AI-Enabled Imaging for Pathogen Detection Under Stress Conditions: A Systematic Review

Food AI + Engineering Lab
MICHIGAN STATE UNIVERSITY

MeiLi Papa[1], Gillian Kuehnle[1], Yoo Jung Oh[2], Jiyoon Yi[1]

[1]Dept of Biosystems and Agricultural Engineering, [2]Dept of Communication
Michigan State University, East Lansing, MI

Department of Biosystems and Agricultural Engineering
MICHIGAN STATE UNIVERSITY

Introduction

- Pathogen detection is critical in food safety, but challenged by sample complexity, stress-induced variability, and limitations of traditional methods.
- Artificial intelligence (AI)-enabled imaging offers new opportunities to detect pathogens rapidly and accurately, including those with varying physiology, by extracting signals not easily visible to the human eye.

Objective

The aim of this systematic review was to evaluate the application, efficacy, and technological advancements of AI-enabled imaging for pathogen detection, including its impact on speed, accuracy, and predictive modeling under stress conditions.

Research Questions

- **RQ1.** Which AI algorithms have been employed in imaging for pathogen classification?
- **RQ2.** How does AI-enabled imaging enhance the speed and accuracy of pathogen detection and classification compared to traditional methods?
- **RQ3.** What are the latest advancements in integrating AI with multimodal imaging techniques for pathogen research?
- **RQ4.** How does AI facilitate early detection of pathogens under stress conditions?

Methods

Search Strategy (Key Terms – Synonyms)

- **Artificial Intelligence –** machine learning, deep learning
- **Pathogen** – microbe, microorganism, microbial, microbiological, bacteria, bacterial
- **Detection** – diagnostics, classification, prediction, physiological signals, stress phenotype, resilience phenotype
- **Imaging** – image analysis, microscopy, microscope, hyperspectral, multispectral, multimodal

Eligibility Criteria (guided by PICOS framework)

- **P** (Population): Bacteria or their physiological signals under stress
- **I** (Intervention): AI-based detection via optical microscopy (original data)
- **C** (Comparison): Traditional detection methods
- **O** (Outcome): Accuracy, speed, predictive capability
- **S** (Study design): Original peer-revised research articles in 2012–2024

Screening, Data Extraction, Risk of Bias: 3 reviewers piloted. MP & GK independently completed all steps. Disagreements resolved by a 3rd reviewer.

- **Screening**: Title/abstract and full-text screening conducted in Covidence.
- **Extraction:** Predefined items based on PRISMA-P guidelines (e.g., biological sample preparation, AI-enabled analyses, performance metrics).
- **Risk of Bias**: Assessed with adapted QUADAS-2 across 4 domains (pathogen selection, index test, reference standard, flow/timing).
- **Synthesis**: Qualitative; meta-analysis not performed due to heterogeneity.

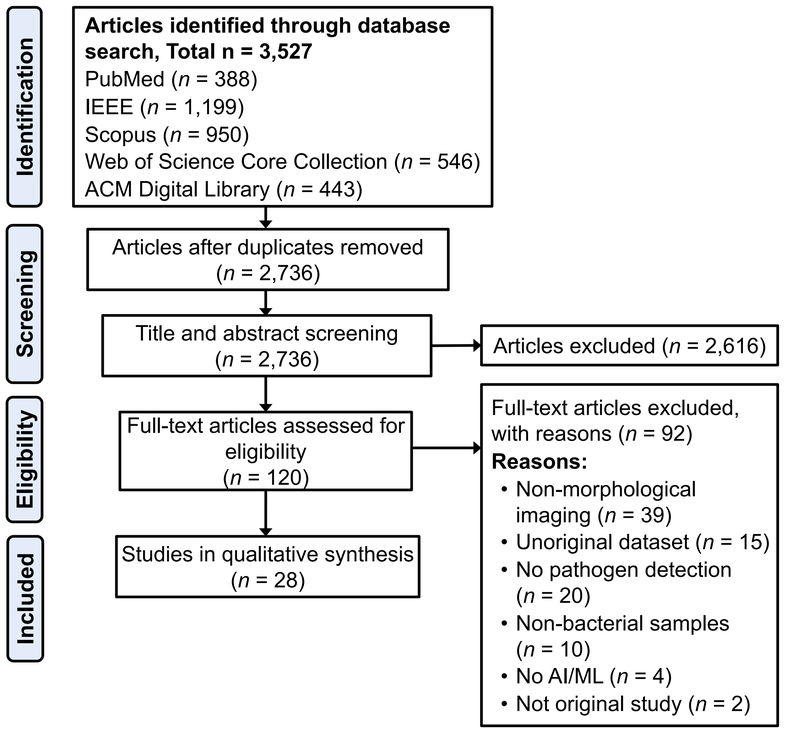

Fig. 1. Flow diagram illustrating article screening & selection process

Results

See handout for selected extraction tables (from master's thesis; manuscript under review).

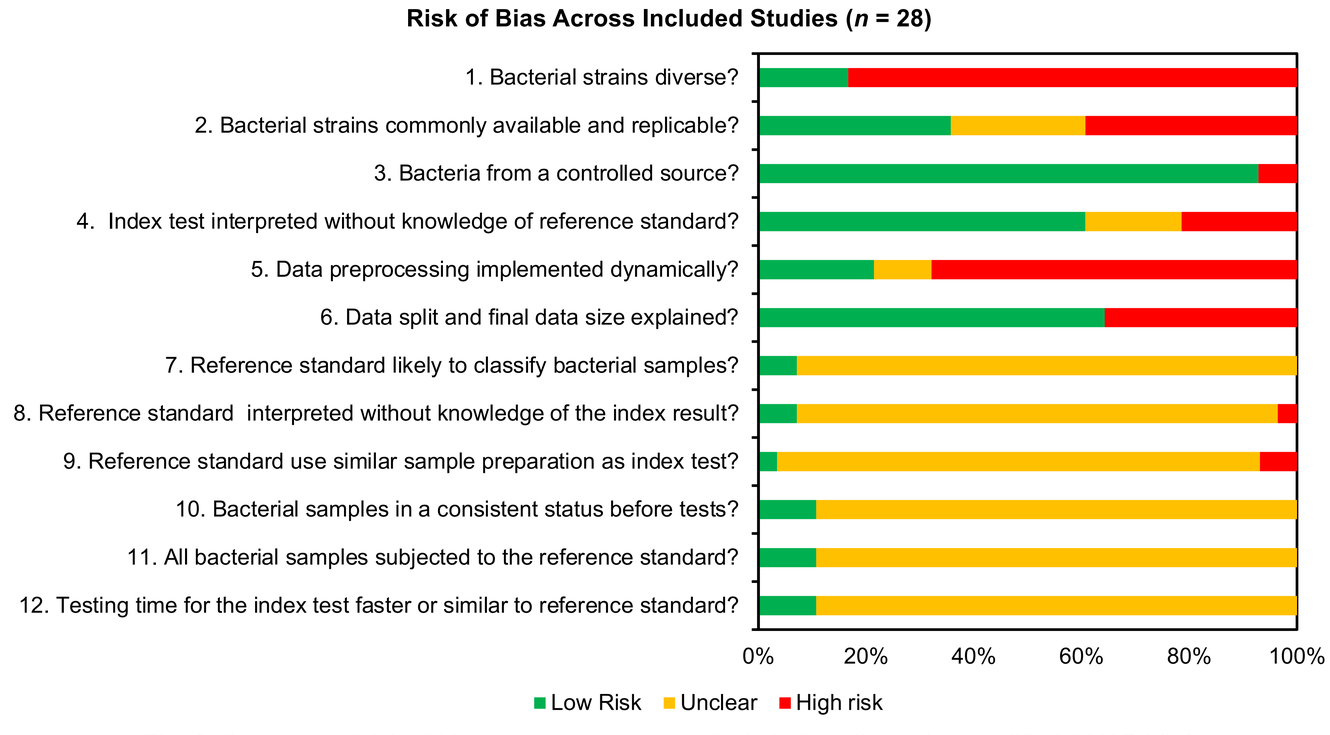

Fig. 2. Summary of risk of bias assessment across included studies using modified QUADAS-2

Conclusions

There is no one-size-fits-all algorithm for AI-enabled pathogen classification:

- Rather than searching for a "best" model, effective performance requires context-aware optimization of both preprocessing workflows and model architectures, particularly in multimodal imaging where tailored processing is critical.

AI modeling accelerates and automates pathogen detection:

- Several studies reported high classification accuracy using bacterial samples incubated for <24 h, highlighting AI's potential for rapid detection.

AI enhances multimodal imaging capabilities:

- Robust preprocessing techniques are essential for extracting meaningful biological signals and improving classification performance from high-dimensional multimodal data.

Emerging applications for detecting stressed pathogens:

- 3 included studies showed that AI-enabled imaging can distinguish pathogens in stressed or non-viable states, beyond conventional viable and culturable conditions.[2–4]

Challenges identified in this systematic review:

- Inconsistent biological protocols, limited reproducibility, and lack of standardized reporting.
- These findings highlight the need for both biological and computational benchmarks, along with unified reporting standards, to improve reproducibility and enable cross-study comparison.

Acknowledgments

This research was supported by MSU startup funds and the Tetrad Award from the MSU Research Foundation.

References

1. Whiting, P. F. et al. (2011). QUADAS-2: A revised tool for the quality assessment of diagnostic accuracy studies. *Annals of internal medicine*, 155(8), 529–536.
2. Ali, N. et al. (2020). Predictive modeling of antibiotic susceptibility in *E. coli* strains using the U-Net network and one-class classification. *IEEE Access*, *8*, 167711–167720.
3. Park, B. et al. (2023). Classification between live and dead foodborne bacteria with hyperspectral microscope imagery and machine learning. *Journal of Microbiological Methods*, *209*, 106739.
4. Wu, C. et al. (2024). Rapid and high accurate identification of *E. coli* active and inactivated state by hyperspectral microscope imaging combing with machine learning algorithm. *Vibrational Spectroscopy*, *130*, 103645.