XAIPath: Temporal-Environmental Explainable AI Framework

for Co-Contaminated Food Pathogen Detection in Microscopic Imaging

Anas AlSobeh, Amer AbuGhazaleh, Namariq Dhahir, Malek Rababa

Southern Illinois University Carbondale

ICPP 2025 HARVEST Workshop

September 10, 2025 | San Diego, CA, USA

The Food Safety Crisis

Global Health Impact

Millions of foodborne illnesses annually worldwide, with significant mortality rates

Economic Consequences

Billions in economic losses from recalls, healthcare costs, and productivity loss

Detection Delays

Current detection methods too slow for modern food supply chains

Supply Chain Complexity

Global food distribution requires faster, more accurate contamination detection

America Has an Onion Problem - The Atlantic

Current Detection Challenges

Traditional Detection Timeline

Sample Collection & Preparation

Homogenization and enrichment (16-24 hours)

Plating & Incubation

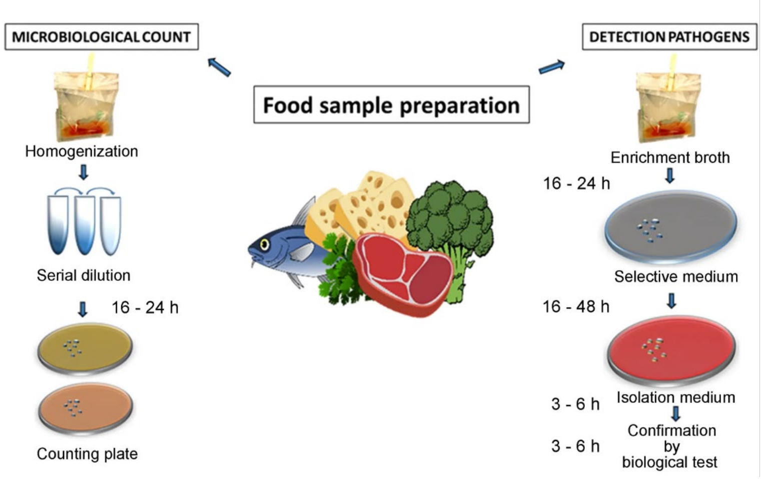
Growth on selective media (24-48 hours)

Confirmation Tests

Biochemical or serological tests (24 hours)

Results & Decision

Total: 3-5 days for definitive results



Time Constraints

Traditional methods require 3-5 days, while food products may be shipped and consumed within 24-48 hours

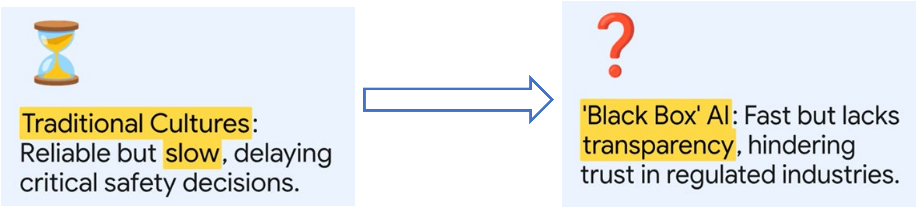
Black Box ML Approaches

Current machine learning methods lack explainability, limiting adoption in regulatory environments

Regulatory Requirements

Food safety decisions require transparent, interpretable evidence for compliance

Source: FDA Food Safety Modernization Act (FSMA) Guidelines



Research Challenges

Images: Microscopic visualization of bacterial samples under standard laboratory conditions

Lack of Interpretability

Current deep learning approaches for bacterial detection lack explainable decision-making mechanisms, limiting adoption in regulatory environments.

Temporal Dynamics Not Captured

Existing methods treat images as static entities without considering the temporal dynamics of bacterial growth that provide crucial diagnostic information.

Environmental Factors Ignored

Antimicrobial compounds in food matrices induce stress responses that alter bacterial morphology, creating variations that current systems cannot account for.

Complex Co-Contamination Scenarios

Multiple pathogen species coexisting under varying environmental conditions present significant classification challenges due to similar morphological characteristics.

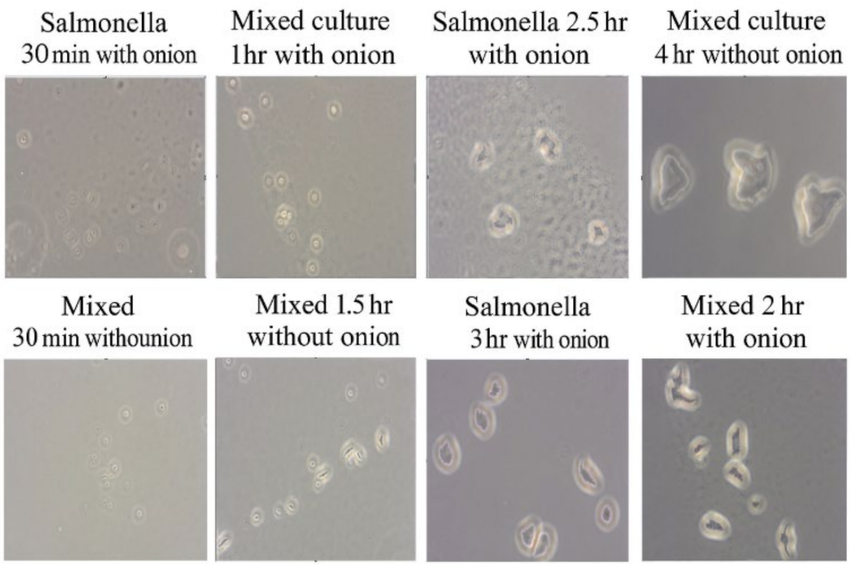
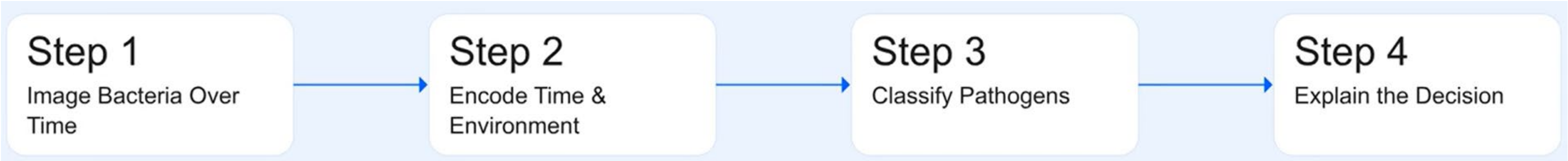


Fig. 1. Comprehensive dataset overview for bacterial contamination detection study.

Challenge: Distinguishing between bacterial species with similar morphology while accounting for environmental and temporal variations

Introducing XAIPath

- **XAIPath is a temporal-environmental explainable AI framework specifically designed to learn to spot not just what bacteria look like, but how they behave over hours**



Temporal Encoding

Captures bacterial growth dynamics through learnable sinusoidal embeddings that represent morphological evolution over time

Environmental Context Modeling

Accounts for biochemical stress responses induced by antimicrobial compounds in food matrices through specialized encoding and gating mechanisms.

Multi-Modal Explainability

Integrates Grad-CAM, and SHAP & LIME techniques with temporal consistency constraints for biologically plausible explanations

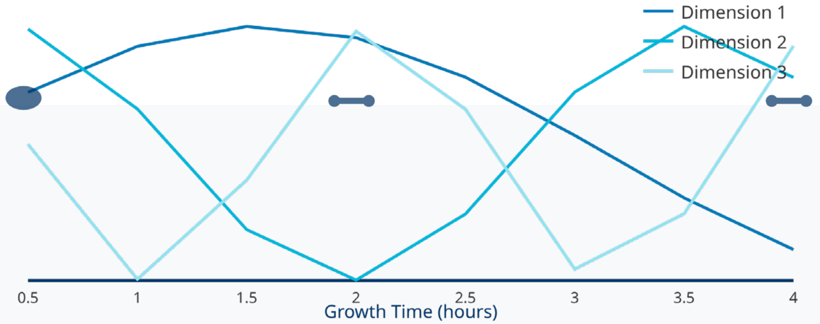
Technical Methodology : Temporal Encoding

How can we be sure its decisions are correct?

XAIPath generates ‘**attention maps**’ that highlight the exact visual evidence it used to identify a pathogen

Learnable Sinusoidal Embeddings

The temporal encoding mechanism transforms growth time information into high-dimensional feature representations integrated with visual features from microscopic images.



- Visualization of temporal encoding capturing bacterial morphological evolution over time, enabling the model to leverage growth kinetics for improved classification.

Temporal Encoding Function

$$\phi_t(t) = \begin{bmatrix} \sin(\omega_1 t + \phi_1) \\ \cos(\omega_1 t + \phi_1) \\ \vdots \\ \sin(\omega_{d_t/2} t + \phi_{d_t/2}) \\ \cos(\omega_{d_t/2} t + \phi_{d_t/2}) \end{bmatrix}$$

where ω_i and ϕ_i are learnable parameters that adapt to bacterial growth kinetics

Cross-Attention Integration

Temporal features are integrated with visual features through a cross-attention mechanism that allows temporal context to modulate spatial feature importance.

Early Detection Advantage

By understanding growth patterns, XAIPath achieves 89.4% accuracy in early growth phases (30-60 min), compared to 76.8% for baseline methods.

Technical Methodology : Environmental Context Modeling

Environmental context encoding captures the influence of conditions on bacterial morphology and behavior.

Environmental Encoding

Maps discrete environmental conditions (presence/absence of onion samples) to continuous feature representations through learned embeddings.

Selective Feature Modulation

Employs a gating mechanism that selectively modulates feature importance based on environmental conditions.

Environmental Gating Function:

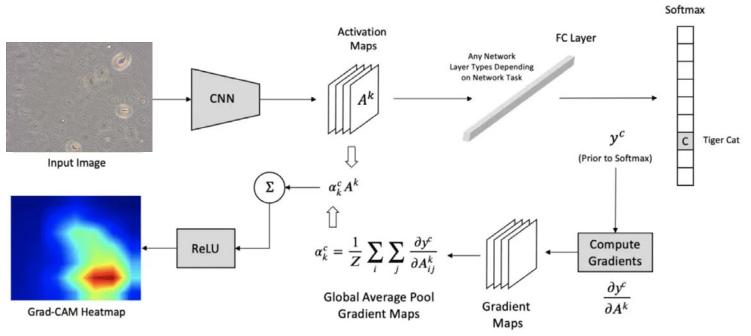
$$g_e = \sigma(W_e \psi_e + b_e)$$

Gated Feature Computation:

$$F_{env} = g_e \odot F_{visual} + (1-g_e) \odot F_{baseline}$$

where $\odot$ denotes element-wise multiplication

Environmental Gating Mechanism



Visualization of the environmental gating mechanism that selectively modulates feature importance based on conditions.

Benefits

Selective feature modulation based on environmental conditions improves robustness across different food matrices

Technical Methodology: Multi-Modal Explainability

Explainability Techniques

Grad-CAM

Generates spatial attention maps highlighting regions of high importance for classification decisions

SHAP & LIME Analysis

SHAP: Quantifies the contribution of individual image patches to final predictions using Shapley values.

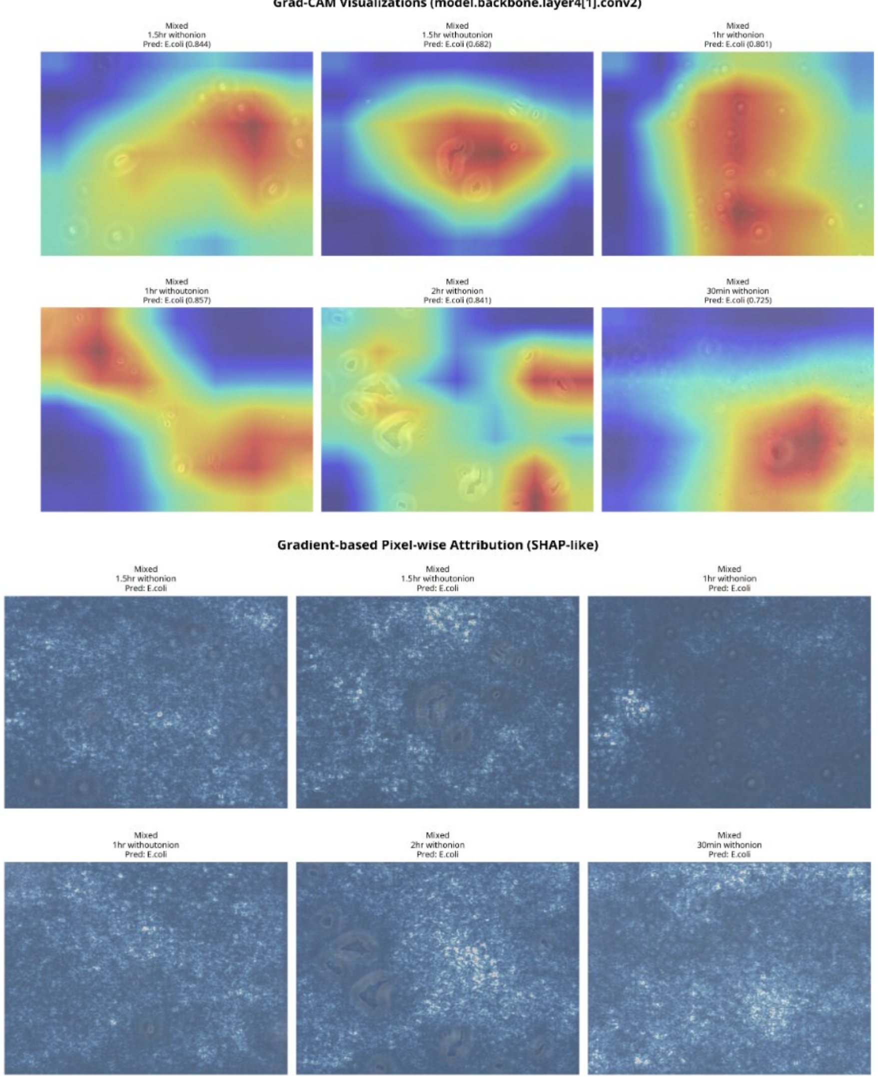
LIME: Generates local explanations through perturbation-based analysis, revealing decision boundaries

Consistency Constraints

Temporal Consistency: Ensures smooth evolution of attention patterns over time

Environmental Consistency: Maintains stable explanations under identical biochemical conditions

Expert Validation: 91.7% localization accuracy between attention maps and ground truth bacterial regions



Experimental Setup

Dataset Characteristics

Total Images: 2,847

High-resolution microscopic images

Sample Composition

1,156 Salmonella, 1,691 mixed cultures

Temporal Growth

8 time points (30 min to 4 hours)

Environmental

With/without onion samples

Annotation Quality: 97.3% inter-annotator agreement

Dataset Distribution

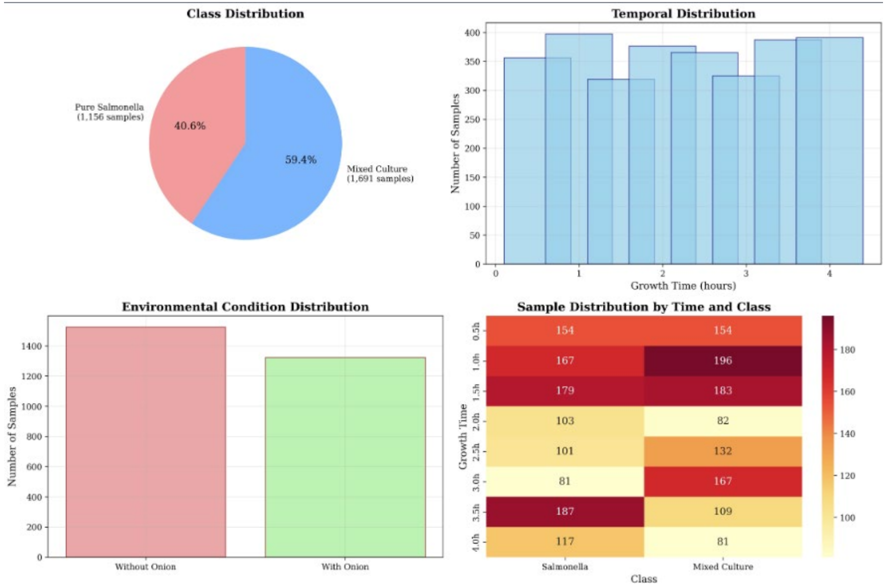


Image Acquisition: Standardized protocol using air objective 60× (Olympus, USA)

Evaluation Methodology

- 5-fold cross-validation
- Localization accuracy measured as intersection-over-union with ground truth

Dataset collected and annotated at Southern Illinois University Carbondale

Performance Results

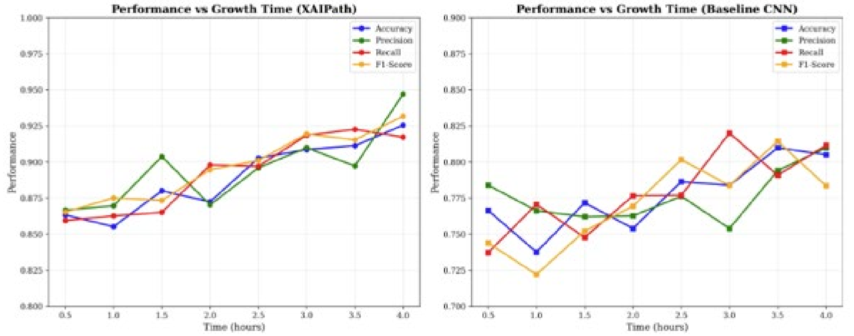
Performance Metrics

94.7% **Precision**
Compared to 87.2% for baseline CNN

91.3% **Recall**
Compared to 84.6% for baseline CNN

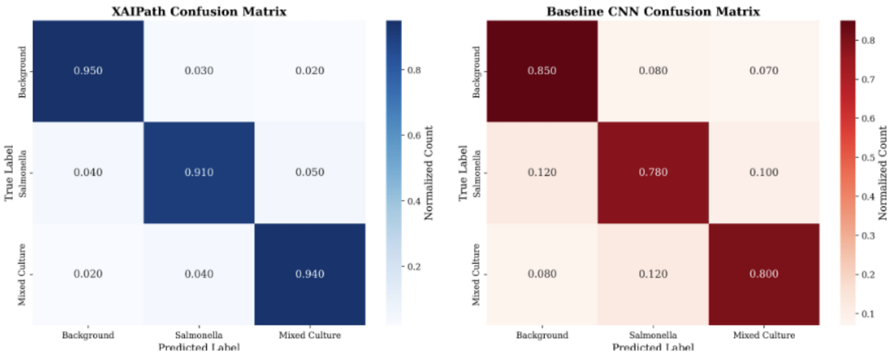
92.9% **F1-Score**
Compared to 85.9% for baseline CNN

91.7% **Localization Accuracy**
Intersection-over-union between attention maps and ground truth bacterial regions



Temporal and environmental robustness comparison showing XAIPath's consistent performance across growth phases and environmental conditions.

Confusion Matrices



Confusion matrices comparing XAIPath (left) and baseline CNN (right) performance across background, Salmonella, and mixed culture classes.

Key Performance Insights

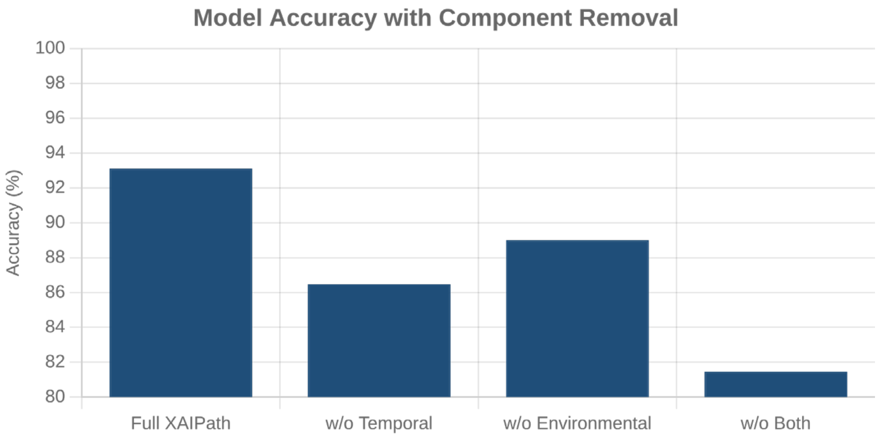
- Early growth phases (30-60 min): 89.4% accuracy vs. 76.8% for baseline
- Environmental robustness: 92.1% ± 1.8% across onion extract conditions
- Localization accuracy: 91.7% intersection-over-union with ground truth

Classification Improvements

- Significant reduction in false negatives for mixed cultures
- Better discrimination between Salmonella and mixed cultures
- Consistent performance across all bacterial classes

Component Analysis

Ablation Study Results



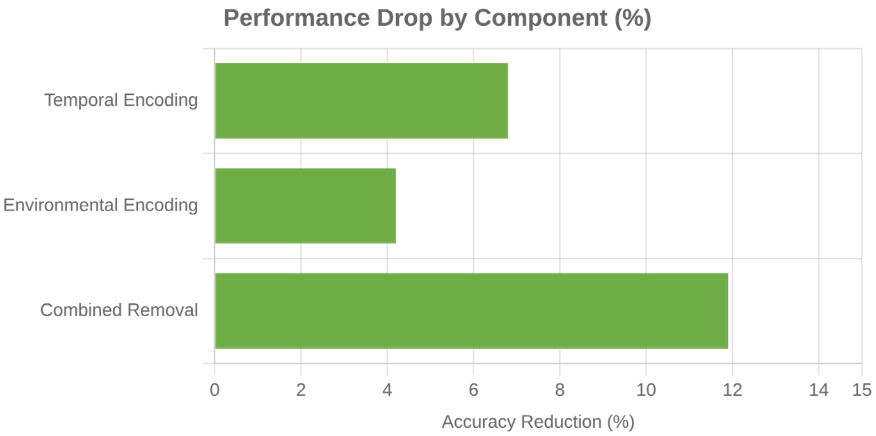
Synergistic Benefits

Removing both temporal and environmental components led to an 11.9% decline in performance, demonstrating synergistic benefits beyond individual contributions

Explanation Quality Impact

Component removal also significantly affected explanation quality: temporal encoding improved localization by 7.3%, while environmental encoding improved it by 4.8%

Component Contributions



Key Findings from Ablation Study

Temporal encoding is critical for early growth phase detection (30-60 min window)

Environmental encoding provides robustness across different food matrices

Combined approach is essential for regulatory-compliant explainability

Real-World Impact

Practical Applications

Early Detection & Rapid Response

Early detection during 30-60 minute window enables rapid-response protocols to mitigate contamination risks

Regulatory Compliance

Explainability features fulfill critical trust and traceability requirements in food safety regulations

Laboratory Adaptability

Robustness across environmental conditions supports deployment in diverse laboratory environments

Human-AI Collaboration

Transparent explanations enable effective collaboration between AI systems and human experts

Implementation Pathway

Laboratory Integration

XAIPath integrates with existing microscopy equipment and sample preparation workflows

Decision Support

Provides real-time analysis with explainable results to support microbiologists

Public Health Protection

Reduces foodborne illness incidents through faster, more accurate contamination detection

Conclusion

- Novel temporal-environmental XAI framework that addresses the critical gap between AI performance and regulatory requirements
- Superior performance metrics: 94.7% precision, 91.3% recall, and 92.9% F1-score for co-contaminated pathogen detection
- Early detection capability with 89.4% accuracy in the critical 30-60 minute post-inoculation window
- Biologically plausible explanations validated by experts with 91.7% localization accuracy
- Practical value for real-world deployment in food safety workflows with robust performance across environmental conditions

Thank You & Questions

Contact Information

Anas AlSobeh

anas.alsobeh@siu.edu

School of Computing, Southern Illinois University Carbondale

Amer AbuGhazaleh

aabugha@siu.edu

School of Agricultural Sciences, Southern Illinois University Carbondale

Namariq Dhahir

namariq@siu.edu

School of Agricultural Sciences, Southern Illinois University Carbondale

Malek Rababa

malekabdelrahmansaleem.rababa@siu.edu

School of Computing, Southern Illinois University Carbondale

Scan for LinkedIn Connect

github.com/aalosbeh/XAIPath