODEL

- **Work done only on simulated data**

- **Data:**
  - Simulated PWR
    - 25 Guide tubes per SNF
  - Intact SNFs + different diversion scenarios

- **Model:**
  - Input: 25 gamma + 25 neutron detection rates per SNF
  - Output: Classification in percentage of replaced fuel pins

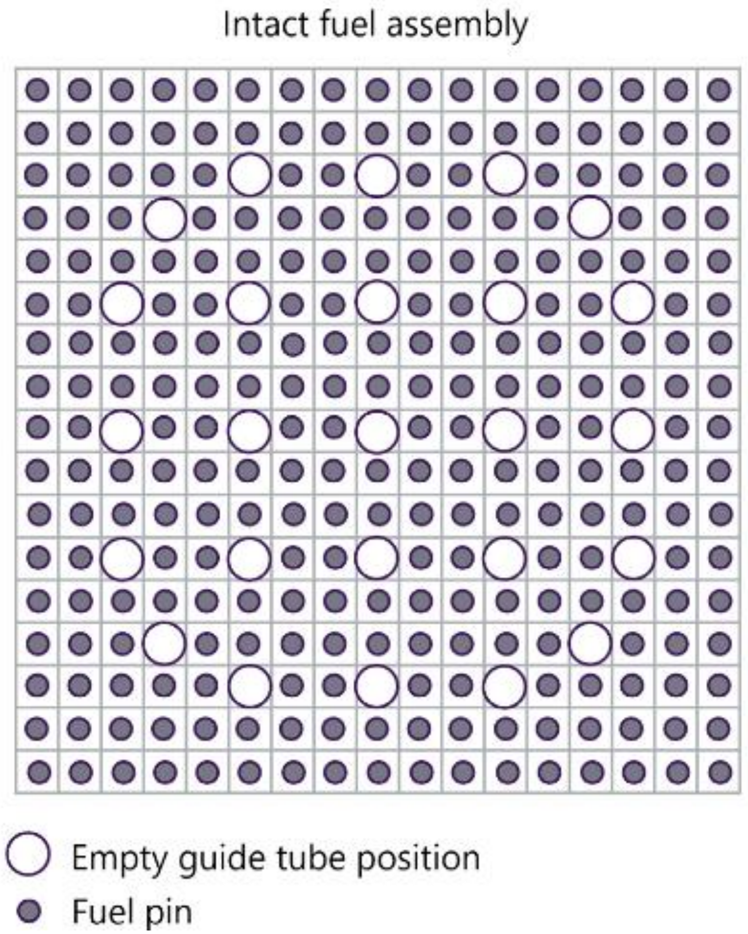

Figure from Al-dbissi et al.

CLASSIFICATION FOR PARTIAL DEFECT TESTER (PDET) FOR SAFEGUARDS APPLICATIONS

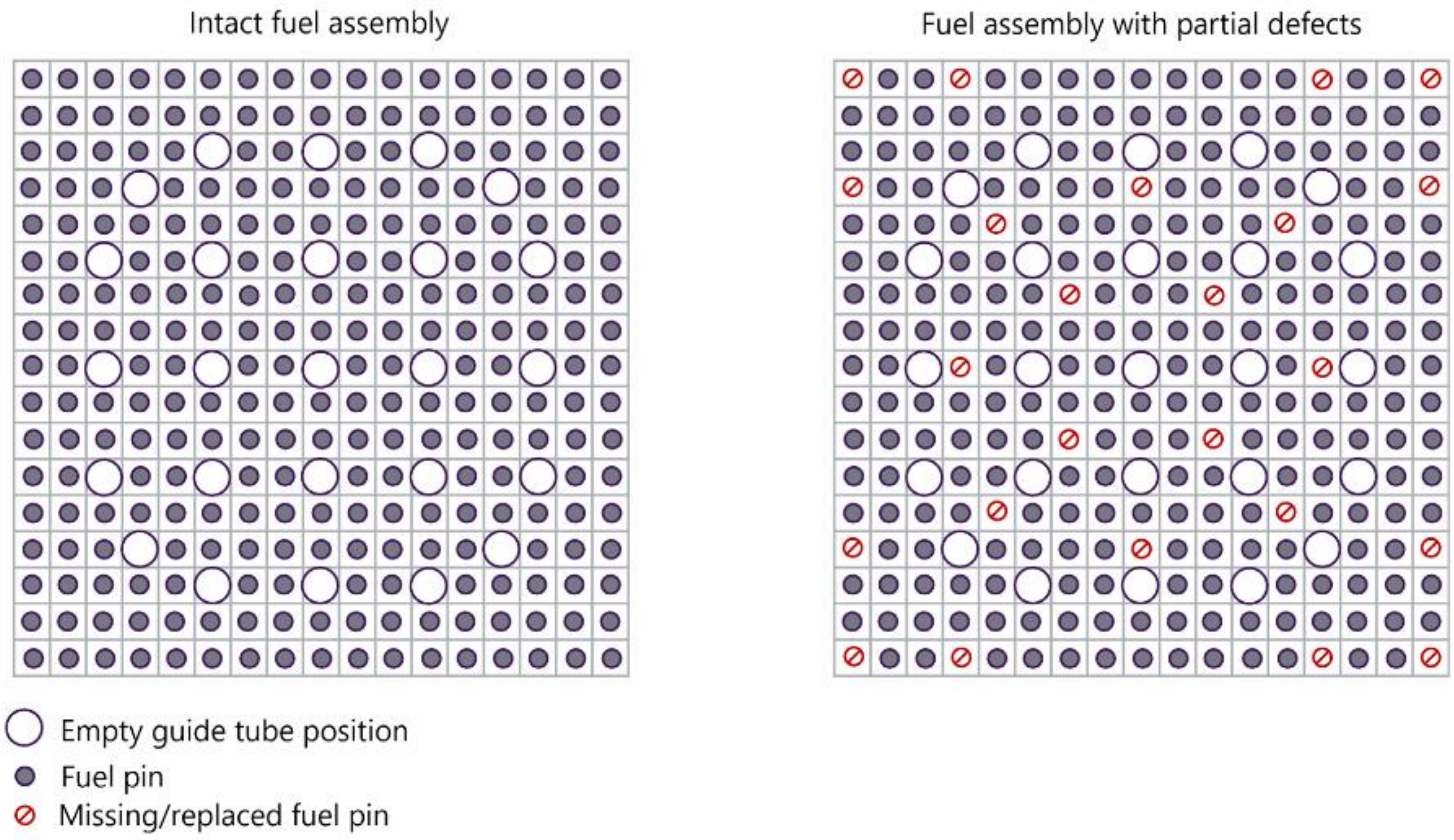

Figure from Al-dbissi et al.

CLASSIFICATION AND RESULTS

- **ANN: Percentage of replaced fuel pins**
  - Classification problem (7 class label)

Percentage of replaced pins (x)	Class label
$x = 0$	0
$x \leq 10\%$	1
$10\% < x \leq 20\%$	2
$20\% < x \leq 30\%$	3
$30\% < x \leq 40\%$	4
$40\% < x \leq 50\%$	5
$x > 50\%$	6

- **Result:**
  - Accuracy 96.5 %
  - Highest misclassification occurs between class 0 (intact SNF) and class 1 (<10%)

CONCLUSION

- **Possible improvements:**
  - Increase dataset
  - Test on experimental data

- **This application shows that ANN can be used to help detecting replaced fuel pins for safeguards applications before encapsulation**

- Identification of diversions in spent PWR fuel assemblies by PDET signatures using Artificial Neural Networks (ANNs). Al-dbissi et al. Annals of nuclear energy (2023).

APPLICATION 2:
ANOMALY DETECTION IN CAMERA DATA FOR IAEA SURVEILLANCE

A Deep Learning Workflow for Spatio-Temporal Anomaly Detection in NGSS Camera Data. Smith et al. Proceedings from INMM & ESARDA Joint Virtual Annual Meeting (2021).

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IAEA

- IAEA has over 1400 surveillance cameras (2016)
- Cameras record all activity
- Only basic motion detection algorithm
- IAEA employees need to review all surveillance images

- <u>Goal:</u> Improve inspector efficiency by only showing irregular activity

Image generated by V.Solans with DALL-E 3

MODEL

- **Input: previous frames from the camera**
- **Output: prediction of the next frame**
- **Goal: highlight any difference between the predicted and the actual frame**

- **Tested at Sandia National Laboratories' Gamma Irradiation Facility**

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SANDIA NATIONAL LABORATORIES' GAMMA IRRADIATION FACILITY

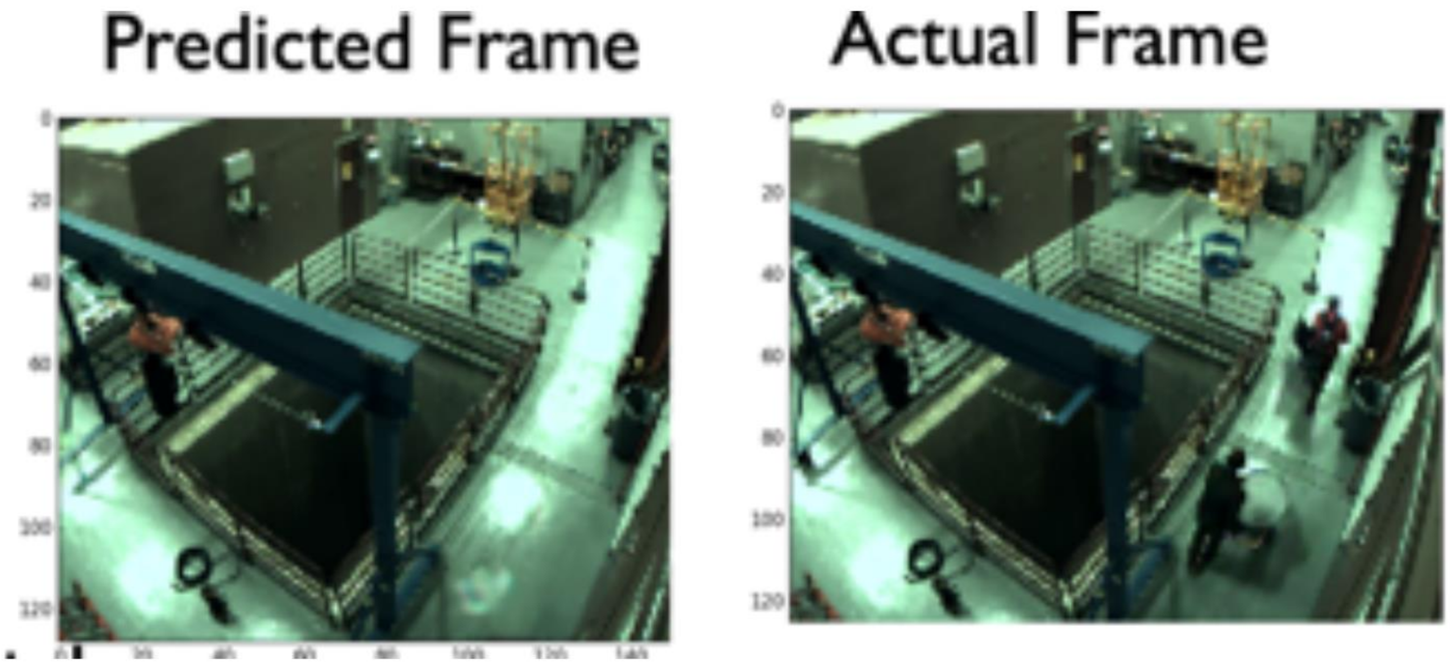

Figure from Smith et al.

SANDIA NATIONAL LABORATORIES' GAMMA IRRADIATION FACILITY

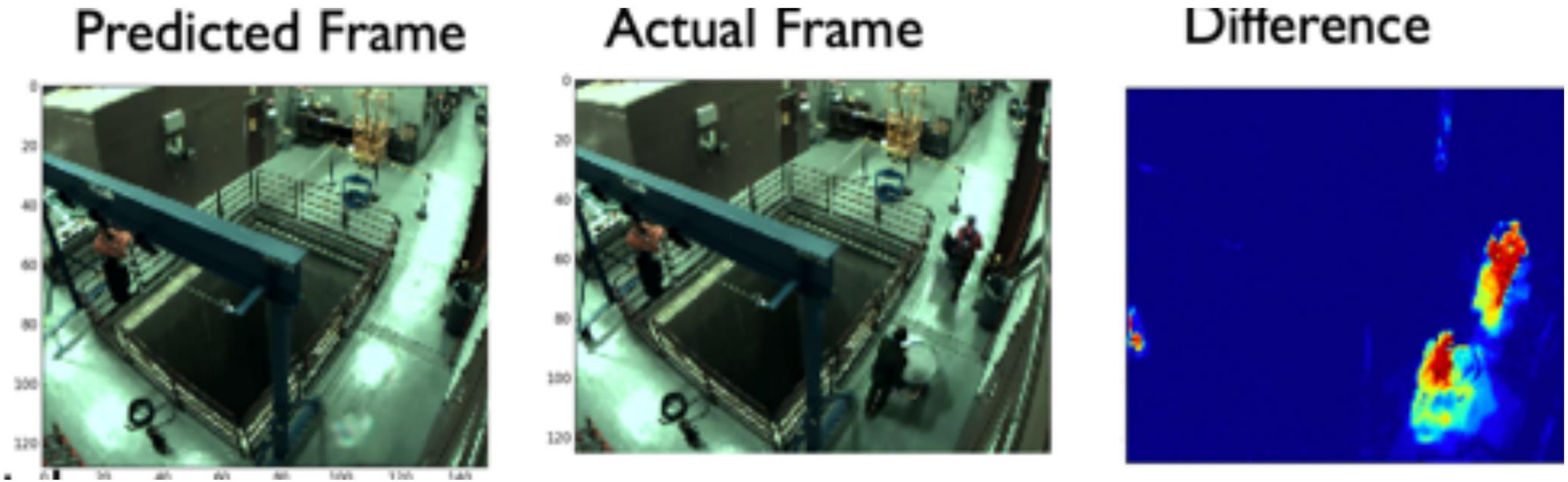

Figure from Smith et al.

ACTIVITIES AT THE FACILITY

Real case test at the facility:

- Used test-container to represent a SNF container
- Leaving the drying area is normal activity
- Entering the drying area is **not** a normal activity
- Background activity: container can be lifted using a crane (normal activity)

Normal activity

Figure from Smith et al.

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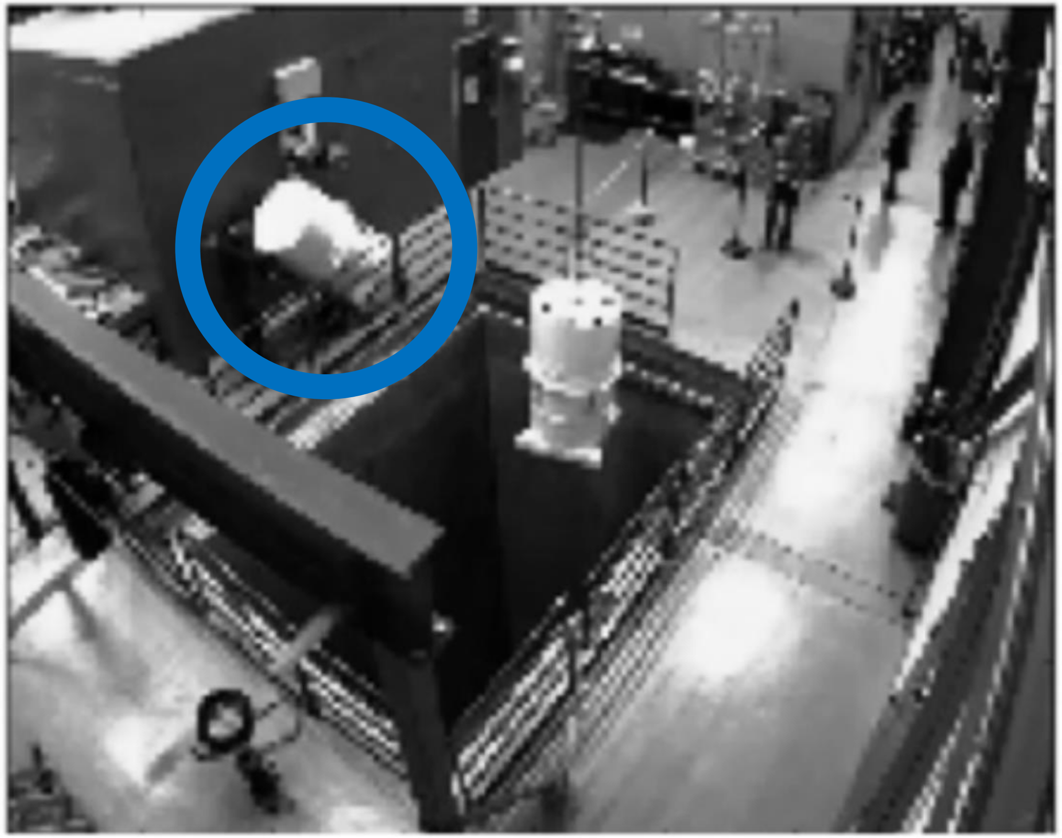

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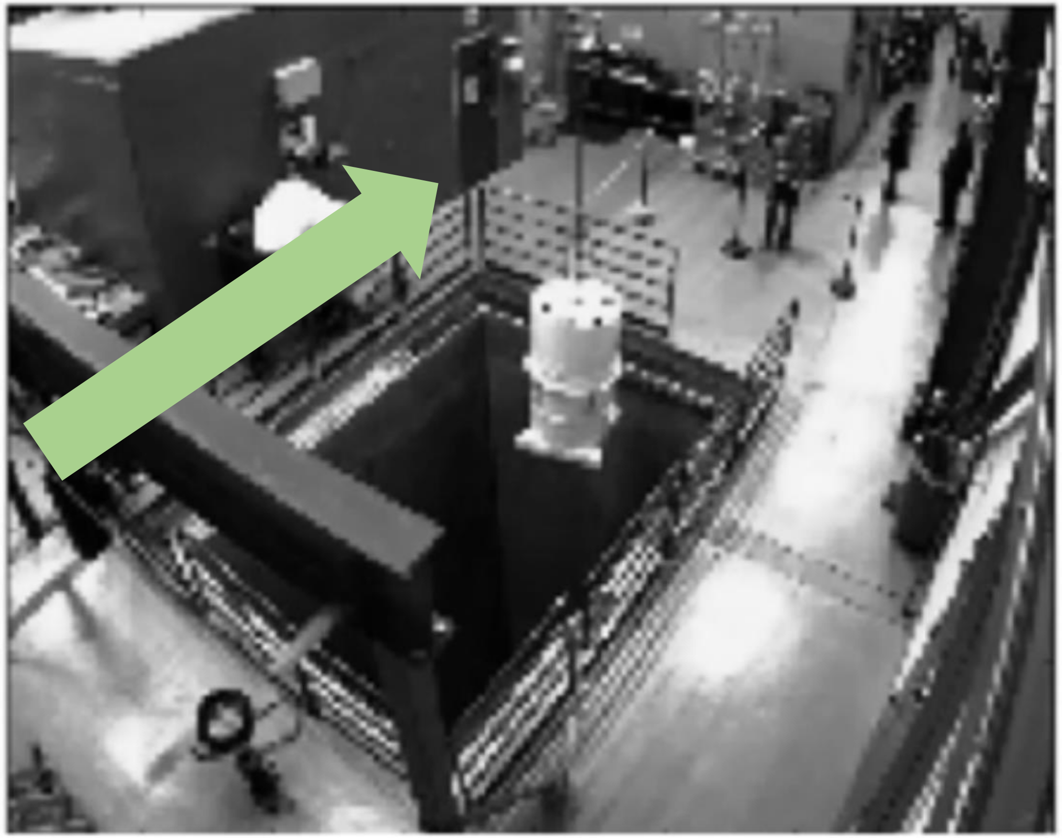

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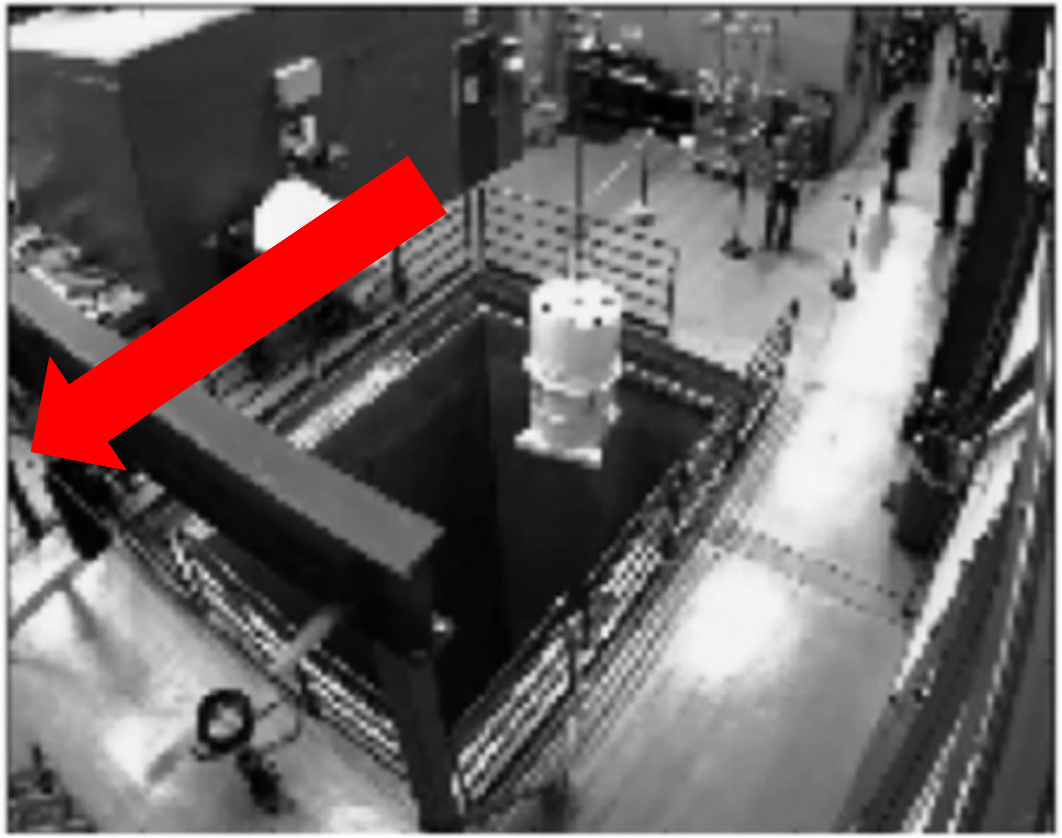

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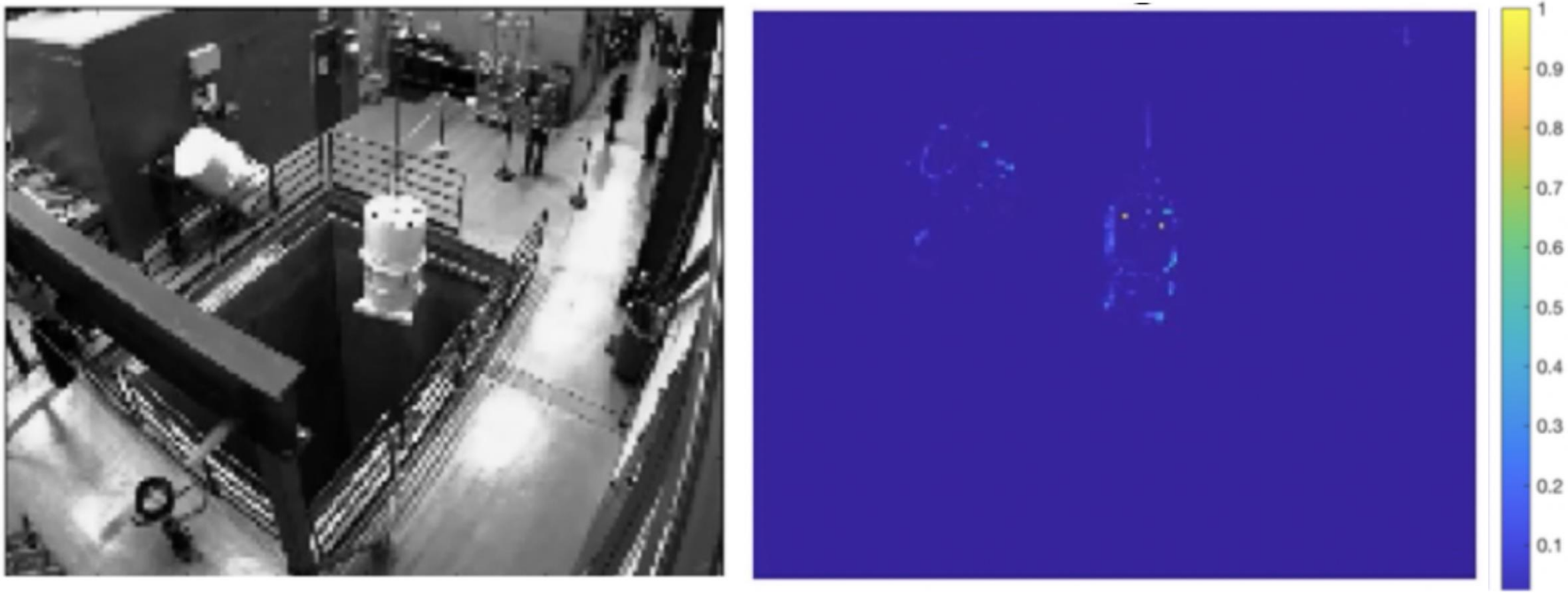
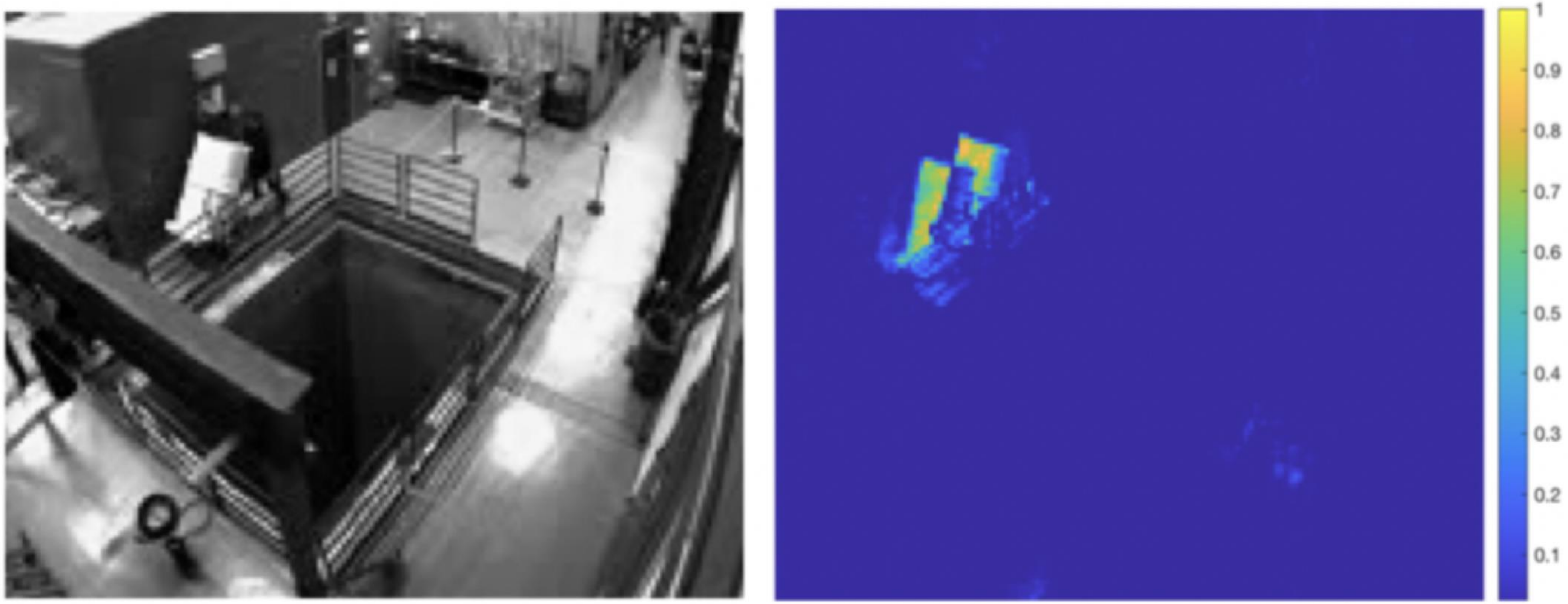
NORMAL ACTIVITY



Normal activity

Figure from Smith et al.

ABNORMAL ACTIVITY



Abnormal activity

Figure from Smith et al.

CONCLUSION

- **This ANN is able to identify abnormal activity in time and space**

- **Challenges:**
    - Would need a different training for each camera
    - Extremely long temporal relationship (decades)

- **Gain in time would be significant for IAEA inspectors**

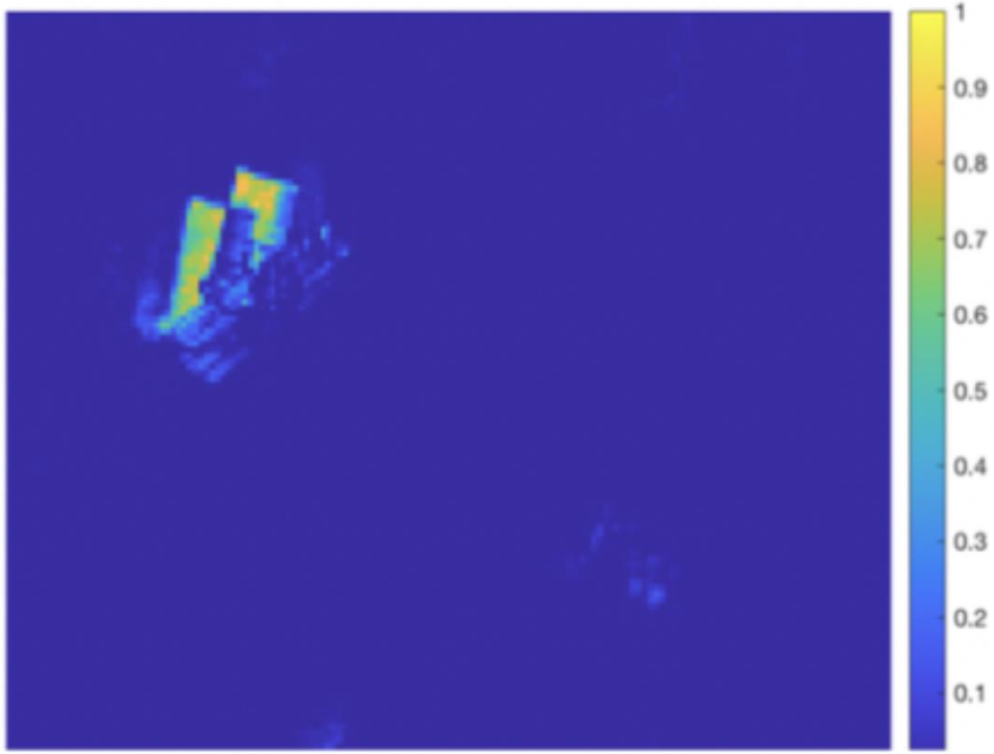


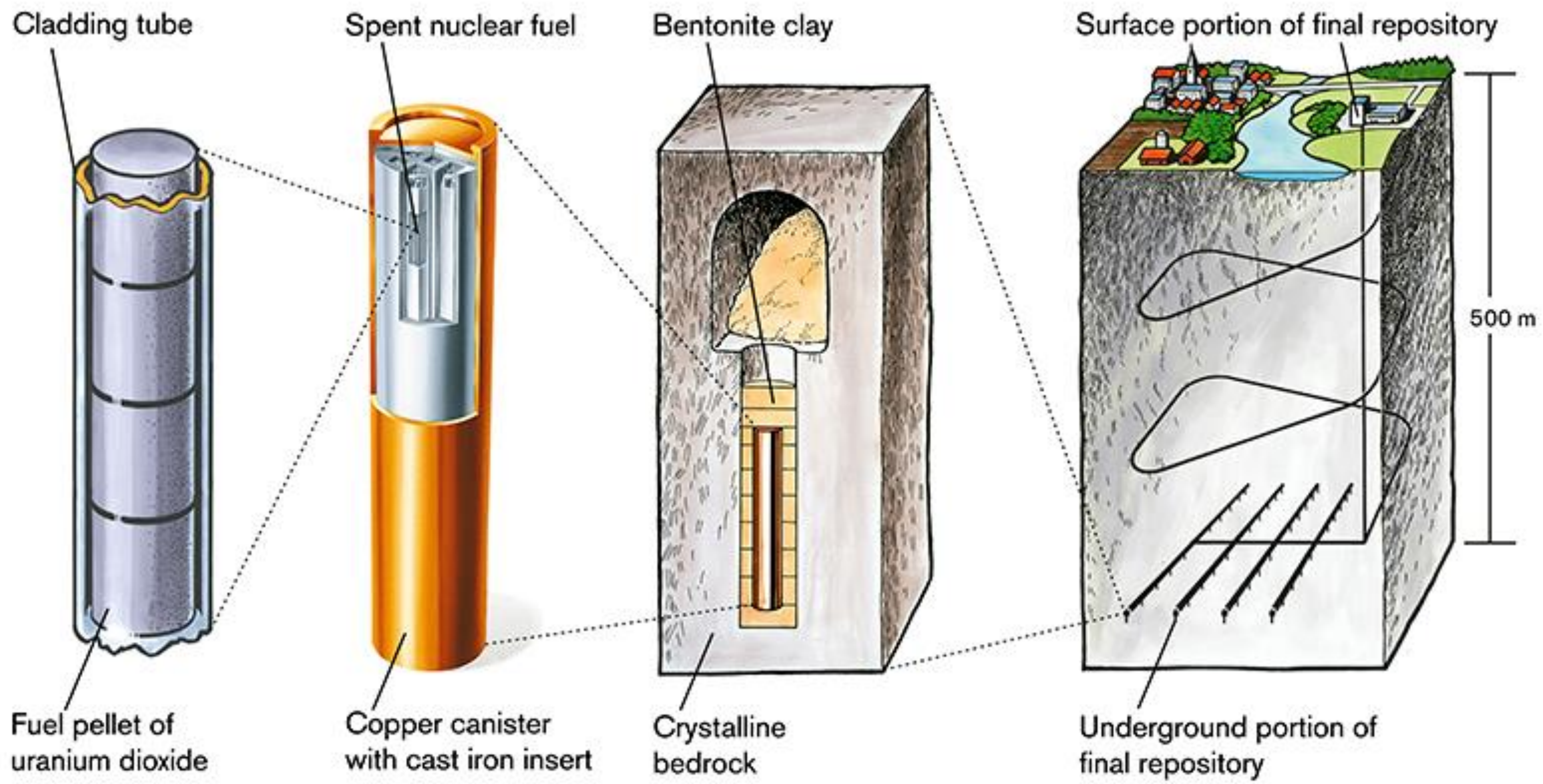
Figure from Smith et al.

APPLICATION 3:
PREDICTION OF SAFETY PARAMETERS BEFORE ENCAPSULATION

Optimisation of used nuclear fuel canister loading using a neural network and genetic algorithm. Solans et al. Neural Computing and Applications (2021).

Current EURAD work

PREDICTION OF SAFETY PARAMETERS FOR CANISTER LOADING OPTIMIZATION



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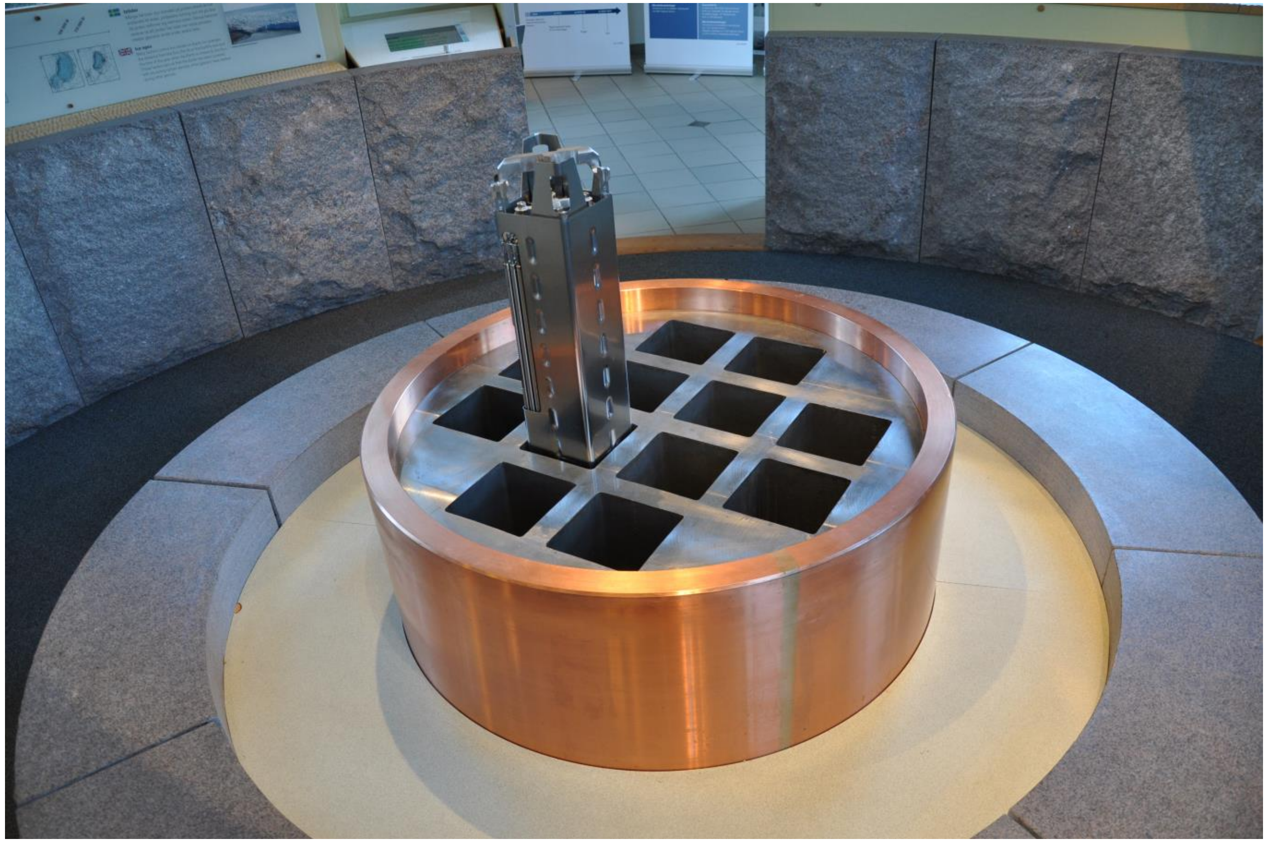
PREDICTION OF SAFETY PARAMETERS FOR CANISTER LOADING OPTIMIZATION

Encapsulation of SNFs in canisters:

- **Some safety parameters (per canister):**
  - Criticality-safety parameter
  - Decay heat
- **Place the SNF in a canister using a pre-established canister loading plan**



PREDICTION OF SAFETY PARAMETERS FOR CANISTER LOADING OPTIMIZATION

- **PART 1: Use ANN to predict k_{eff} from radionuclide concentration (for canister optimization strategies)**
- **PART 2: Use ANN to predict decay heat from experimental measurements (for SNF verification)**

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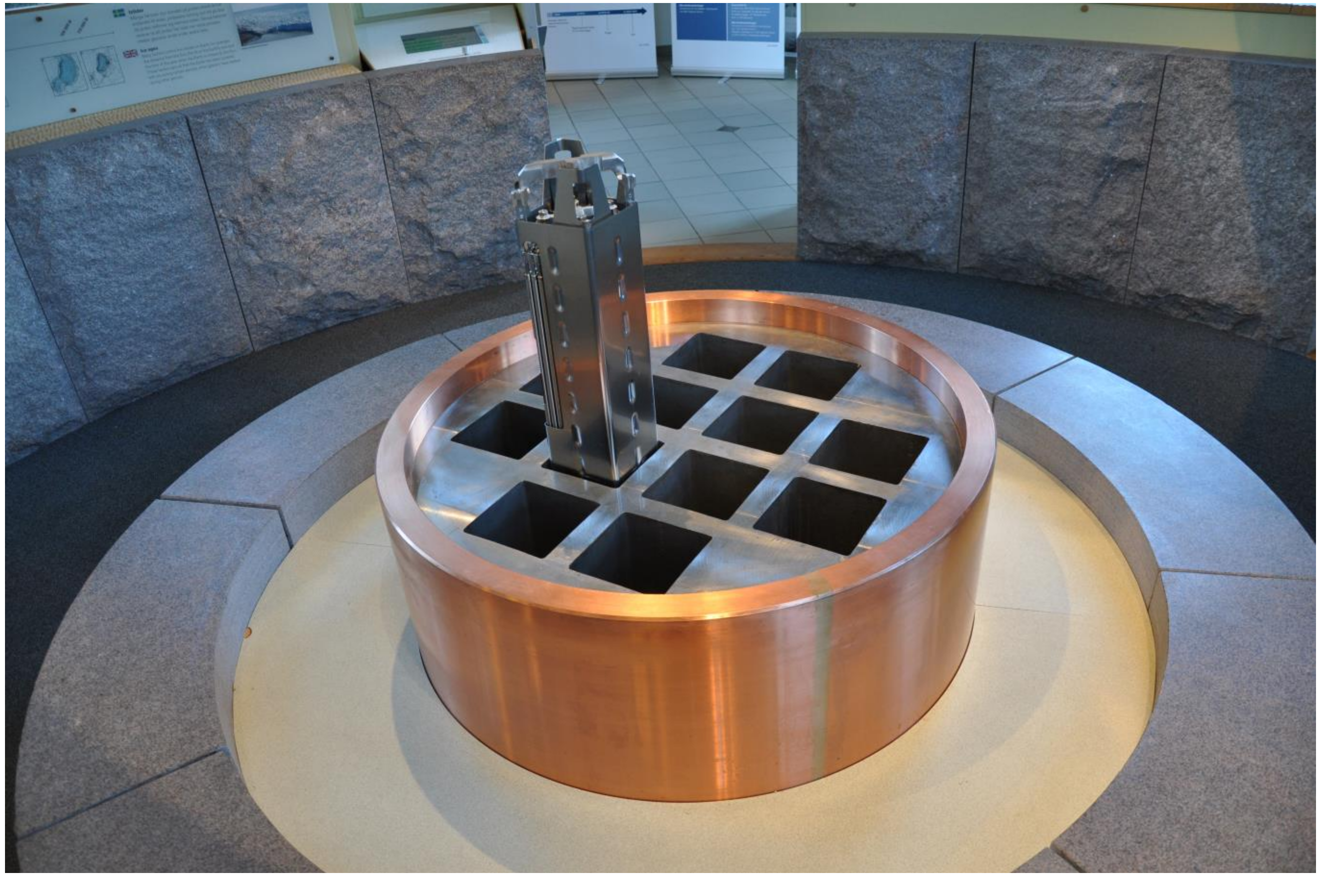
PREDICTION OF SAFETY PARAMETERS FOR CANISTER LOADING OPTIMIZATION

- More than 50 000 SNFs are expected for the final repository in Sweden (base scenario)
- Up to 4 PWR or 12 BWR SNFs per canister
- Need fast computation of the canister's k_{eff} to evaluate different loading combinations



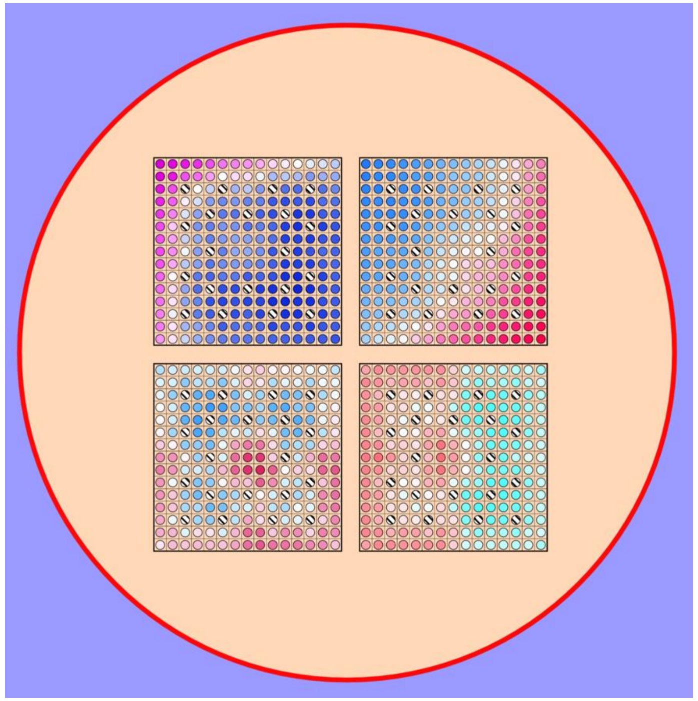
PREDICTION OF K_{EFF} FROM RADIONUCLIDE CONCENTRATION

- **Canister k_{eff} is calculated using Serpent (Monte-Carlo code)**
- **~1h calculation per canister using Serpent**

- **Goal: Use ANN as a surrogate model for Serpent in the canister loading optimization algorithm**

PREDICTION OF K$_{EFF}$ FROM RADIONUCLIDE CONCENTRATION

- **Model:**
  - Input: Nuclide concentrations per pin for each SNF
  - Output: Canister k_{eff}
- **Data:**
  - 212 different PWR SNFs
  - 46 746 canisters filled with 4 SNFs (randomly loaded)



$k_{eff} = 0.95533$

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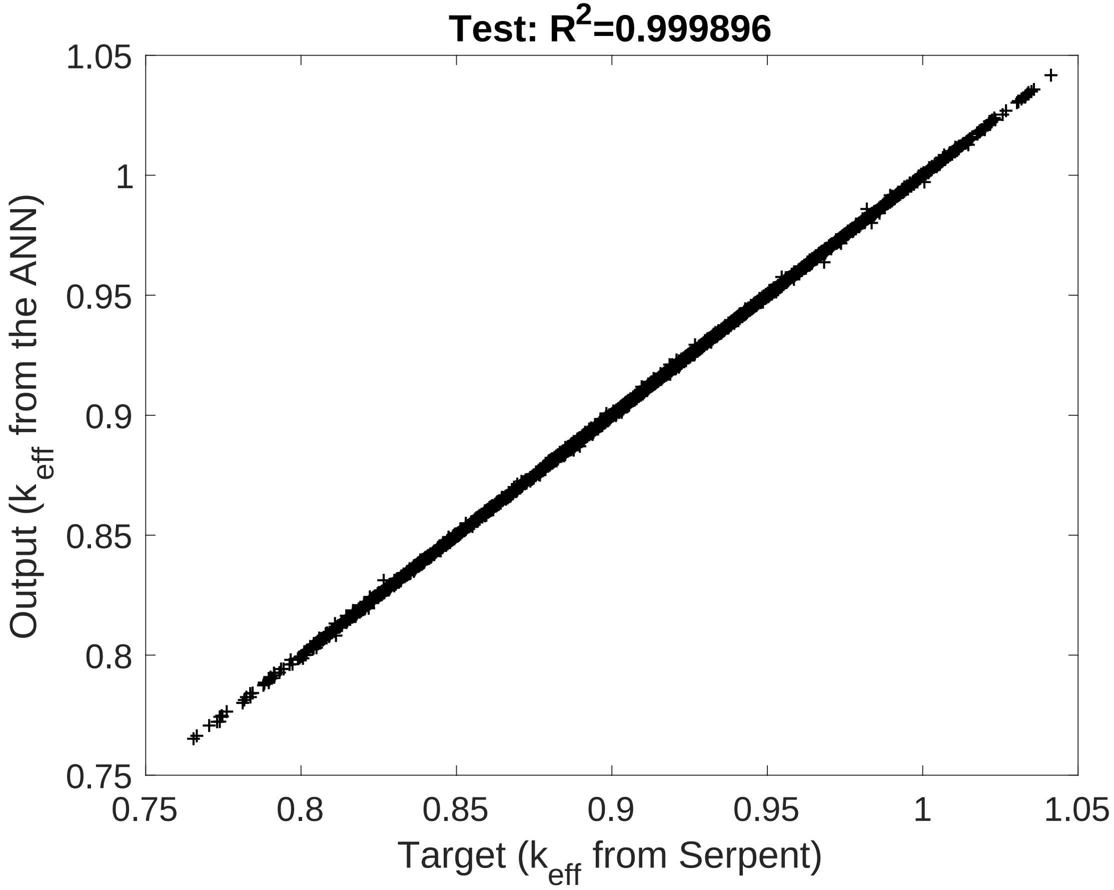
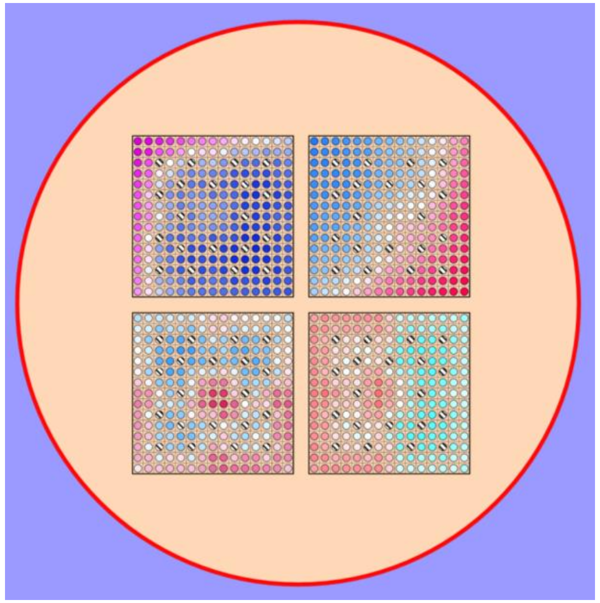
PREDICTION OF K_{EFF} FROM RADIONUCLIDE CONCENTRATION

- **Results (ANN-Serpent):**
  - Std= 55 ± 2 pcm,
  - Mean= 0 ± 1 pcm
  - Uncertainty from Serpent is 20 pcm



PREDICTION OF K_{EFF} FROM RADIONUCLIDE CONCENTRATION

- **It allows to calculate the canister k_{eff} with various combinations, including the same SNFs but with different axial rotations**



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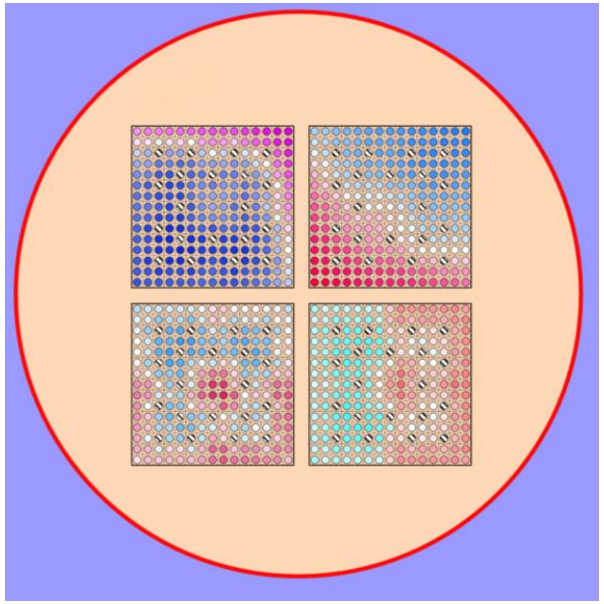


k_{eff} = 0.94803

WHY ARE WE USING AN ANN?

K_{eff} and DH can be calculated by state-of-the-art codes such as SIMULATE/Serpent. So why it is interesting to use an ANN?

WHY ARE WE USING AN ANN?

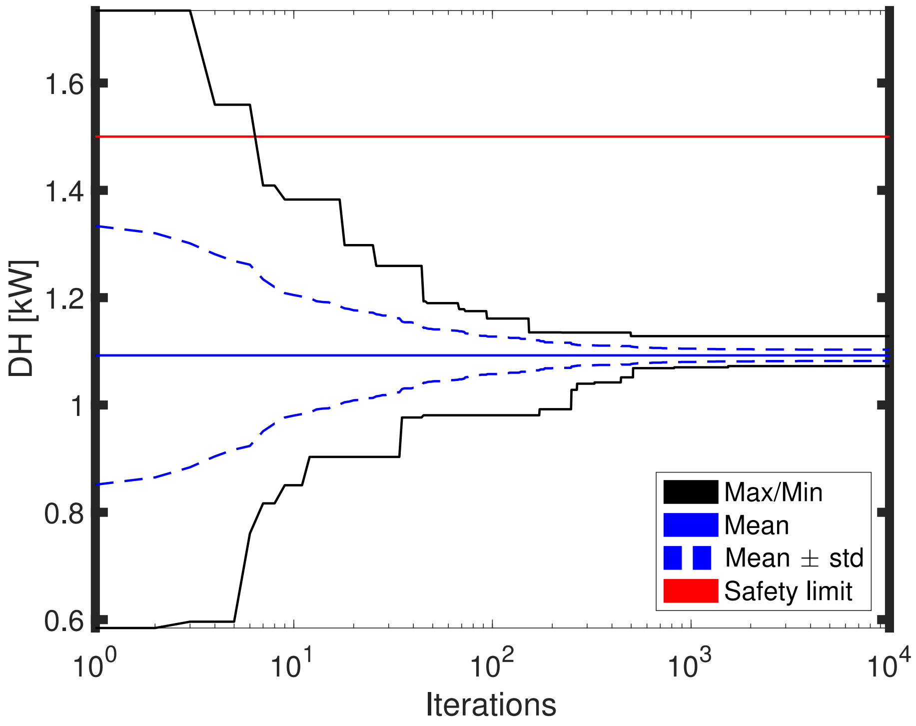
K_{eff} and DH can be calculated by state-of-the-art codes such as SIMULATE/Serpent. So why it is interesting to use an ANN?

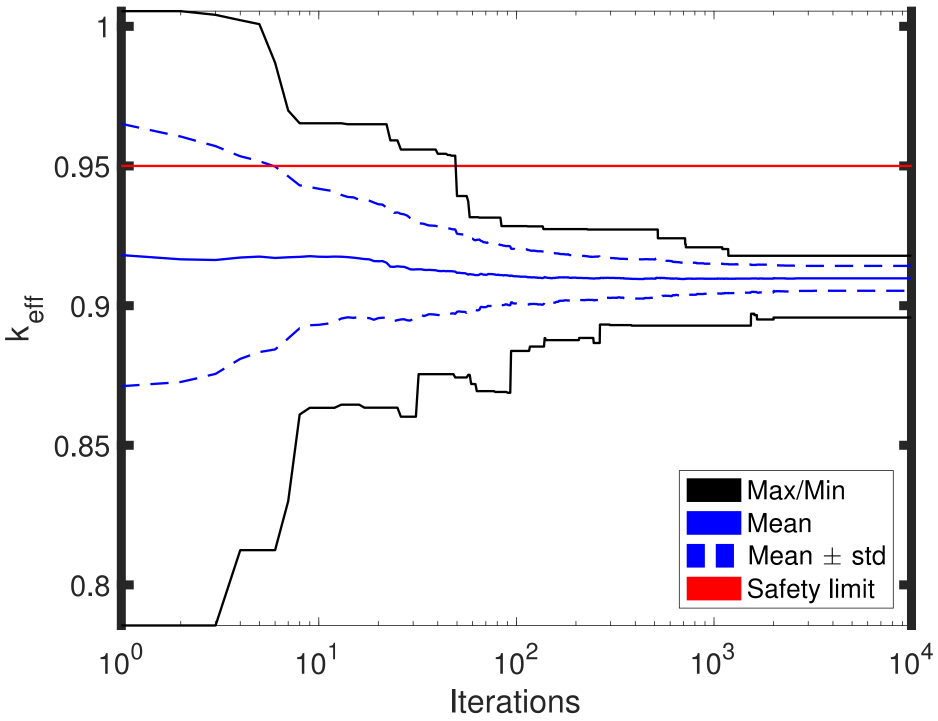
It can be useful when fast estimation is needed, for instance for canister optimization

CANISTER LOADING OPTIMIZATION

- **Canister loading optimization using a genetic algorithm (ML but not ANN)**
  - Axial rotation of SNFs to minimize k_{eff} is included
- **Find an optimized loading for 212 PWR assemblies into the 53 canisters**
  - k_{eff} computed with the neural network
  - DH of each SNF is known
- **Goals:**
  - Minimize the maximum k_{eff} and DH
  - Homogeneous distributions for k_{eff} and DH

CANISTER LOADING OPTIMIZATION





Validation with Serpent: Mean difference is 30 pcm.

Minimum number of canisters reached (53 canisters)

CANISTER LOADING OPTIMIZATION

- **Simple test with only 212 PWR assemblies**
  - The algorithm has 10^4 iterations, where the k_{eff} and DH need to be calculated for each of the 53 canisters.
- **There is a need to calculate the k_{eff} of the canister in a fast way.**

- **In particular it becomes interesting when different scenarios, (therefore different) canister loading optimization is needed**
  - Reference scenario of the country
  - Increase life time of the NPPs
  - Mixed canister are allowed or not (MOX with UO_2, old and newly discharged SNFs, bended SNFs)
  - With SMRs SNFs

PREDICTION OF SAFETY PARAMETERS FOR CANISTER LOADING OPTIMIZATION

- PART 1: Use ANN to predict k_{eff} from radionuclide concentration (for canister optimization strategies)

- PART 2: Use ANN to prediction decay heat from experimental measurements (for SNF verification)

PREDICTION DECAY HEAT FROM EXPERIMENTAL MEASUREMENTS

Each SNF needs to be experimentally measured before final encapsulation and disposal to be in agreement with international regulations.

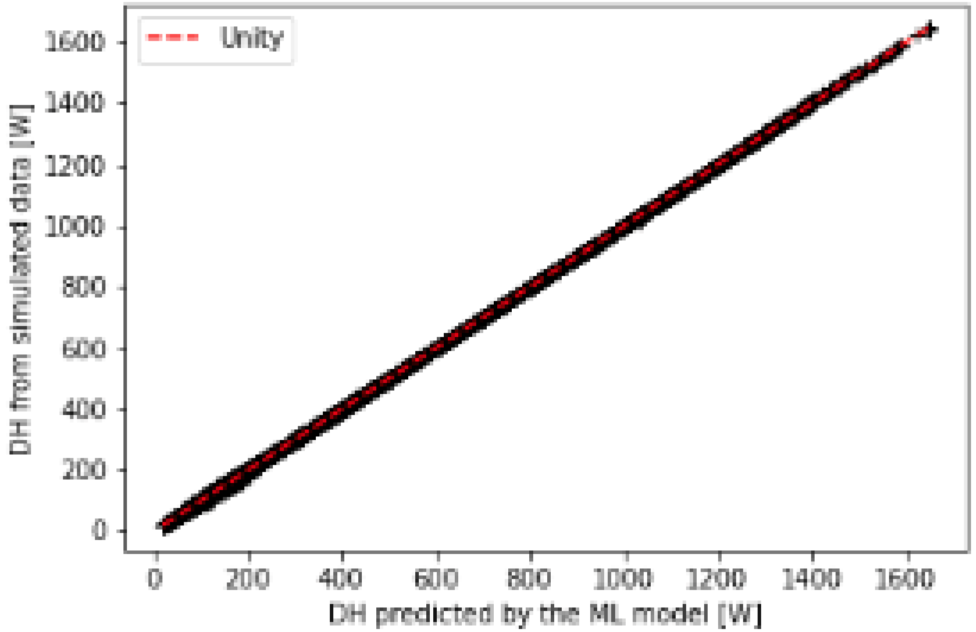
Decay heat can be obtained via calorimetric measurements

Model:

- Input: gamma and neutron measurements
- Output: Decay heat of the SNF

RESULTS

- **Train on simulated data**
  - Why? More data, good coverage
- **Tested on simulated and experimental data using a calibrated model**



	Relative error [%]
Simulated test set	1.2
SKB-50	3.7

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WHY ARE WE USING AN ANN ?

- No direct equation between gamma and neutron measurements to the decay heat.

- The simulated library is used to map the space and ML is used to interpolate between simulated points that have been obtained using Serpent.

- Can easily be extended for more inputs that will represents the different detectors used at encapsulation.

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SYNTHESIS: ANN PROS, CONS, AND FORWARD VISIONS

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ADVANTAGES

- Capability to handle large datasets (IAEA)
- Ability to learn complex patterns from data
- Adaptability to various data types (security camera, neutron/gamma measurements)
- Potential for automation and optimization

CHALLENGES

- Need for large amount of data
- Results depend on the quality of the training data
- Cannot extrapolate
- The model doesn't know physics (data-driven)

IN THE FUTURE?

- **Nuclear waste management is a very long process over several decades, and the technology around it will also evolve.**

- **Have you heard about Chat-GPT? How it is related to ANN?**
  - It is a language model where you can ask questions. (Warning: the model can give inaccurate information)
  - GPT (Generative Pre-trained Transformer), Transformer Neural network (part of the deep learning)

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CHAT-GPT 4

V

What is the decay heat limit at encapsulation in Switzerland?

Finished browsing

The decay heat limit at encapsulation in Switzerland has been mentioned as 1.5 kW in a study, although it's noted that this limit could change based on various engineered barriers involved in the process[1].

CHAT-GPT 4

V

What is the decay heat limit at encapsulation in Switzerland?

Finished browsing

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Nuclear Engineering and Design
Volume 370, 15 December 2020, 110897

Loading optimization for Swiss used nuclear fuel assemblies into final disposal canisters

V. Solans [a b], D. Rochman [b], H. Ferroukhi [b], A. Vasiliev [b], A. Pautz [a b]

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IN THE FUTURE?

Must think about:

- **How research articles/ waste management organisation reports and websites are integrated in the training of these AI models?**
- **How to make our research work readable/found by AI?**

CONCLUSION

- **ANN and ML in general, can make predictions or combine different information.**

- **Can be used for a large range of applications.**

- **ANN usually requires large amount of data.**

- **Use of AI will most probably increase in our daily life in the future, as well as in nuclear waste management.**

Image generated by V.Solans with DALL-E 3

Thank you for listening