Leveraging Machine Learning for Early Detection and Monitoring of *Xylella fastidiosa* in Olive Cultivation: Implications for Technological Diffusion

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INTRODUCTION & AIM

Xylella fastidiosa subsp. *pauca (Xfp)* has caused significant economic losses in EU agriculture (**Figure 1**). *Xfp* triggers **olive quick decline syndrome (OQDS),** disrupting the flow of ecosystems, biodiversity, and economic stability. **OQDS** has affected **>1 M** hectares in the Mediterranean basin, causing over **€5 B in losses** since its first detection in Europe (**Figure 2**).
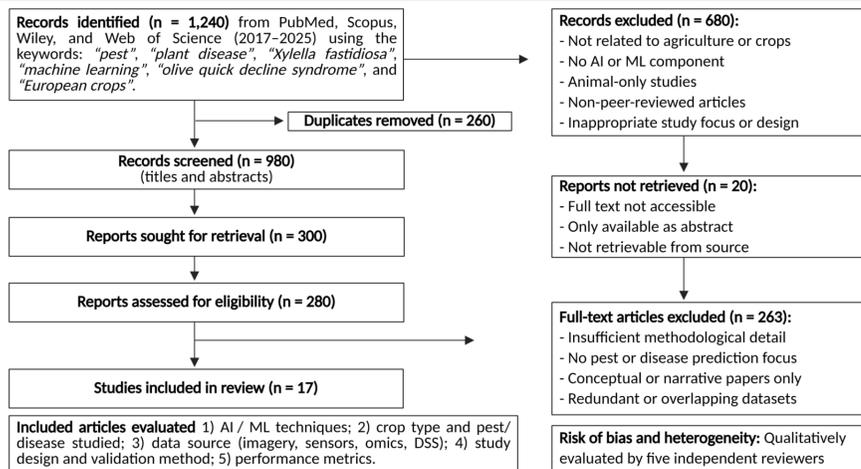
Current surveillance relies on **visual inspections plus molecular confirmation, typically detecting infestation once symptoms have appeared, limiting the effectiveness of containment efforts.** To control *Xfp*, the **EU** has implemented quarantine protocols, including eradicating infected plants, vector suppression, and restricting trade barriers in plant material.

Machine Learning (ML) technologies **can help control pest pressures**, while **Deep Learning (DP) algorithms** can detect spectral signatures in leaf reflectance caused by infection **with over 90% accuracy.** This systematic review the application of **ML** for the early detection of *Xfp* in olive cultivation.

North, Central and South America
1. Canada (BC, SK, ON)
2. USA (AL, AZ, AR, CA, DE, FL, GA, IN, KY, LA, MD, MS, MO, MT, NE, NJ, NM, NY, NC, OK, OR, PA, RI, TN, SC, TX, VA, WA, WV)
1. Mexico
2. Costa Rica
3. Puerto Rico
4. Venezuela
5. Brazil (PA, SE, BA, GO, MG, ES, RJ, SP, PR, SC)
6. Paraguay
7. Argentina

Europe and Asia
10. Portugal
11. Spain (present – Balearic islands)
12. France (present – Corsica)
13. Italy
14. Lebanon
15. Israel
16. Iran
17. Taiwan

X. fastidiosa distribution by countries

☐ Absent
⚫ Transient (mainland) and Present (islands)
⚫ Present (country)

Figure 1: Global distribution of the plant pathogen *Xfp* by country.

METHODOLOGY

Records identified (n = 1,240) from PubMed, Scopus, Wiley, and Web of Science (2017–2025) using the keywords: *"pest", "plant disease", "Xylella fastidiosa", "machine learning", "olive quick decline syndrome", and "European crops".*

→ Duplicates removed (n = 260)

Records screened (n = 980) (titles and abstracts)

Reports sought for retrieval (n = 300)

Reports assessed for eligibility (n = 280)

Studies included in review (n = 17)

Included articles evaluated 1) AI / ML techniques; 2) crop type and pest/ disease studied; 3) data source (imagery, sensors, omics, DSS); 4) study design and validation method; 5) performance metrics.

Records excluded (n = 680):
- Not related to agriculture or crops
- No AI or ML component
- Animal-only studies
- Non-peer-reviewed articles
- Inappropriate study focus or design

Reports not retrieved (n = 20):
- Full text not accessible
- Only available as abstract
- Not retrievable from source

Full-text articles excluded (n = 263):
- Insufficient methodological detail
- No pest or disease prediction focus
- Conceptual or narrative papers only
- Redundant or overlapping datasets

Risk of bias and heterogeneity: Qualitatively evaluated by five independent reviewers

RESULTS & DISCUSSION

A. Data acquisition
- **Unmanned aerial vehicle–borne multispectral and hyperspectral sensors** were used in **~65%** of the studies.
- **Thermal infrared imagery** was included in **~30%** of cases, primarily to detect canopy temperature anomalies.
- Ground-based spectroradiometry was used in **~40%** of studies for model validation.

B. ML approaches
- **Traditional supervised learning:**
  i. Support Vector Machines (used in **~70%** of studies)
  ii. Random Forests (used in **~55%** of studies)
- **DP :**
  i. Convolutional Neural Networks (CNNs) applied in **~35%** of studies.

C. Model performance
- Reported classification accuracy ranged from **85% to 98%** under **controlled experimental conditions.**
- Sensitivity values above **90%** were frequently reported for early-stage infection detection.
- Performance decreased by **10–25%** when models were applied across:
  i. Different geographic regions
  ii. Different olive cultivars
  iii. Multi-year datasets

D. Validation and generalization
- Only **~20%** of studies included independent **external validation datasets.**
- Only fewer than **15% assessed the robustness model** under multiple stress conditions, such as **water stress, nutrient deficiency, and co-infections.**
- Most models lacked **uncertainty quantification** and **explainability metrics.**

E. Operational limitations
- Limited **interoperability** between sensing platforms and regulatory surveillance systems.
- High dependence **on sensor calibration**, **flight altitude**, and **lighting conditions.**
- Lack of **standardized protocols** regarding **data acquisition** and/or **annotation.**

X. fastidiosa multiplies in the xylem and secretes virulence factors (Type II secretion system).

A — Virulence factors, Type II secretion system, *X. fastidiosa*, Outer membrane vesicle

Sharpshooters acquire *X. fastidiosa* from an infected plant. The insect inoculates the bacteria into the xylem of a healthy plant during feeding.

Biofilm

X. fastidiosa

Plant secreted proteins

Cell wall

Xylem vessel

B — The bacteria form biofilms, blocking water flow, causing wilting and vascular tissue death (OQDS).

Economic losses: Damages olive and other crops, reducing production.

Job losses: Affects agricultural workers.

Social impact: Hurts rural communities' income and culture.

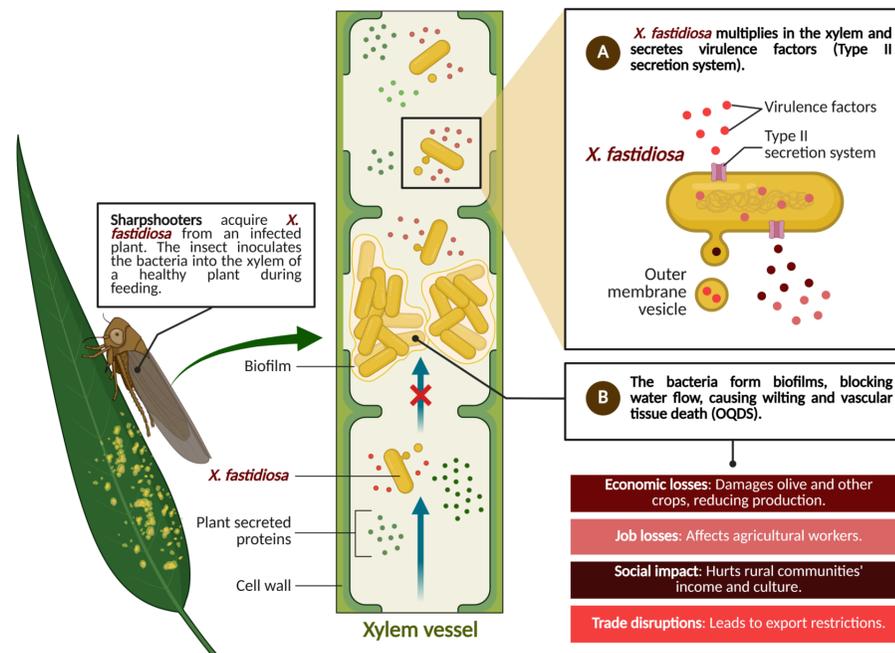**Trade disruptions:** Leads to export restrictions.

Figure 2: Representation of key actors in the evolution of OQDS.

CONCLUSION

ML-enabled **sensing technologies** complement **existing phytosanitary measures** with **precision agriculture** support for **crop health, water use,** and *Xfp* **detection**. However, achieving widespread adoption requires robust field validation, which involves **regulatory** and **farm-level decision-making frameworks.**

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