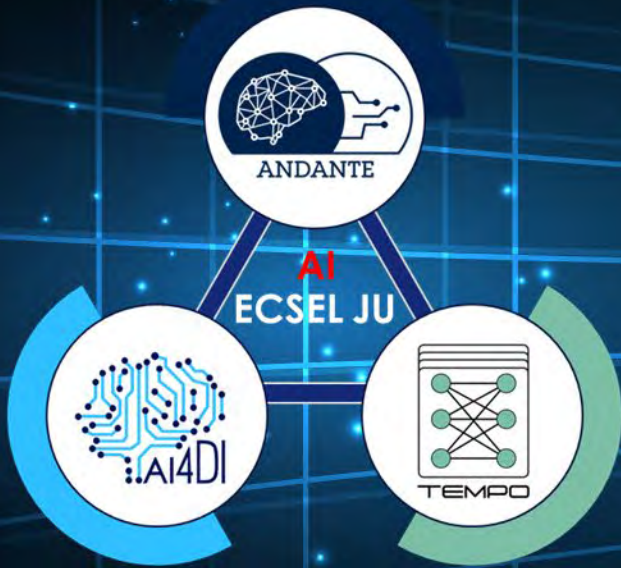
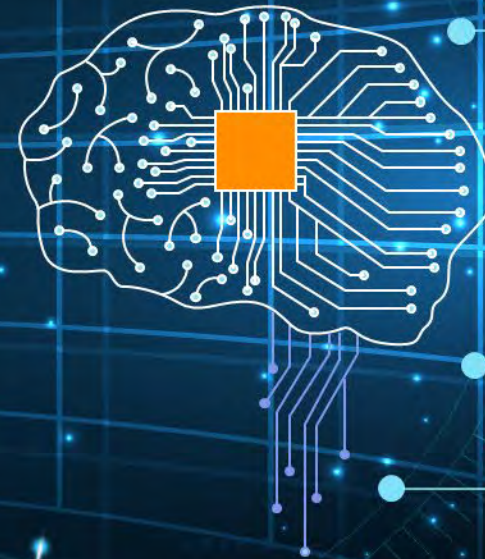


The International Workshop on Edge Artificial Intelligence for Industrial Applications (EAI4IA)

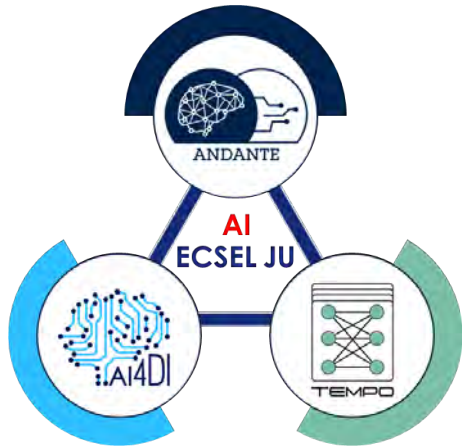


AI



Vienna, Austria
25-26 July 2022

The International Workshop on Edge Artificial Intelligence for Industrial Applications (EAI4IA)



AI-Driven Strategies to Implement a Grapevine Downy Mildew Warning System

**Lucas Mohimont, University of Reims,
France**

Vienna, Austria 25-26 July 2022

Presentation Outline



- Background
- Existing approaches
- Why using AI?
- Objectives and Experiment Description
- Results
 - 1st infection alert
 - 2nd infection alert
- Discussion and Future Works

Grape Vine Diseases

- Loss in grape yield and/or wine quality
- Common diseases include:



Black rot



Downy Mildew



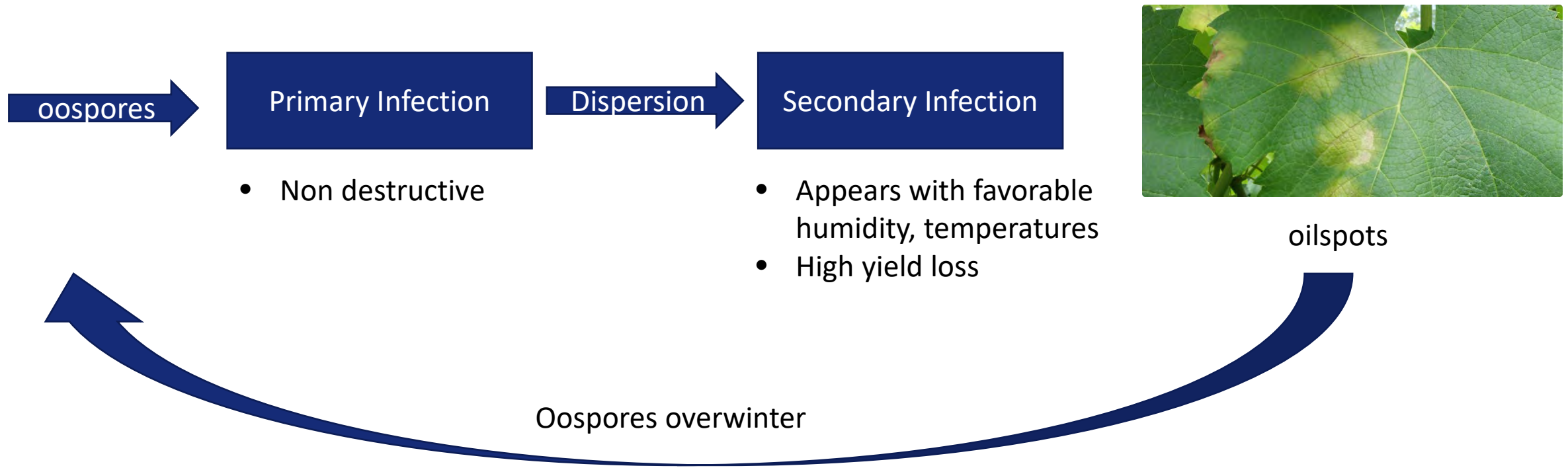
Powdery Mildew



Grey mold

Identifying Downy Mildew Infection

- Downy Mildew incubation cycle described in 1936
- Simplified representation of the cycle:



Why using AI for Down Mildew detection?

- The main goals:
 - Limiting the yield/quality loss
 - Managing the amount of intrants(pesticides)
- Existing mechanistic models use static rules based on weather conditions
- AI could solve many limitations of these models
 - Adaptation to different parcels and varieties
 - Processing of more variables
 - Generating precise warning with local sensors and on-site analysis (edge)

Objectives and Methodology

- **Goals**

- Verify if AI algorithms present enough precision to concurrence "mechanical" algorithms
- Identify AI algorithms better suited to the task

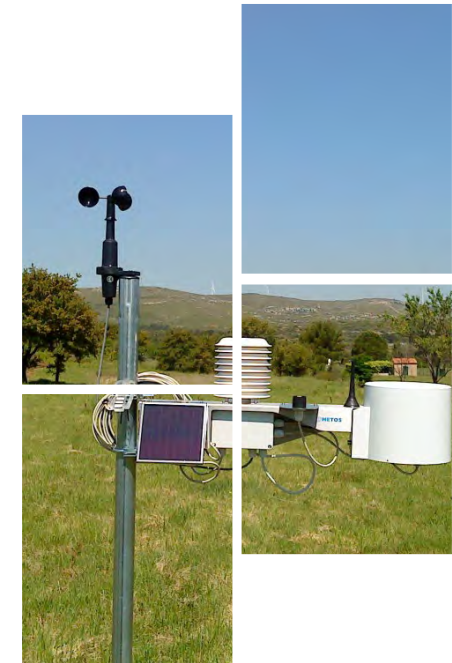
- **Methodology**

- Use a real dataset from a vineyard in Reims, France
- Label the dataset using a "mechanical" algorithm for 1st and 2nd infection alerts
- Train different machine learning algorithms for binary classification
- Cross-validation between different years



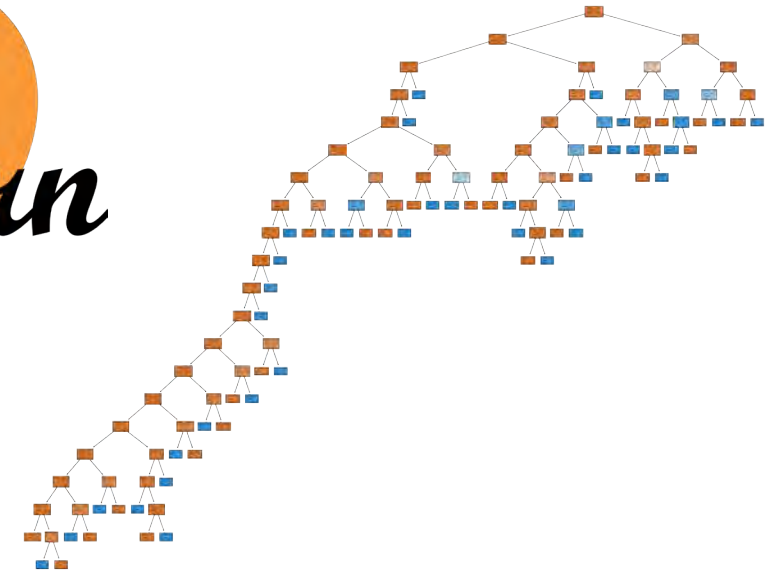
Dataset description

- Data obtained from a Promété 300 agri-meteorological station installed in a Vranken-Pommery vineyard at Reims, France
- Hourly readings from January 2019 to December 2021
- Available sensor variables :
 - **Wind speed** [Km/h] (max, **average**)
 - Wind gust [Km/h] (max)
 - **Relative humidity** [%] (max, **min**, average)
 - **Pluviometry** [l/m²]
 - **Leaf wetting duration** [min] (only available from 2019 to 2020)
 - Dew point [C] (min, average)
 - **Solar radiation** [W/m²] (average) -> **used to determine "nighttime"**
 - **Air temperature** [C] (max, **min**, average)
 - Vapor press deficit [kPa] (min, average)
- Total of 16 variables
- **Binary labels are generated with mechanistic models for primary and secondary infections (True or False).**



ML Algorithms Compared in this Work

- Input data: 16 features x 48 hourly readings (768)
- Models are trained twice for primary and secondary infections
- Decision Trees
- Random Forest (1000 iterators)
- Support Vector Machine (SVM)
- Feed Forward Neural Network (7 layers, relu)
- Convolutional Neural Networks(CNN)
 - 2 conv2D layers, dropout, relu activation
 - 2 fully connected layers



Example of decision tree for 2020 data

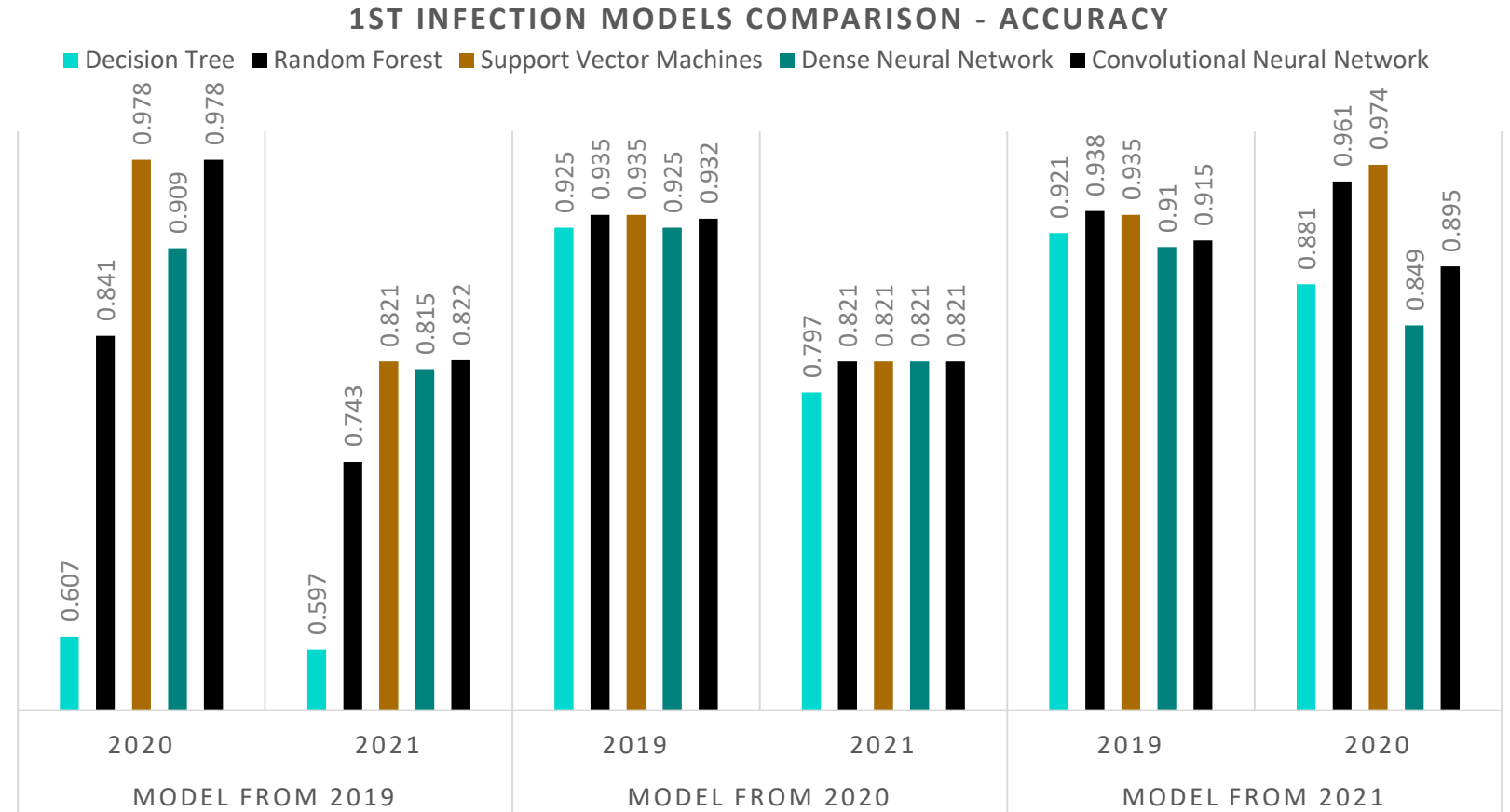


Training the models

- Generating several models
 - For each algorithm, a different model was generated for each year
 - 2019, 2020 and 2021 for 1st infection alerts
 - 2019 and 2020 for 2nd infection alerts (lack of data from 2021)
 - A 90/10 split between training/testing was used as alerts are not frequent
- Having different models for each year allows
 - To foresee specific conditions from each year (e.g. 2021 was a wet year)
 - To check the model's robustness via cross-validation

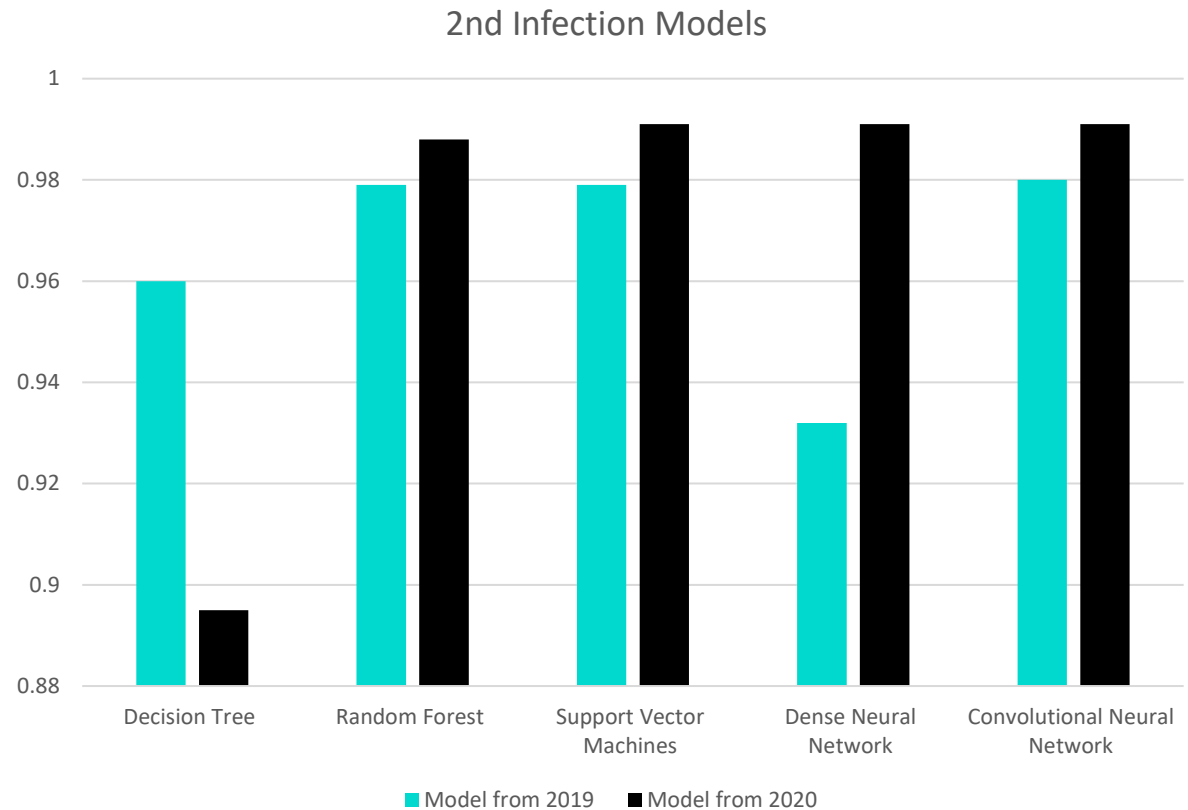
Some Results: 1st infection alerts

- 2021 was a "weird" year due to excessive wetness
 - Hard to predict with other models
 - Robust to detect 1st infections on other years
- SVM and CNN show good performances in most cases



Some Results: 2nd infection alerts

- Only two years available due to leaf wetness sensor failure
 - Cross-validation between 2019 and 2020 models
- High accuracy for RF, SVM and CNN, especially from the model trained with 2020 data

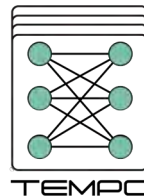


Discussion and Future works

- This preliminary work only compares machine learning models with the synthetic output of a known "mechanical" algorithm
 - Good performances ($\gg 90\%$ accuracy) to reproduce the labeled results
- Future works include
 - Evaluation against real infections identified on the vineyards
 - Training models with subsets of the data variables
 - Search for important or alternative variables not considered in traditional works
- Algorithm deployment at the deep-Edge
 - Explore the capabilities of STM32
 - SVM and CNN are both supported
 - Several agricultural sensors have been deployed in Reims as part of the AI4DI project



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

The AI4DI project has received funding from the ECSEL Joint Undertaking (JU) under grant agreement No 826060. The JU receives support from the European Union's Horizon 2020 research and innovation programme and the national authorities. www.ai4di.eu

The TEMPO project has received funding from the ECSEL Joint Undertaking (JU) under grant agreement No 826655. The JU receives support from the European Union's Horizon 2020 research and innovation programme and Belgium, France, Germany, The Netherlands, Switzerland. www.tempo-ecsel.eu

The ANDANTE project has received funding from the ECSEL Joint Undertaking (JU) under grant agreement No 876925. The JU receives support from the European Union's Horizon 2020 research and innovation programme and Belgium, France, Germany, The Netherlands, Portugal, Spain, Switzerland. www.andante-ai.eu



Thank You

For your attention

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