International Workshop on Embedded Artificial Intelligence Devices, Systems, and Industrial Applications (EAI)

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International Workshop on Embedded Artificial Intelligence Devices, Systems, and Industrial Applications (EAI)

ANDANTE

AI ECSEL JU

AI4DI

TEMPO

Food Ingredients Recognition Through Multi-label Learning

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ESSCIRC

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Presentation Outline

- Introduction
- Background
- Research Goal — Focus
- Design and Implementation
- Experimental Results
- Conclusions & Future Work

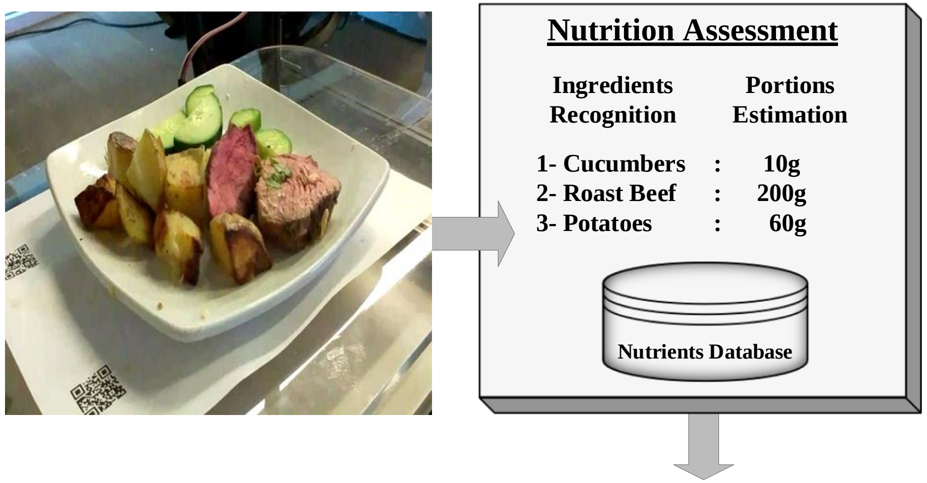
Introduction

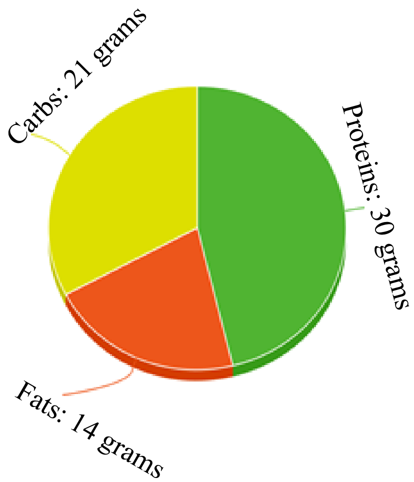
Automated Food Ingredient Recognition

1) Visual recognition of the food-items
2) Estimation of portion sizes
3) Database lookup service

Multi-Label Deep Learning

A deep neural network is trained to predict the presence of a multitude of ingredients or food-items. Generally, the final read-out layer consists of a fixed number of neurons, each representing a unique class label.





Nutrition Facts

Serving Size		270 g
Amount Per Serving		
Calories		**329**
		% Daily Values
Total Fat	13.69g	**18%**
Saturated Fat	4.036g	**20%**
Trans Fat	-	
Polyunsatrated Fat	1.118g	
Monounsatrated Fat	6.985g	
Cholestrol	73mg	**24%**
Sodium	483mg	**21%**
Total Carohydrate	21.22g	**8%**
Dietary Fiber	2.g	**9%**
Sugars	3.19g	
Protien	29.84g	

Background

Why Automated Diet Assessment?

Empowers communities to take control of their own health by providing them with insights and a precision guidance.

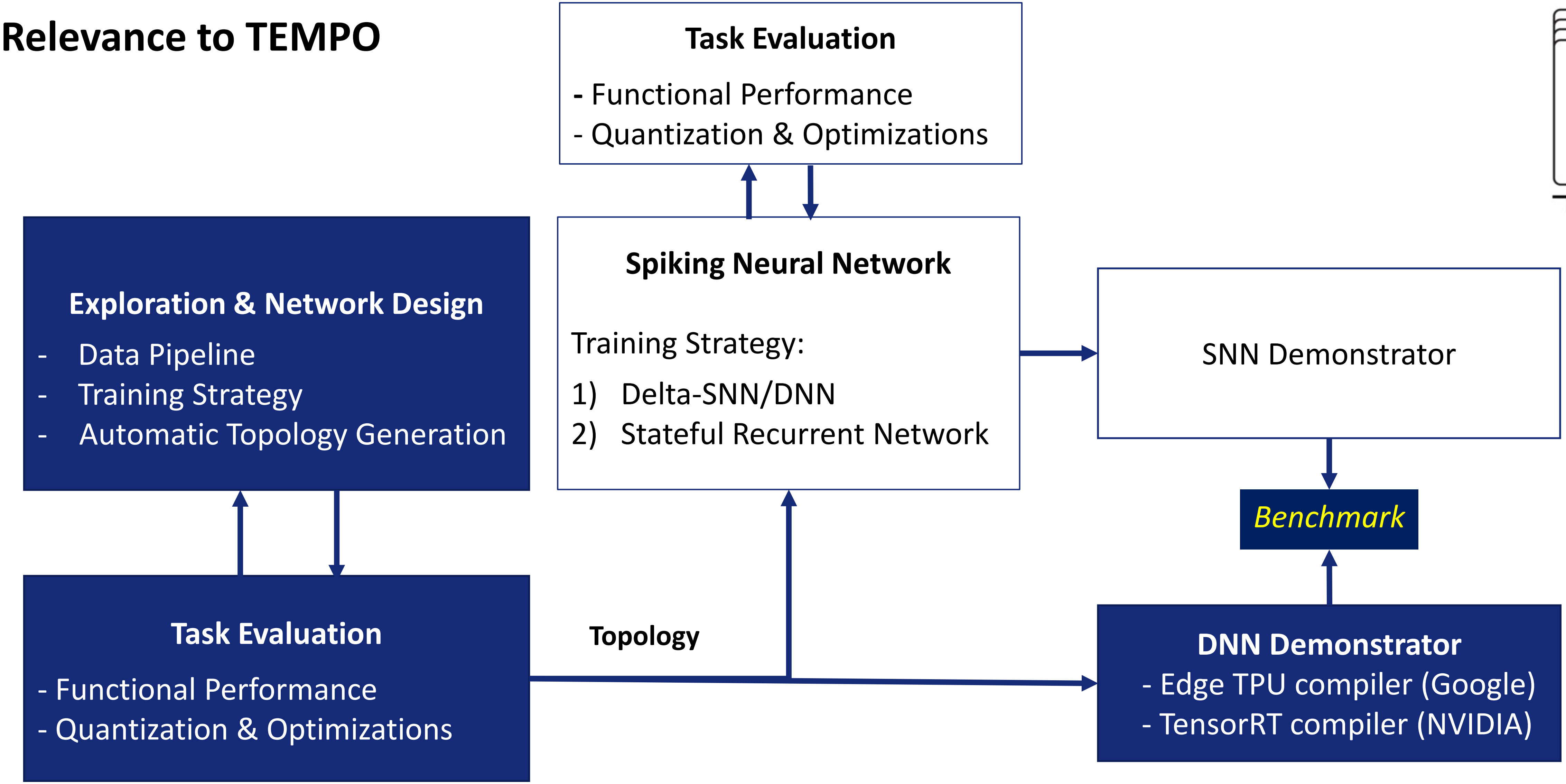
Enables better management of various nutrient-related health conditions and diseases at scale.

Besides providing an introspection ability to consumers, tracking dietary data is fundamental to understanding the diet and disease relationship.

Source: Lori Nedescu, MS RD CSSD, 'The Pros and Cons of Tracking Your Food', 2019.

Background

Relevance to TEMPO

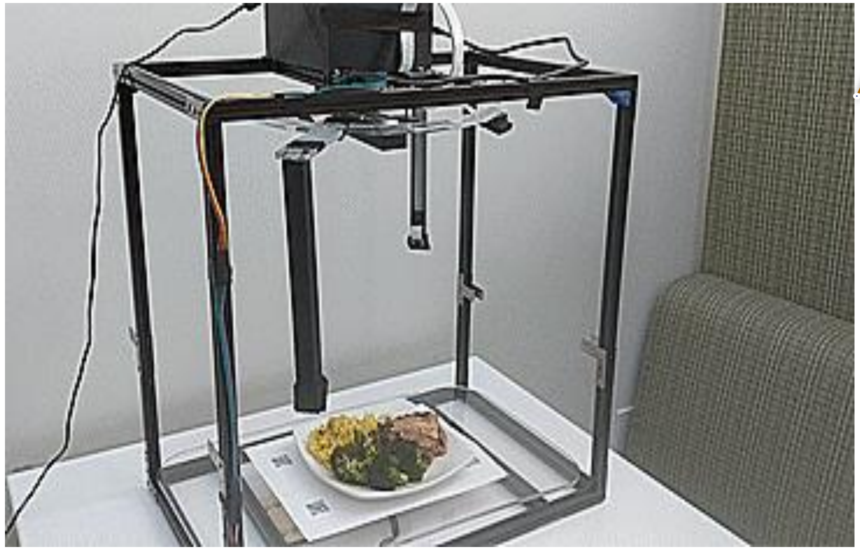


Research Goal

Focus of this Work

Evaluate state-of-the art deep learning modules for the task of ingredient recognition.

For training and evaluation, we employed `**Nutrition5k**` dataset. A dataset comprised of 5k unique dish images containing over 250 different ingredients.



Source: Thames, Quin, et al. "https://github.com/google-research-datasets/Nutrition5k. 2021.

Examples of dish images from the test dataset.

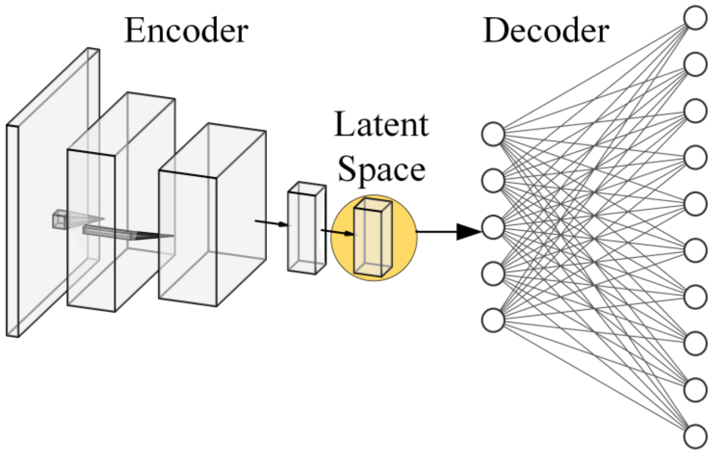
Design and Implementation

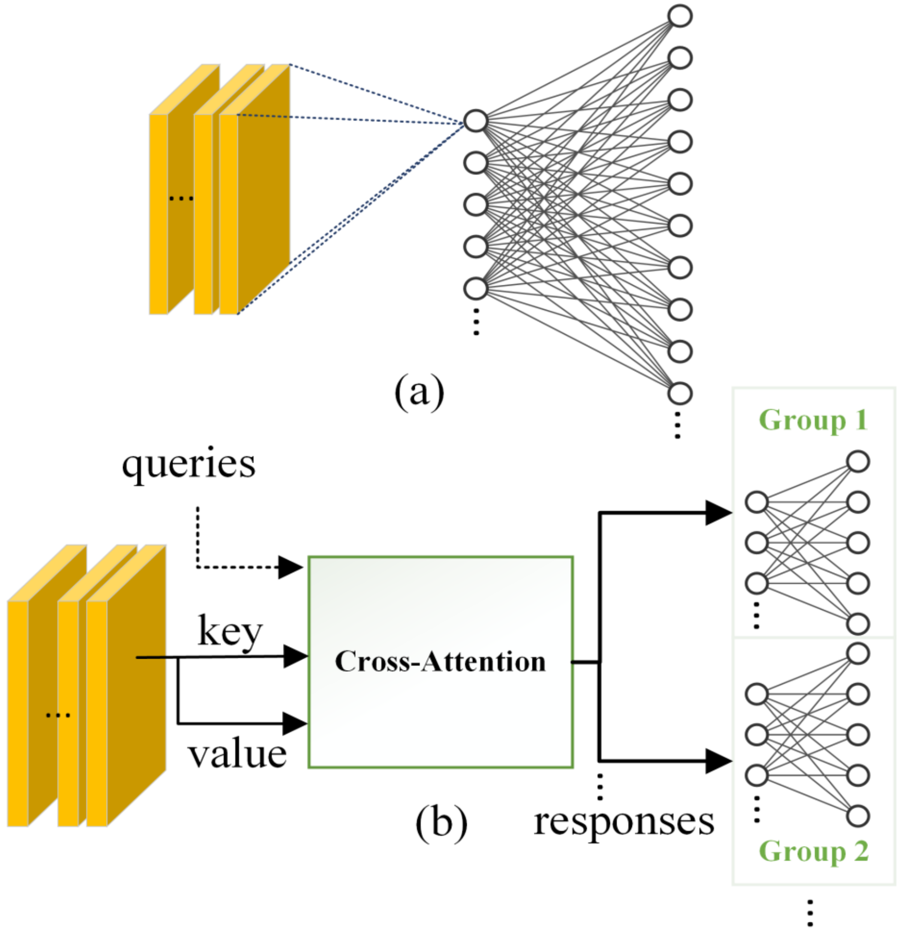
Design of Experiments and the Benchmark

All models consist of an encoder and a decoder component.

The various implementations evaluated for the encoder include, DenseNet, MobileNet, EfficientNet, Inception and Exception Network families.

Two distinct decoding schemes: global average pooling based and the other based on attention mechanism are evaluated and benchmarked.





Experimental Results

Results

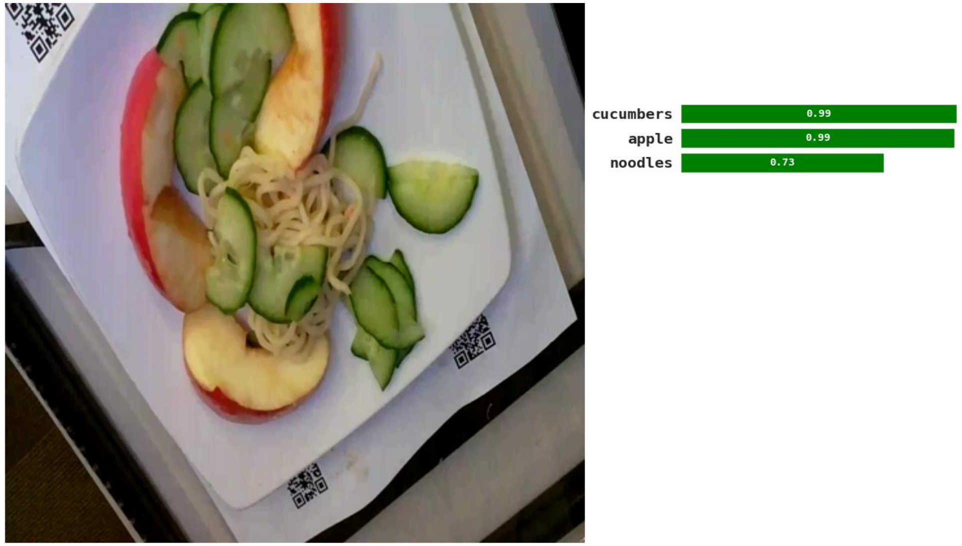
In the first set of experiments, we explored a global average pooling (GAP) based decoding, with different classification neural networks acting as the encoder.

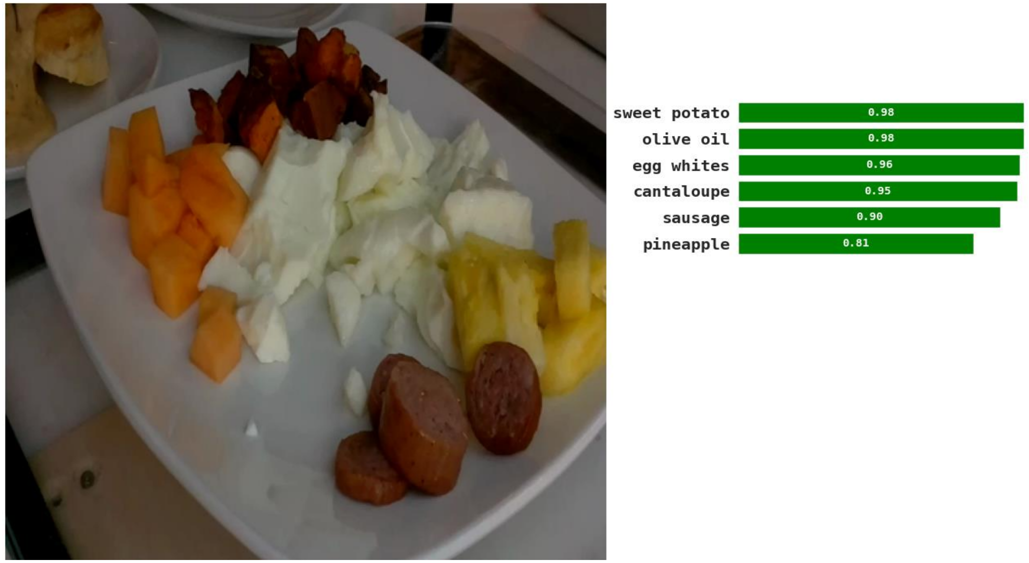
In the second set, we selected four encoders to couple with the ML-Decoder, based on their performance in the previous experiments and the compute specifications.

The GAP decoder performs best with Xception encoder reaching an accuracy of **78.4%** on the test set. The large performance differences, when using ML-decoder highlights its weakness as a drop-in replacement for GAP-based decoder.

Models		Performance	Compute	
Encoder	Decoder	mAP %	Operations (GFLOPs)	Parameters (MParams)
DenseNet121	GAP	75.6	22.6	7.6
DenseNet169		76.5	26.9	13.6
DenseNet201		74.7	34.3	19.4
MobileNetV1		72.4	4.5	3.8
MobileNetV2		74.5	**2.4**	**2.9**
EfficientNetB0		73.3	3.1	4.8
EfficientNetB1		71.9	4.6	7.3
EfficientNetB2		72.2	5.3	8.6
EfficientNetB3		71.5	7.8	11.6
EfficientNetB4		72.7	12.9	18.7
Xception		**78.4**	36.6	22.0
InceptionV3		72.8	26.4	23.0
MobileNetV2	ML-Decoder	68.0	3.4	9.3
EfficientNetB0		73.4	4.2	11.1
DenseNet169		67.9	28.0	19.9
Xception		70.0	38.0	28.5

Experimental Results





Discussion and Conclusion

A framework for automated diet assessment and encouraging results for image-based ingredient recognition using deep learning.

The current decoding schemes are unable to reliably extract the inter-label relationships. In future, we will further explore attention networks and graph neural networks that can exploit this information.

Refine the product and value proposition and pursue a Health-Suite Digital Platform offering.

Event Organisers

The Key Digital Technologies Joint Undertaking - the Public-Private Partnership for research, development and innovation – funds projects for assuring world-class expertise in these key enabling technologies, essential for Europe's competitive leadership in the era of the digital economy. KDT JU is the successor to the ECSEL JU programme. www.kdt-ju.europa.eu

ECSEL Joint Undertaking

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AI4DI

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TEMPO

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Thank You

For your attention

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