The use of AI in food safety and food fraud: early warning systems

Hans Marvin & Yamine Bouzembrak (WFSR)

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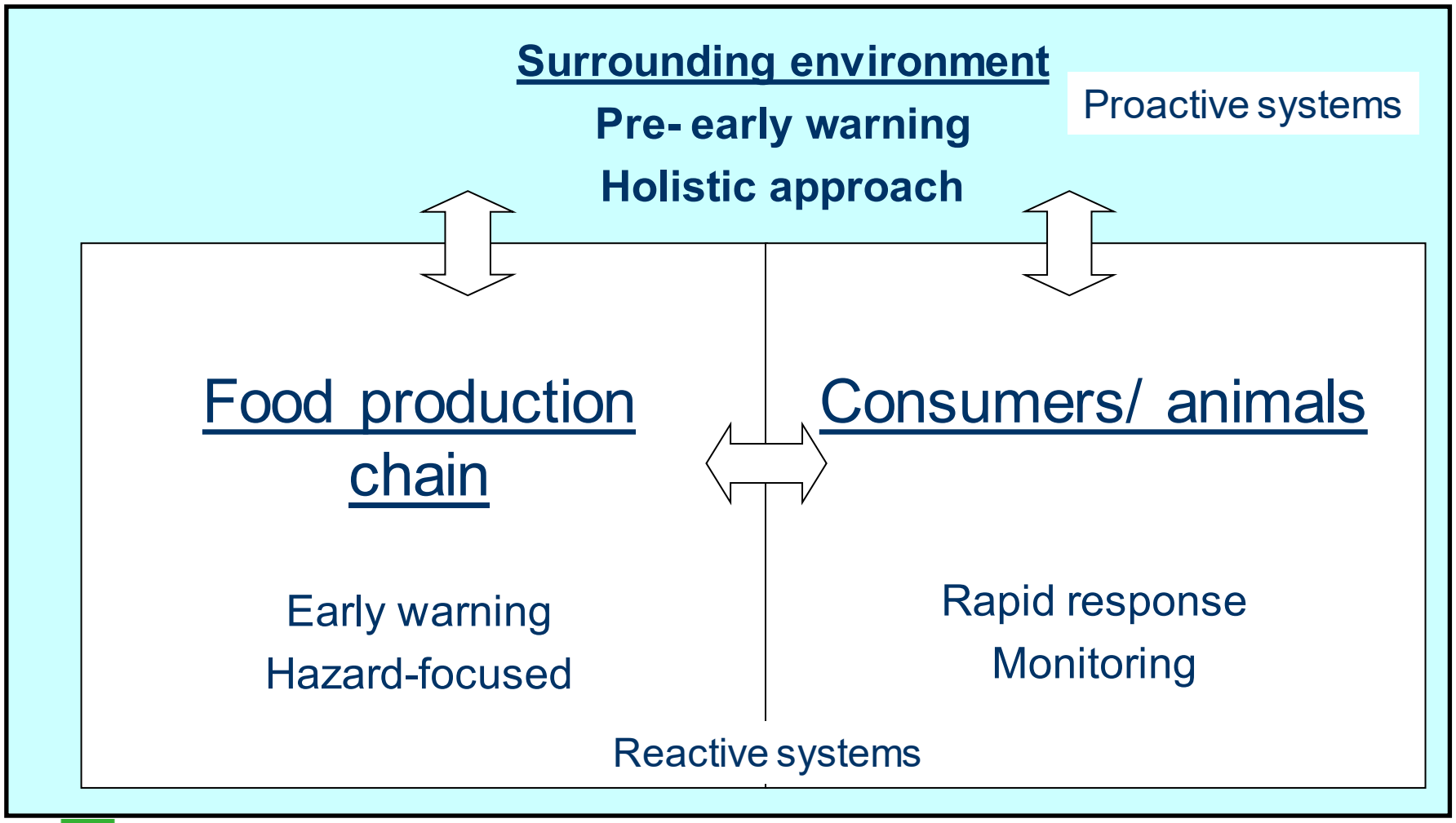
Outline

- State of the Art
  - Motivation
  - Experience (including limitations)
  - Challenges of AI
- Next Steps & Future challenges

Reactive early warning approaches not satisfactory; proactive systems needed



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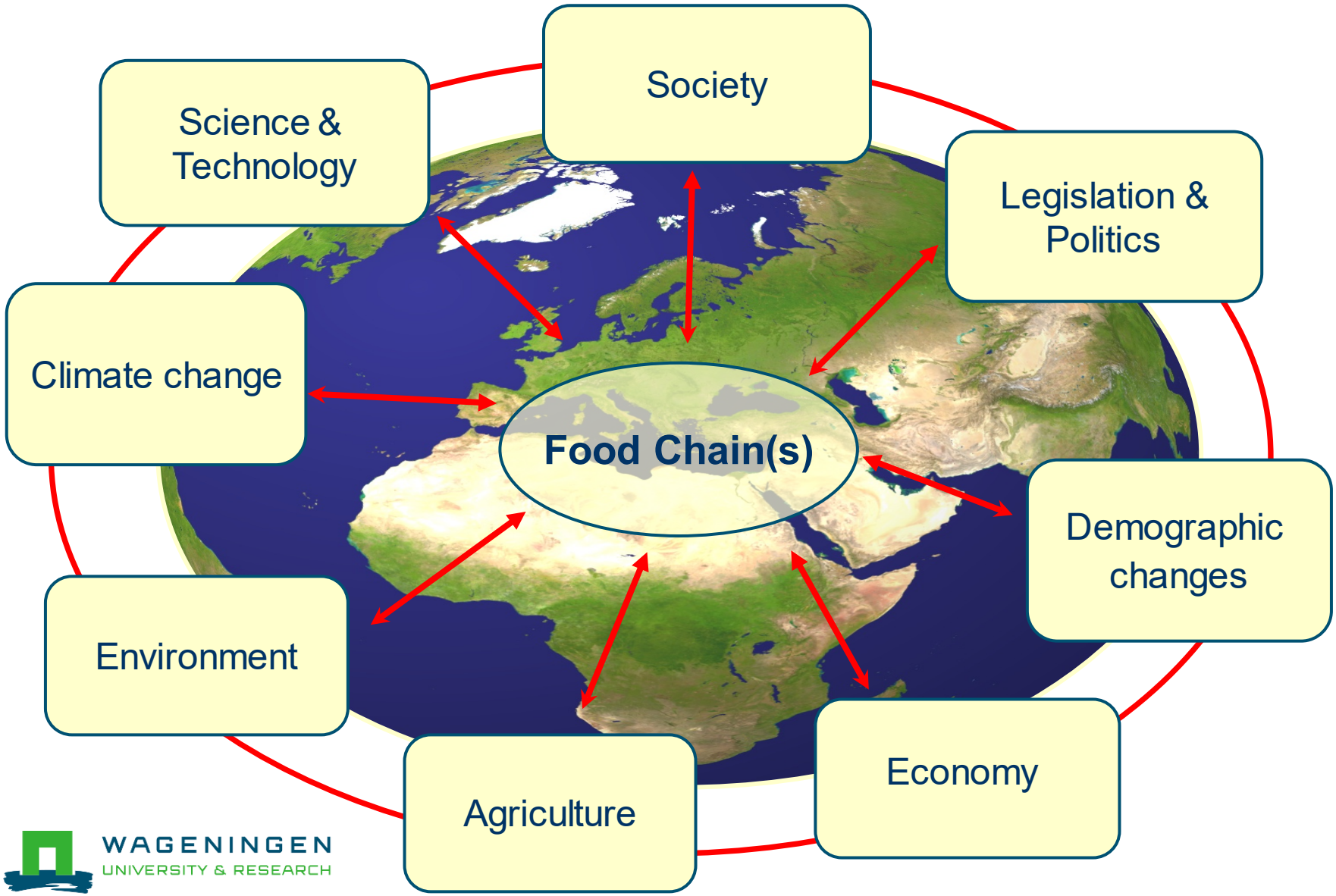
Source: Kleter & Marvin 2008

Drivers of change having direct/ indirect impact on food safety (Marvin et al 2019; https://efsa.onlinelibrary.wiley.com/doi/epdf/10.2903/sp.efsa.2019.EN-1619)



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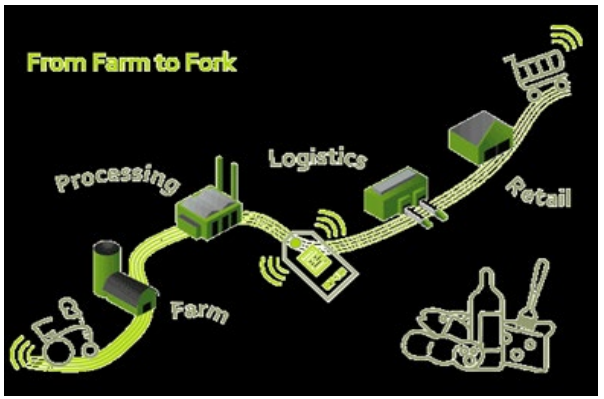
Potential system approach

Data of drivers

Expert knowledge



Chain analysis

Method needed that can:

- integrate expert knowledge and data,
- handle huge amount of data and knowledge gaps,
- use a variety of data sources of divers nature.

Bayesian Networks?

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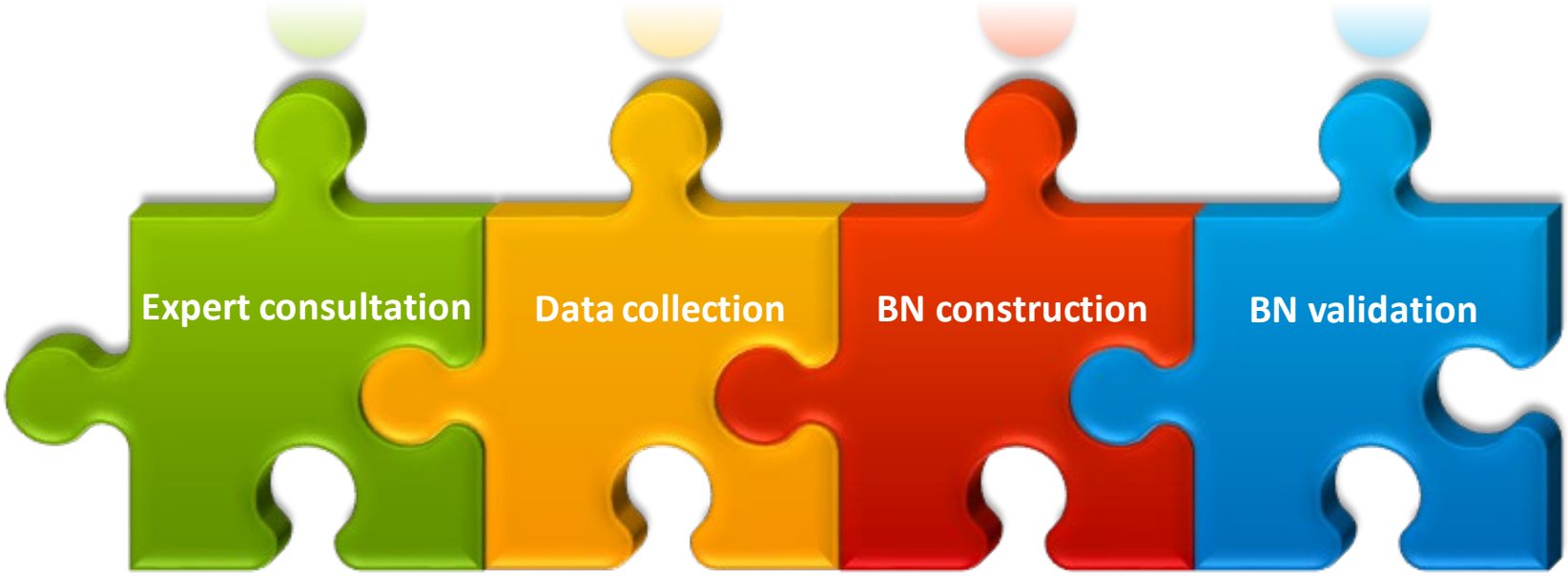
Bayesian Network (BN) approach

Steps in the development



Data sources used in the BN model

Linking 36 factors (18 data sources and 8 expert judgements)

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BN modelling applied in many cases

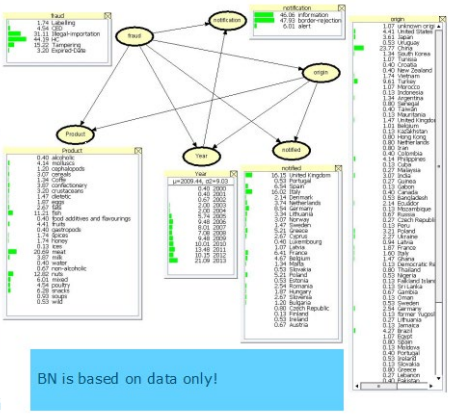
Example 2: Prediction of food fraud type as reported in RASFF

Model developed with RASFF data up to 2013

Model validated with RASFF data of 2014

Model performance:
- 82% correct prediction of fraud type
- 51% prediction of new fraud combinations
- static

Higher performance with dynamic model approach



BN is based on data only!

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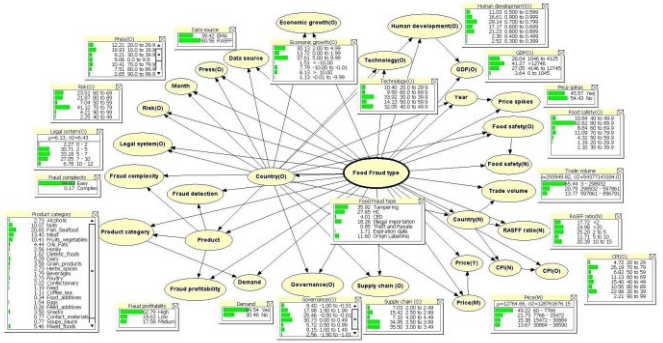
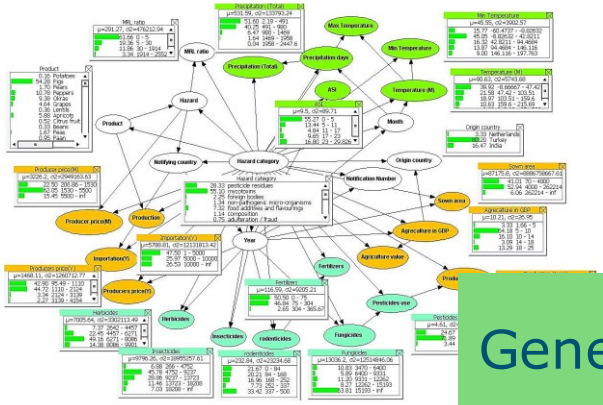
BN model for food fraud type



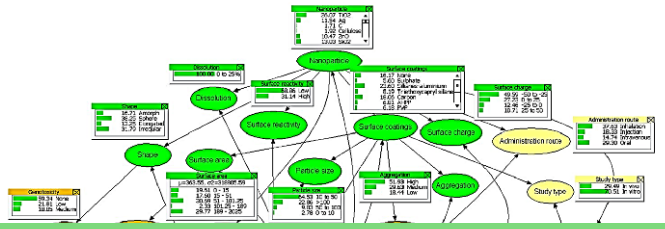
FOOD INTEGRITY

BN model for fruits & vegetables



Model performance: Prediction of the hazard type is 50%

BN model for hazard prediction of NM hazard



Generally the prediction accuracy > 90%

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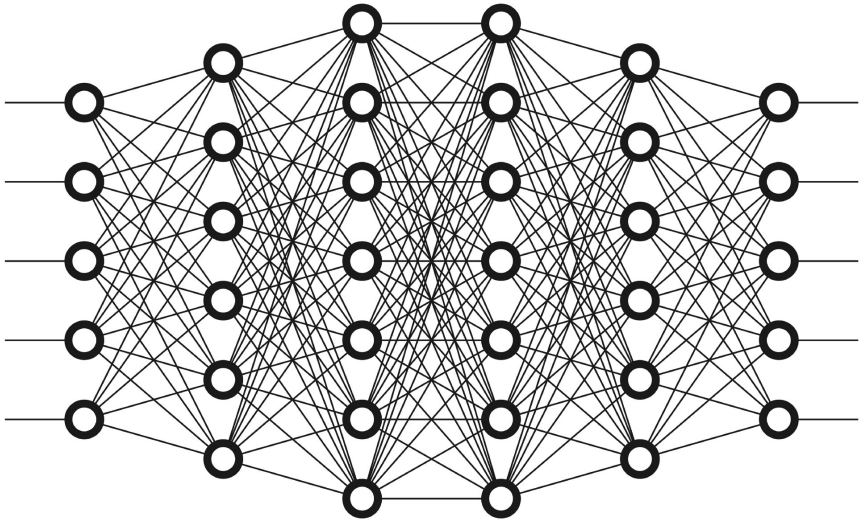
Machine learning

In our studies we compared the prediction accuracy of BN to other (>20) machine learning algorithms:

1. Neural network
2. Logistic regression
3. Support vector machines
4. Random forest
5. Ensemble classifiers



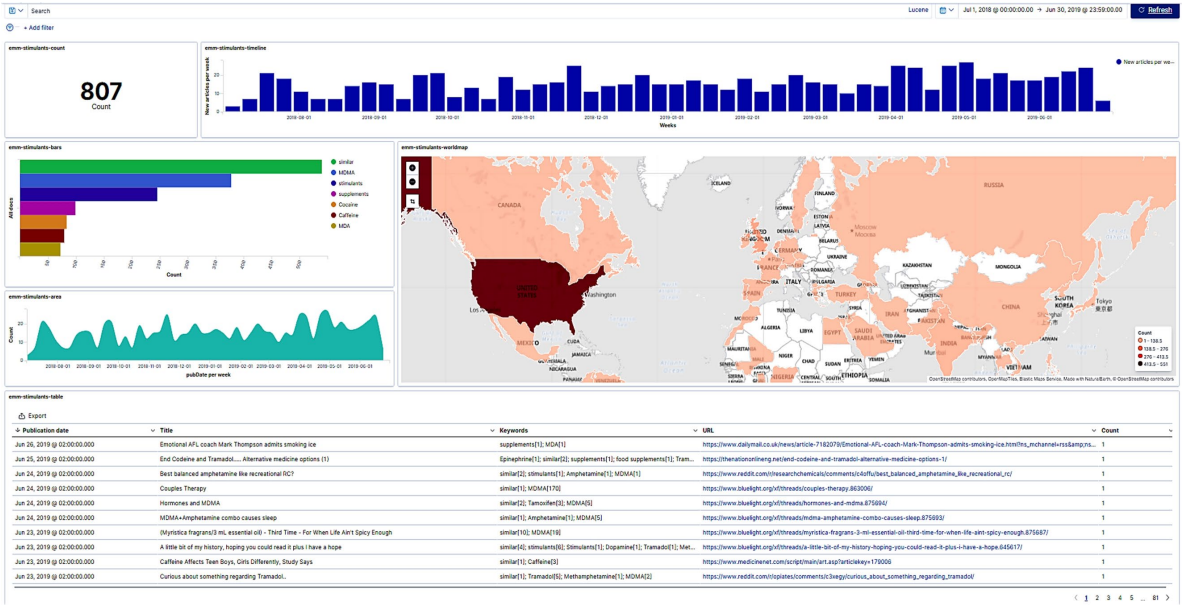
Prediction accuracy of BN was often superior in classification problems

Other AI approaches developed for early warning of food safety and food fraud

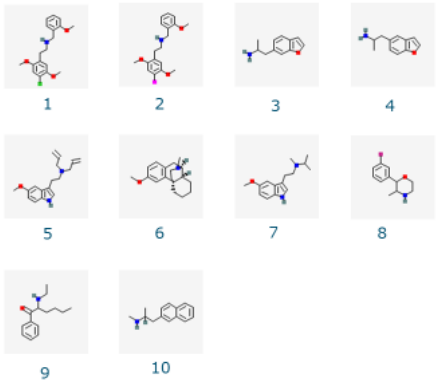
- Detecting food safety & food fraud trends from media (text mining, network analysis)
- Searching *unknown* food safety hazards in scientific literature (word embedding)
- Predicting food safety from satellite images and mobile pictures (deep learning)
- Automate data collection processing, analysis & visualization

Example: media & blogs using European Media Monitor (EMM); early warning & emerging risk

Collection, processing & visualization of media reports from EMM (food fraud, food supplements, various food safety topics)



Detected 10 "unknown" compounds used as stimulant in food supplements



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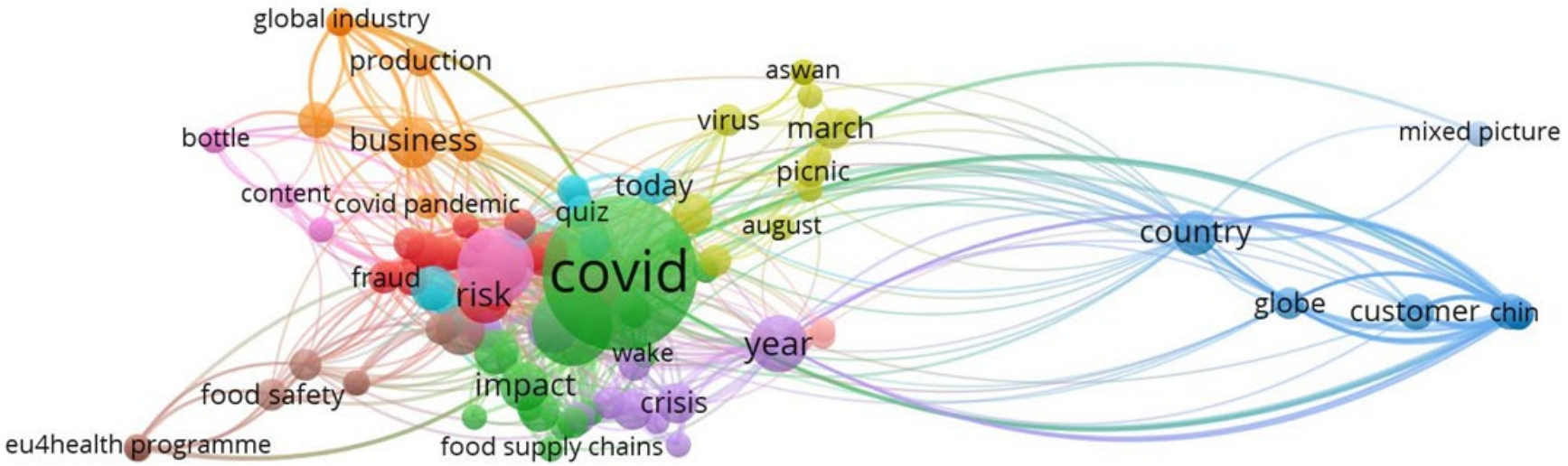
New trends and unsafe products (food supplements) detected

Example: Network visualisation; early warning

Food fraud publications in the media collected by the WFSR MedISys-FF filter also mentioning COVID



COVID-19 is expected to drive food fraud and food safety risks (meat and alcohol)

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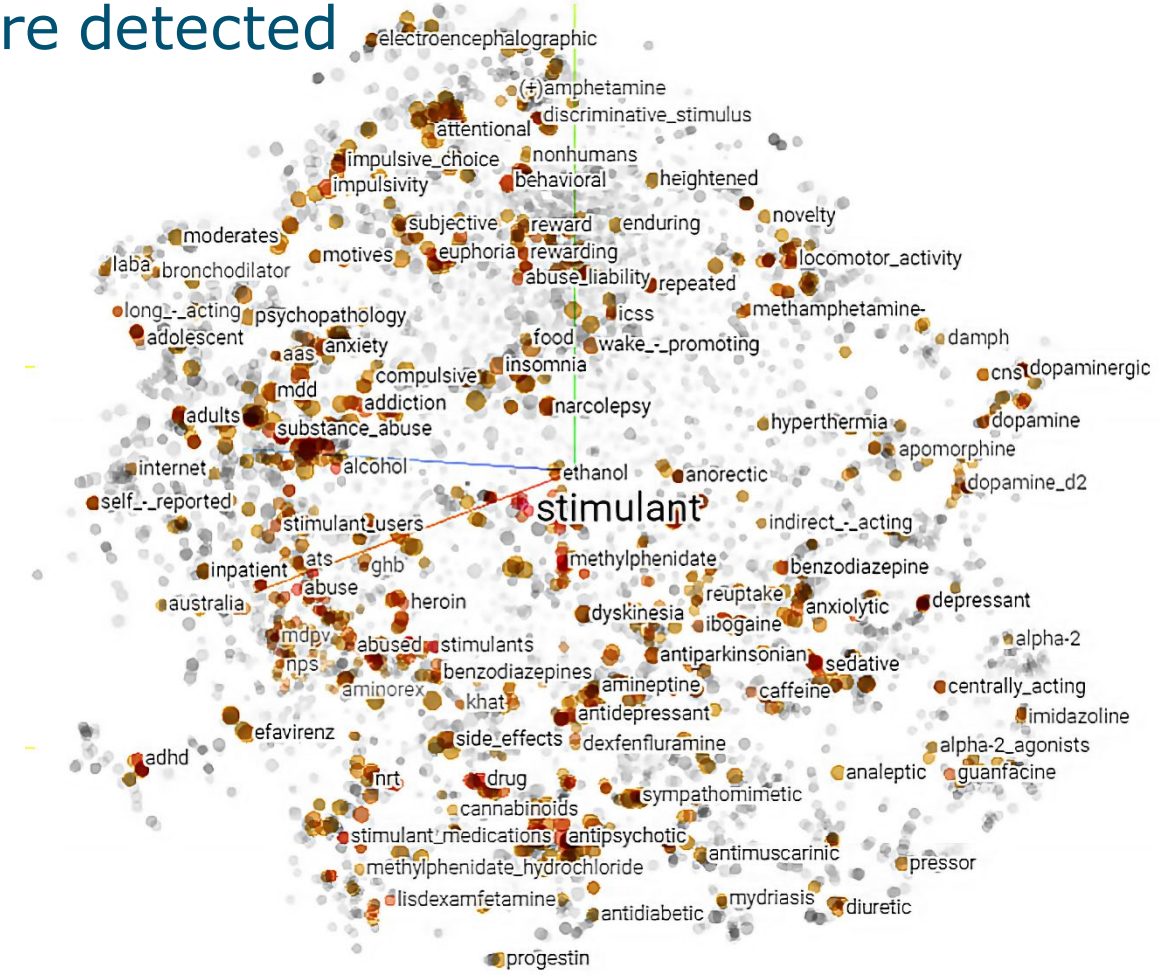
Example: Word embedding with scientific literature; emerging risk

Analyzing > 2 million abstracts and titles, 10 "unknown" stimulants were detected



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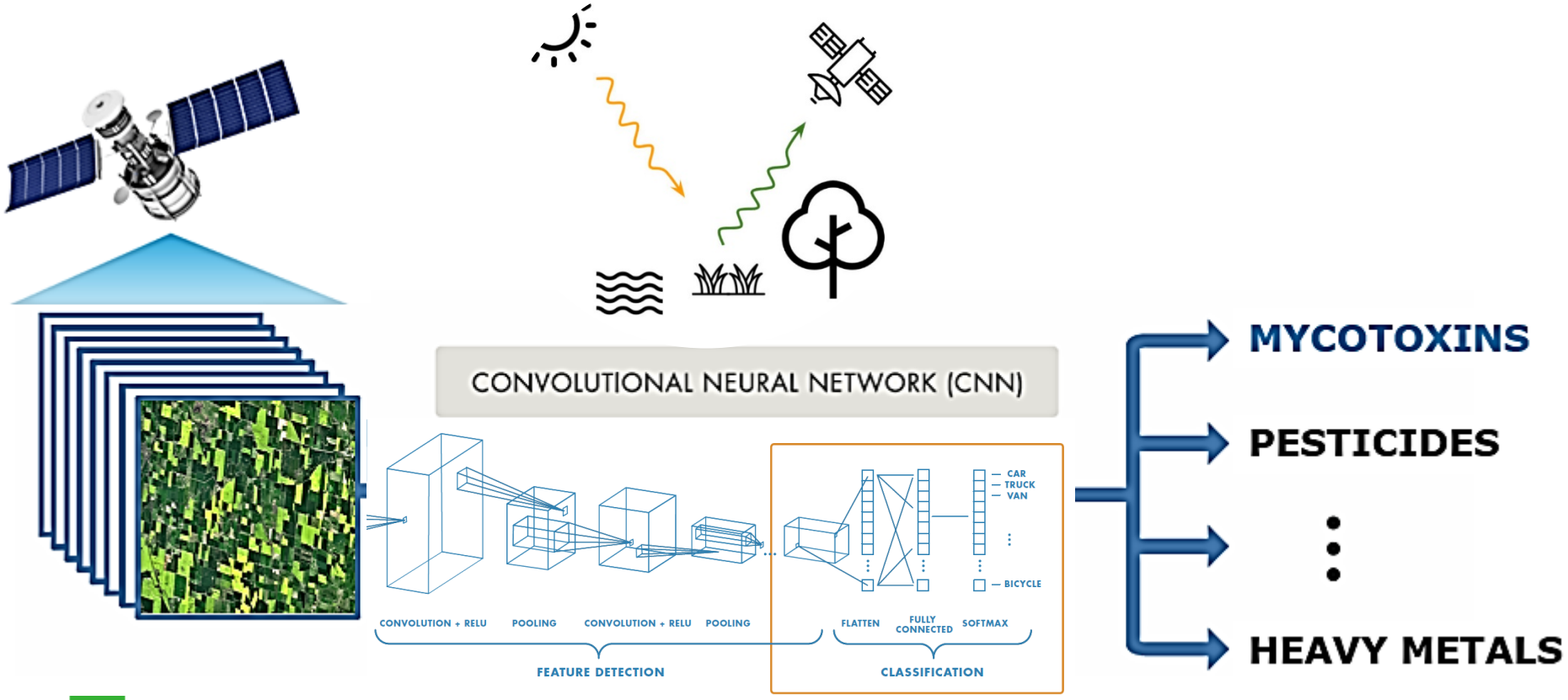
Example: AI (deep learning) to predict food safety in grass & maize using satellite images (Sentinel-2); early warning

Efficiency of models: up to 62 % of individual hazards



Deep leaning to detect food safety hazards using mobile phone images

- Deep leaning to detect melamine in milk powder using mobile phone images

Milk powder polluted with melamine:
- 0 mg/kg melamine
- 1 mg/kg melamine
- 50 mg/kg melamine

Take pictures with a Samsung Galaxy A8 smartphone

DEEP LEARNING

- 0 mg/kg
- 1 mg/kg
- 50 mg/kg

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Example: detection of abnormalities in drivers, prediction of hazards in milk and automatic alerts; early warning & emerging risk

Develop workflows in KNIME to automatically collected & process data from identified data sources to show abnormalities and to predict hazards in milk in the Netherlands

eurostat

Food and Agriculture Organization of the United Nations

.....

elasticsearch

GitLab

mongoDB

Acquiring data

Cleaning data
- Filtering by countries
- Filtering by time
- Deleting cells of 'no information available'
- Structuring data in table

Checking updates and saving data
- Compared with previous record, checking if the database has been updated
- Yes, store the latest updated data and operate abnormality detection;
- No, break

Detecting abnormality and sending alerts
- Automatic reporting
- Automatic alert
- Saving results

Bayesian Network to predict hazards in milk
- Run the BN when there is anomalies

Visualization in KIBANA

Cloud Infrastructure
HPC

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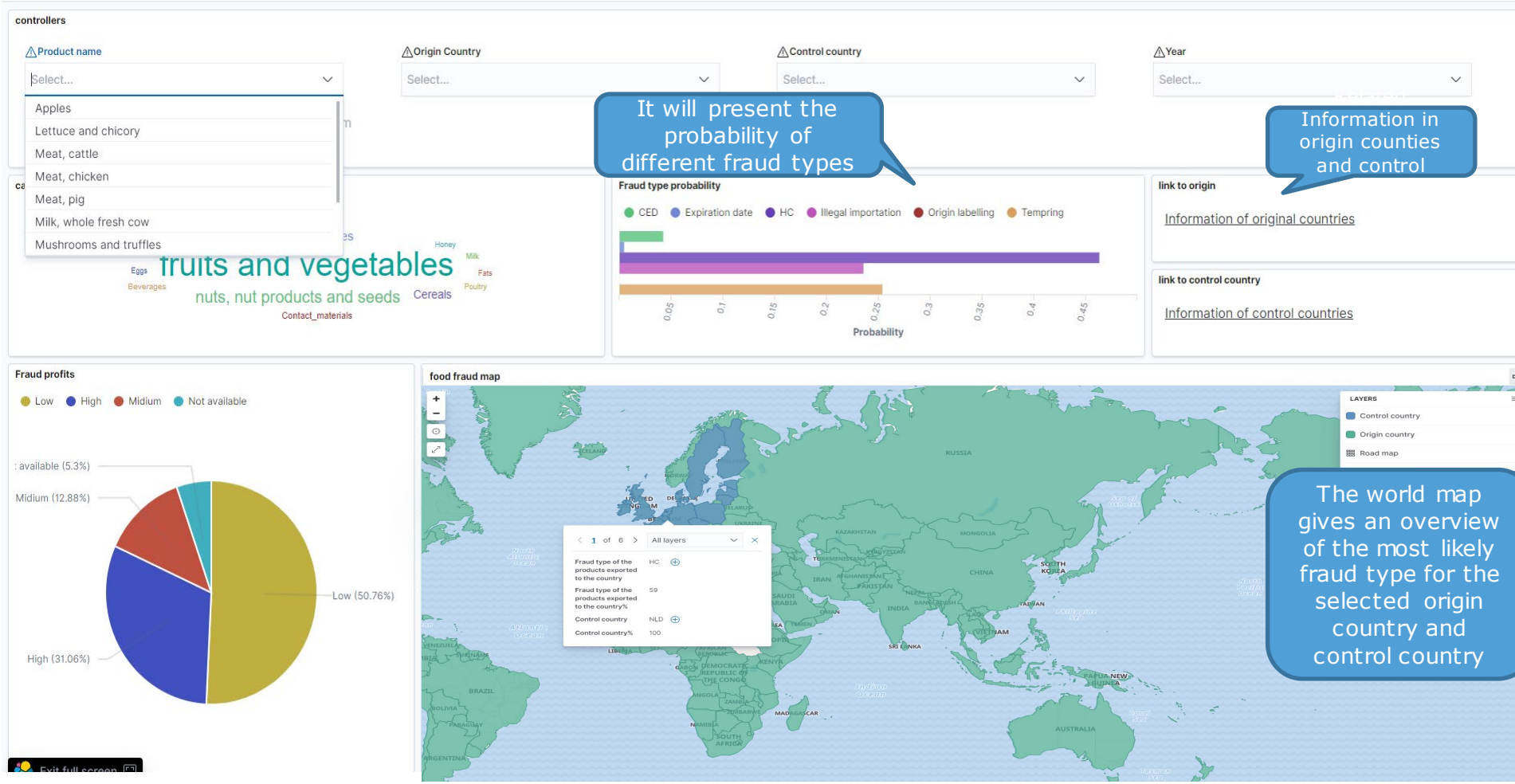
Workflows of drivers and BN prediction results visualised in Dashboard



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Limitations (food safety/ food fraud domain)

- AI developments occur in other domains
- Slow uptake of technologies by authorities (lack of AI skills)
    - Lack of trained personnel => more education (secondary school, university)
- FAIR principle not well established
    - Embed FAIR principle in legal framework
- Communication on AI to society must be improved
    - Explainable AI
- Sharing data by stakeholders remains a big challenge
    - Federate learning a solution? (FAIR data train concept)

Next steps: Federate learning a solution?

Design FDT Data Station

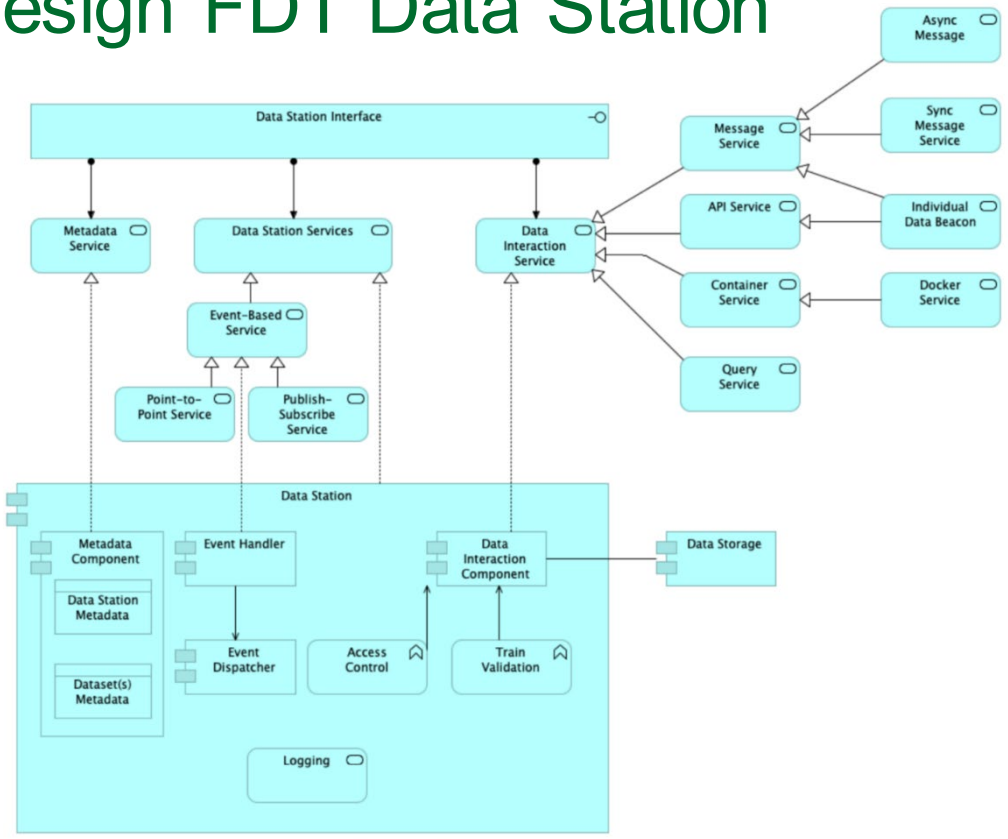
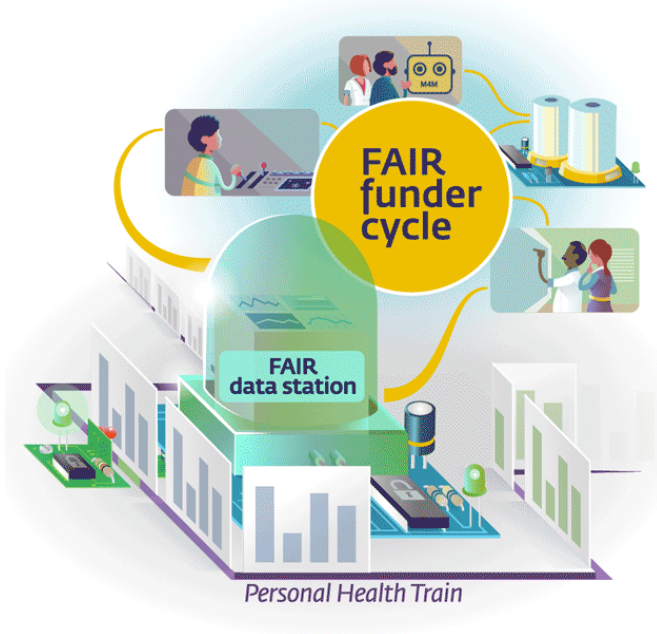


Figure 2 - Data Station

Source: Farm Data Train Blueprint.
Luiz Bonino, 2018



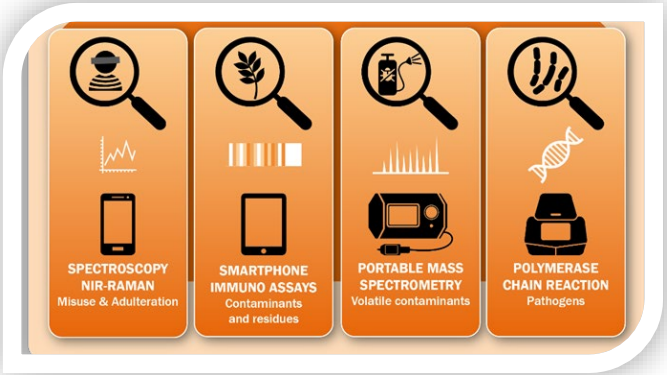
Next steps: AI integrated in hazard detection and assessment

Broad screening => AI to process large data streams

Internet of things (IoT)

Onsite, online analysis

Hand held devices



Fast processing technologies

Data e-infrastructures

Thank you

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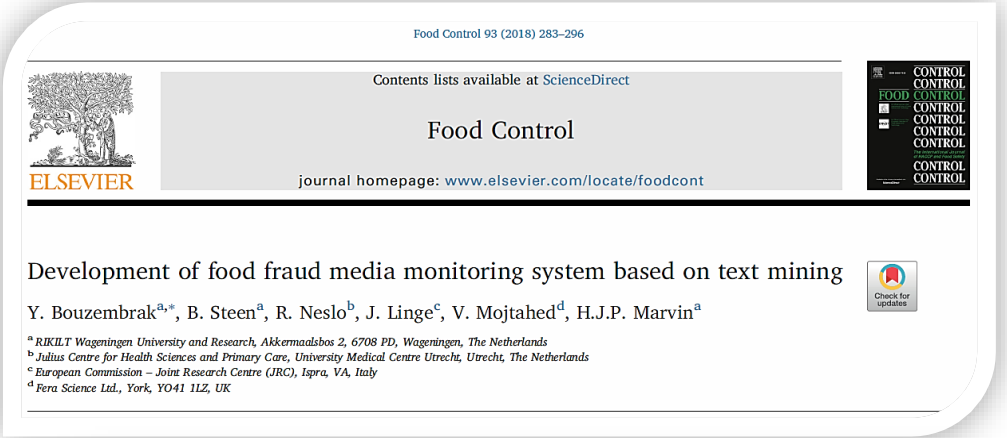
www.wur.eu/bigdata-foodsafety

References:



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Development of food fraud media monitoring system based on text mining

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A holistic approach to food safety risks: Food fraud as an example

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END

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