

# Needle in a Haystack:

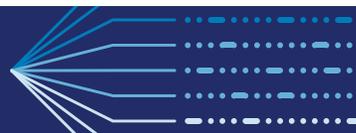
*Using Machine Learning for Improved  
Compliance Targeting in the Human Food  
Program*

**FDA's Center for Food Safety and Applied  
Nutrition  
Office of Compliance**



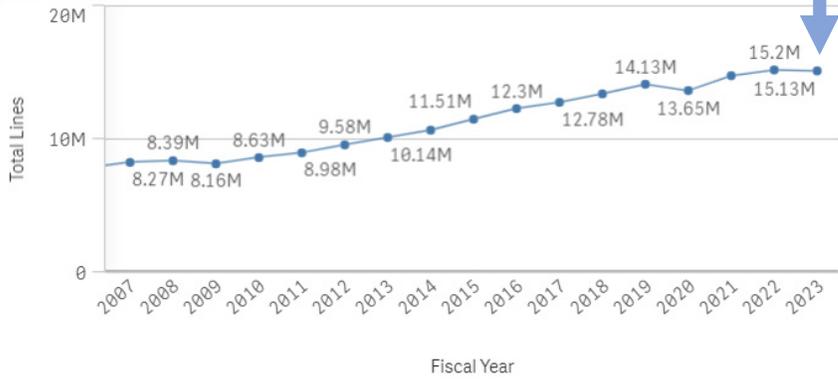
# Background

“ *FDA is responsible for protecting the public health by assuring the safety, efficacy and security of human and veterinary drugs, biological products, medical devices, our nation's food supply, cosmetics, and products that emit radiation.* ”



# Which container would you pick?

74% increase last decade  
to 15M shipment lines in 2023



94%  
Seafood

55%  
Fresh Fruit

32%  
Fresh Vegetables

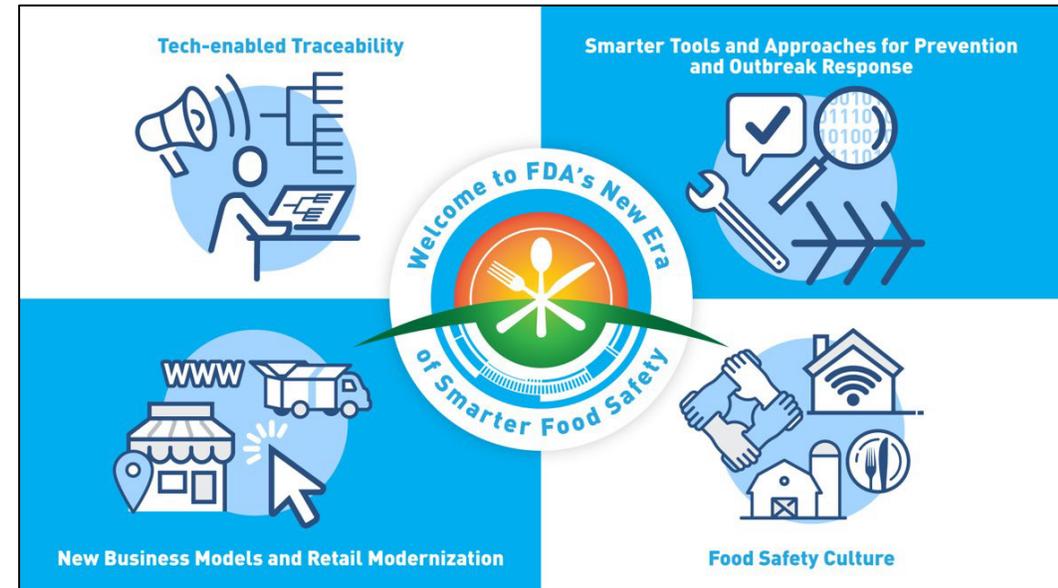


\*Source: FDA Data Dashboard (<https://datadashboard.fda.gov/ora/cd/impsummary.htm>)

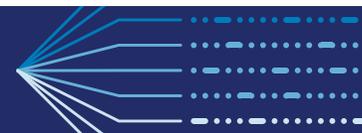
# How Could Machine Learning Support FDA's Mission?



- Increasing amounts of food imported and produced domestically.
- Limited regulatory resources to sample foods, inspect facilities, etc.
- Ever changing inventory and supply chains
- FDA's New Era of Smarter Food Safety Initiative
  - Goal: Expand predictive analytic capabilities via AI and ML, etc.
  - Progressive Exploration and Implementation, to include most recently the Phase III of Imported Seafood AI Pilot



<https://www.fda.gov/food/new-era-smarter-food-safety/new-era-smarter-food-safety-blueprint>



# What is Machine Learning?



Statistical technique that feeds the computer large amounts of data and asks it to “learn” from it to:

1. **Supervised** learning: Predict an outcome (risk classification, violative (OAI) inspection, violative (LC3) sample, etc.)
2. **Unsupervised** learning: Find hidden patterns in a dataset by analysis and clustering (e.g. are those that fail to register more likely to not implement corrective actions?)
3. **Reinforcement** learning: Reward desired behaviors and/or punishing undesired ones (e.g. gaming)

CFSAN OC is mostly focused on supervised learning, but aspires to explore other uses of ML as regulatory needs dictate





# Modeling Approach

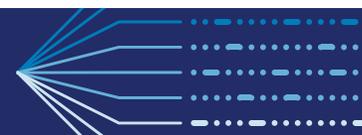
# Portfolio of ML Models Developed So Far



## Sampling Models:

Hazard Code	Hazard Description	Hazard Examples	Target Feature	Commodities of Interest	Domestic / Import?
<b>MIC</b>	<u>M</u> icrobiological (pathogenic bacteria)	<i>E. coli, Salmonella, Listeria, etc.</i>	Presence of pathogen	Most commodities	Imports and domestic
<b>DEC</b>	<u>D</u> ecomposition (toxic compounds from spoilage)	Histamines, scrombotoxins, etc.	Detection of decomposition in sensory test	Seafood only	Imports only
<b>ANT</b>	Unapproved <u>A</u> ntibiotics	Tetracyclines, florfenicol sulfonamides, etc.	Antibiotic concentration above safe threshold	Seafood only	Imports only
<b>ELE</b>	Toxic <u>e</u> lements	Lead, arsenic, mercury, etc.	Element concentration above safe threshold	Most commodities	Imports and domestic

**Inspections Models:** Various models to predict violative inspections for domestic and foreign food facility inspections, farms, and importers.



# Data and Modeling Process Overview

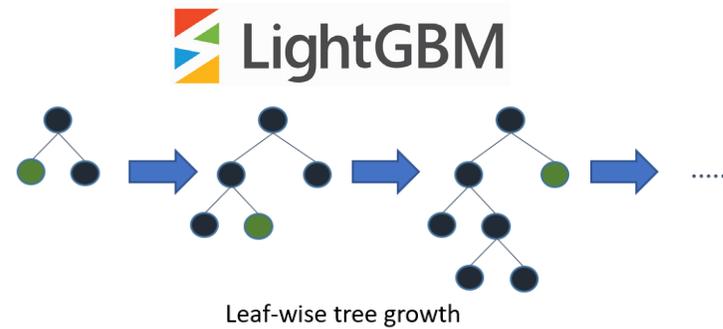


Data

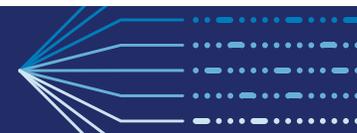
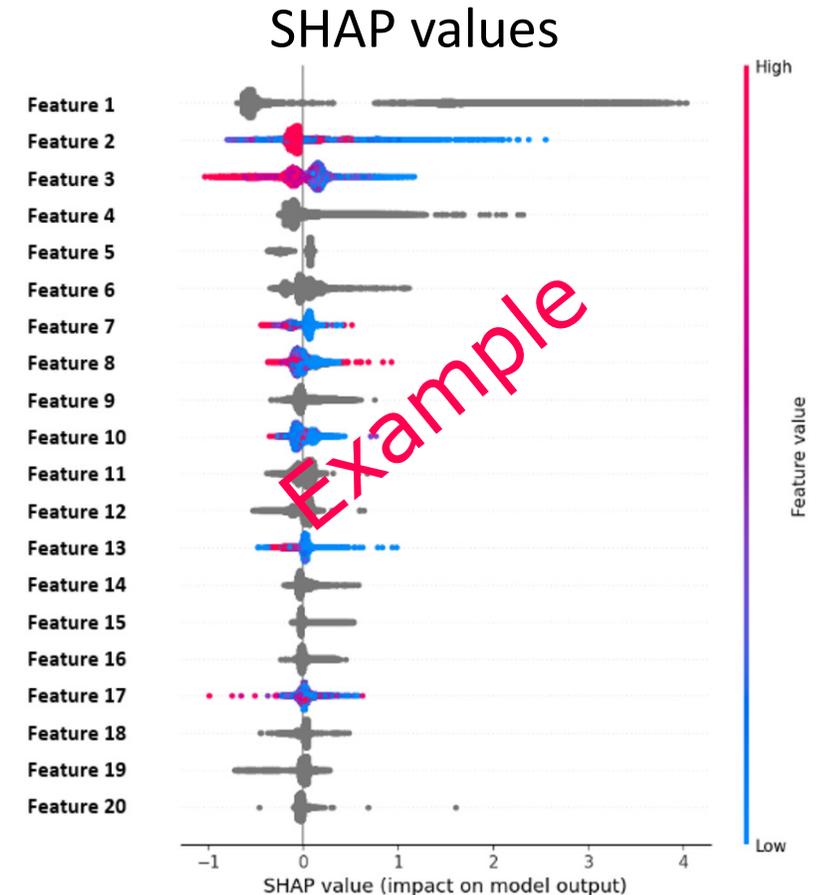
Model Training

Feature Evaluation

- Identify relevant features (variables) from FDA and external databases
- Clean and merge data with input from team of SME's and data scientists



- Boosted Tree algorithm
- Target: predict violative supply chain hazards



# More about SHAP: Increasing Transparency and Stakeholder Trust in ML Modeling



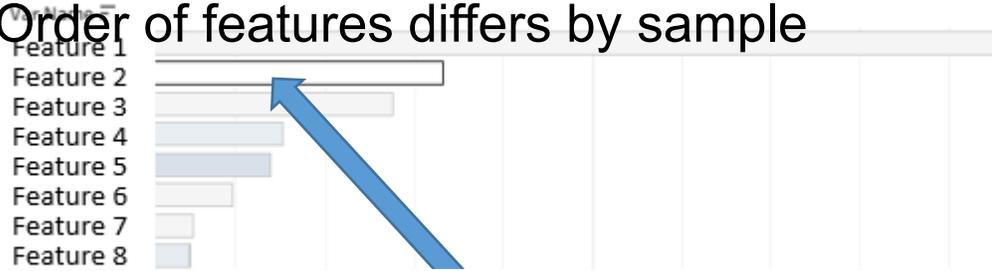
- SHAP Dashboard for Categorical Features

- (MIC-Imports model)

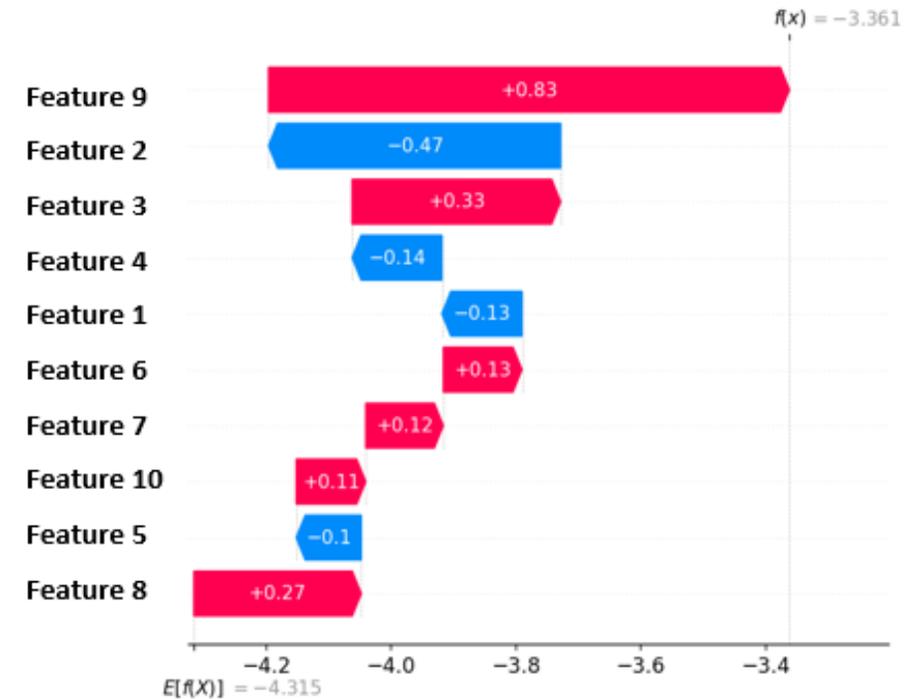
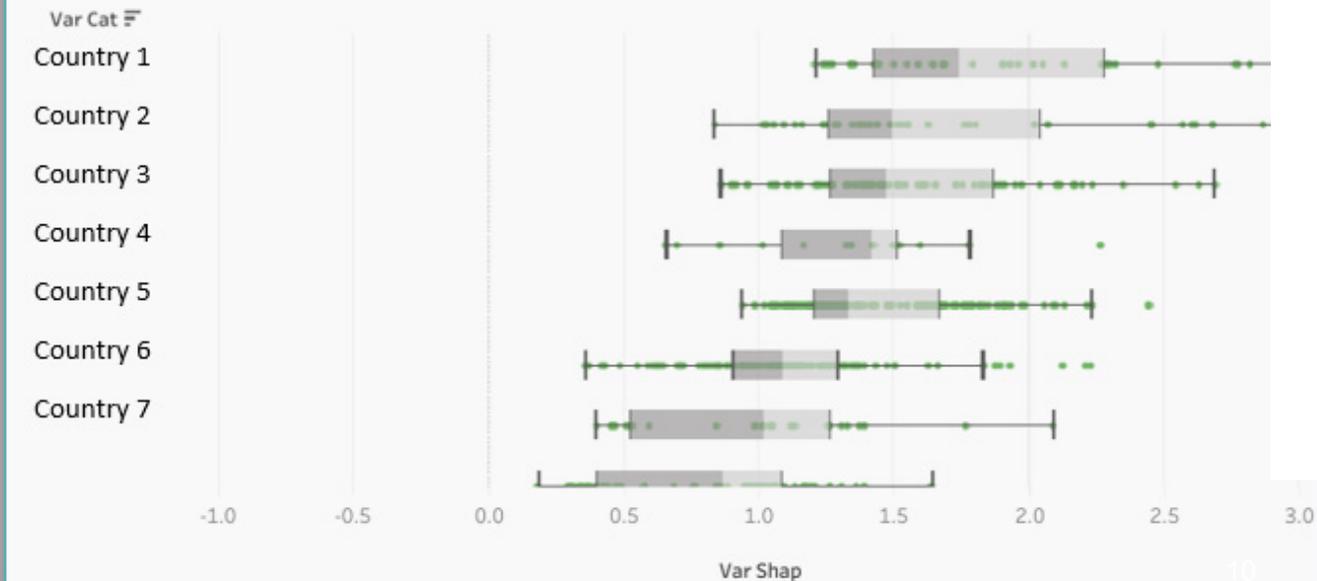
Example: Tuna from Firm ABC

- SHAP for Individual Supply Chains: Waterfall Plots

- Order of features differs by sample



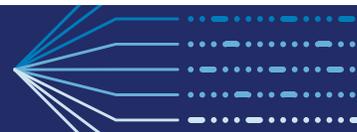
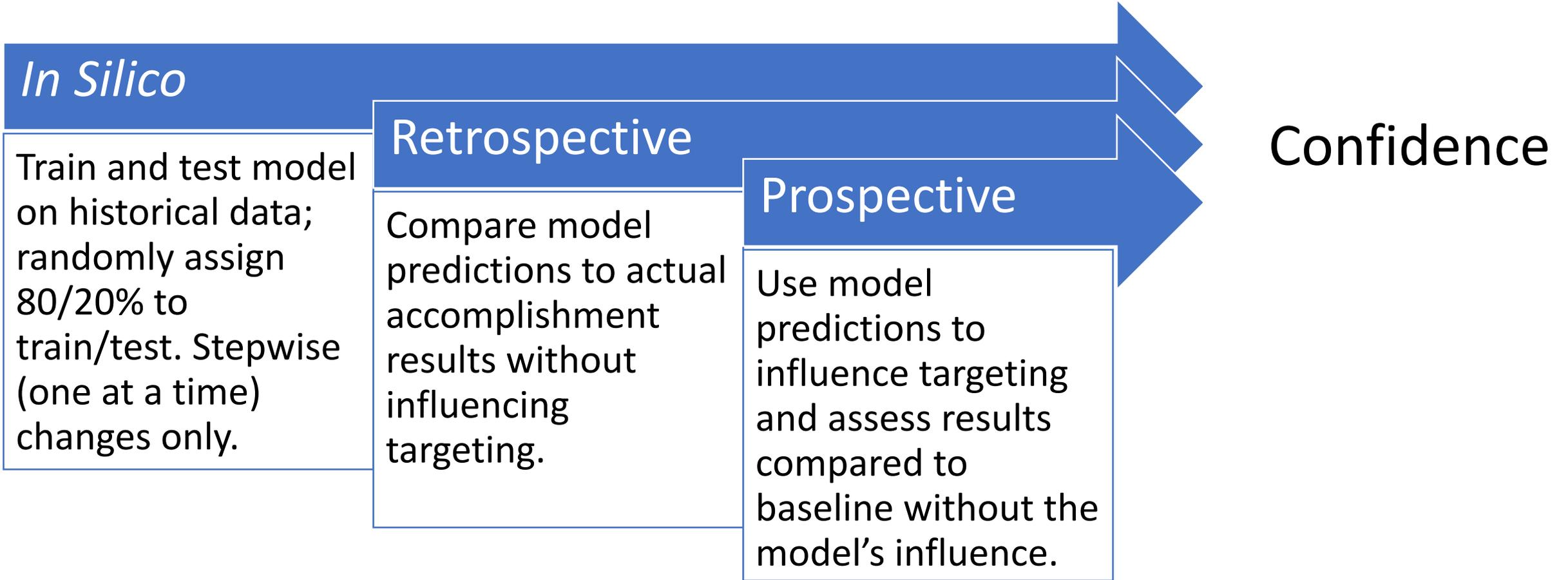
Categorical Feature Boxplot: Country.of.Origin.Name





# Modeling Performance

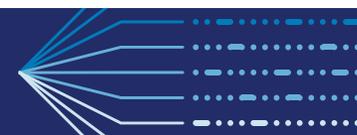
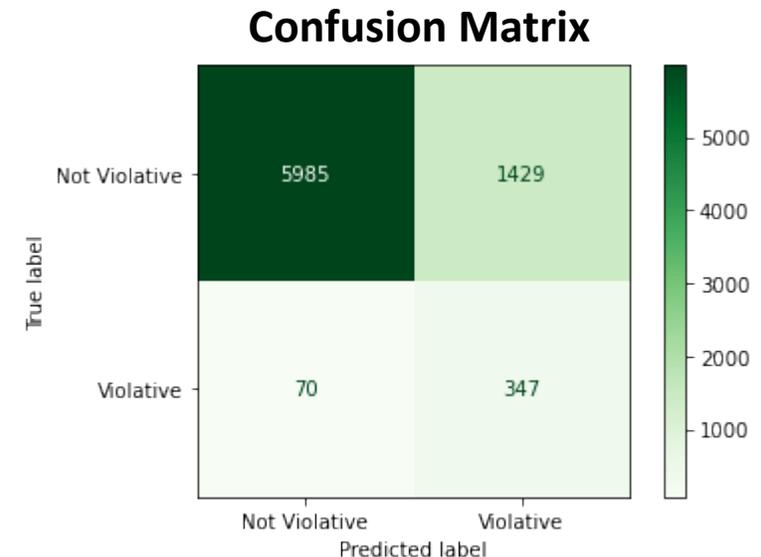
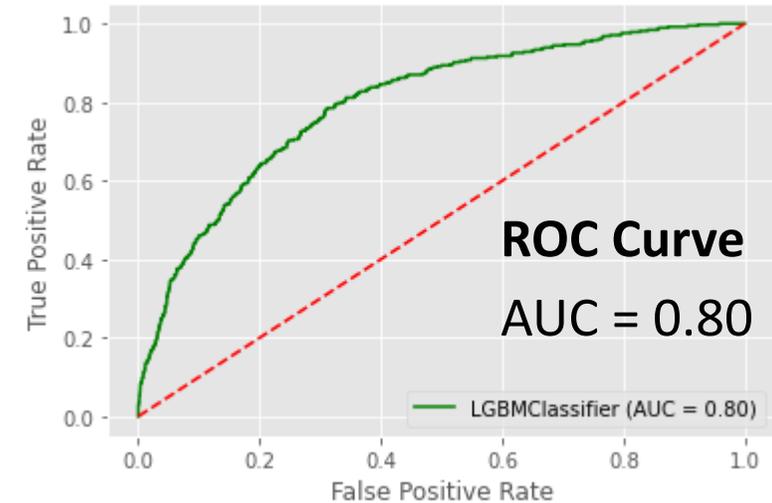
# How we assess our models



# In Silico Model Results (DEC-Imports example)



- Trained model on 80% of data, reserve 20% for testing
- Selected results
  - Accuracy: 72.4%
  - Sensitivity/Recall: 74.3%
  - Specificity: 72.2%
  - PPV (Positive Predictive Value)/Precision: 22.4%
  - Historical Violative Rate: 5.5%



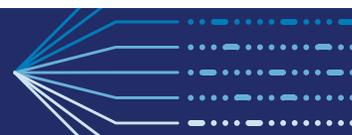
# ML Model Retrospective Results\*



Model	Import vs Domestic	Date Started	Number of Observations	Accuracy	Positive Predictive Value (PPV)	Baseline Violative Rate (Model Period)	Statistically significant (Model vs. Baseline PPV) (p<0.05)
MIC	Import	7/14/22	3,726	73%	5.5%	3.4%	Yes
ELE	Import	1/2/22	1,355	78%	18.34%	11.44%	Yes
DEC	Import	7/14/22	2,133	73%	11.3%	4.6%	Yes
ANT	Import	8/19/21	977	91%	11.1%	4.4%	Yes
Inspections	Domestic	3/16/23	2,786	83%	7.9%	3.0%	Yes

- Model makes predictions for known supply chains. If FDA collects sample for it, results are compared to ML prediction.
- All models show significant increase (p<0.05) in samples predicted to be violative (PPV) vs. baseline violative rate.

\*Data as of 10/23/23



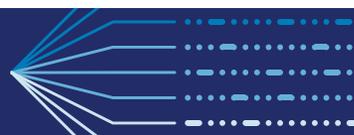
# Experimental Design for the Seafood AI Phase III Pilot



## 2x2 Factorial Design

		PREDICT	
		<u>YES</u>	<u>NO</u>
ML	<u>YES</u>	<b>Group A</b> n=250 MIC n=250 DEC	<b>Group B</b> n=250 MIC n=250 DEC
	<u>NO</u>	<b>Group C</b> n=250 MIC n=250 DEC	<b>Group D</b> n=250 MIC n=250 DEC

- Selected target hazards
  - MIC: microbiological (n=1000)
  - DEC: decomposition (n=1000)
- Control for main effects of:
  1. PREDICT (existing risk-targeting algorithm)
  2. ML model
  3. Expert knowledge (group D)
- FDA Consumer Safety Officers (CSO's) collecting samples are **blinded** from group identities.



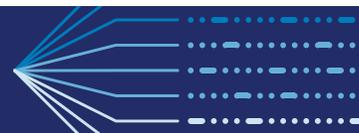


# Forging Ahead

# Implications of ML Results

- Better protecting public health
- Better using limited resources
- Identifying emerging trends
- Facilitating trade
- Complimenting/codifying human intelligence

Moving towards “smart” regulation



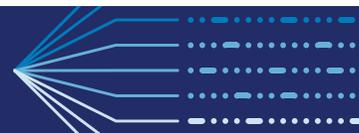
# Next Steps



**Learn:** Solicit feedback from public, academia, and industry on how to improve models or consider additional data or features

**Grow:** Continue to expand model deployment and carefully monitor results

**Evolve:** Move into a more dynamic deployment to support regulatory decision making in real-time



# Acknowledgments

## CFSAN Office of Compliance ML Team

- Jeff Chou (Biologist / Data Scientist)
- Michael Fesko (Operations Research Analyst)
- Chuck Hassenplug (Senior Policy Analyst)
- Christina Owens (Supervisory Consumer Safety Officer [CSO])
- Erica Pomeroy (Lead CSO)
- Michael Rinaldi (Program Analyst / Data Scientist)
- Shilpa Sainath (CSO)

## Support

- Office of Analytics and Outreach, Biostats and Risk Analysis Branch
- Office of Regulatory Affairs (Office of Import Operations, Division of Planning and Evaluation)

