Total Recall

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The Problem

Motivation

FDA to suspend quality-control program for food testing due to staff cuts

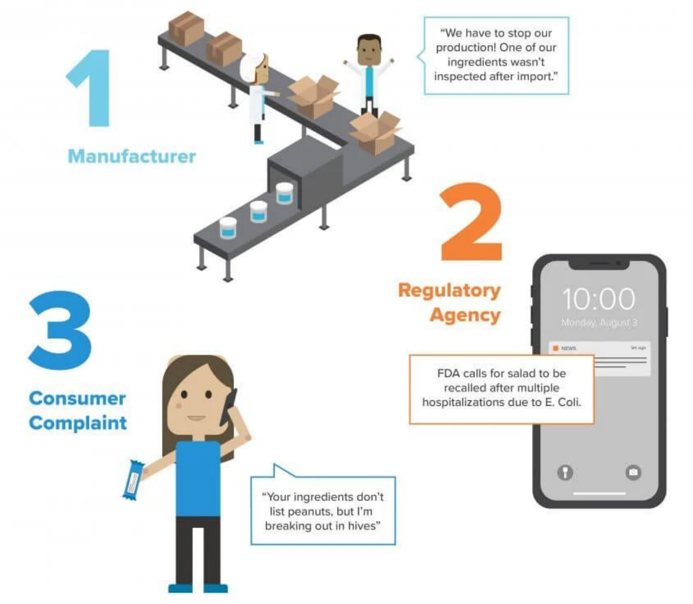
Research Question

Can we predict food products likely to be recalled by the FDA?

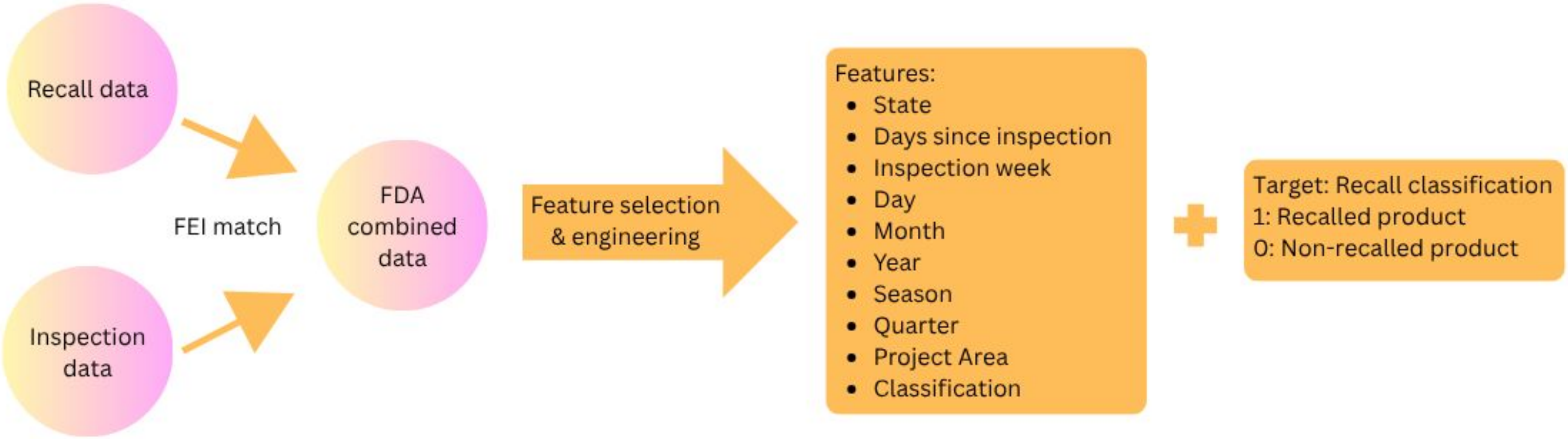
Intended Impact

Reduced contaminated products reaching consumers

Reduced costs to manufacturers


1
Manufacturer
"We have to stop our production! One of our ingredients wasn't inspected after import."
2
Regulatory Agency
10:00
Monday, August 3
FDA calls for salad to be recalled after multiple hospitalizations due to E. Coli.
3
Consumer Complaint
"Your ingredients don't list peanuts, but I'm breaking out in hives"

Datasets



Recall data

Inspection data

FEI match

FDA combined data

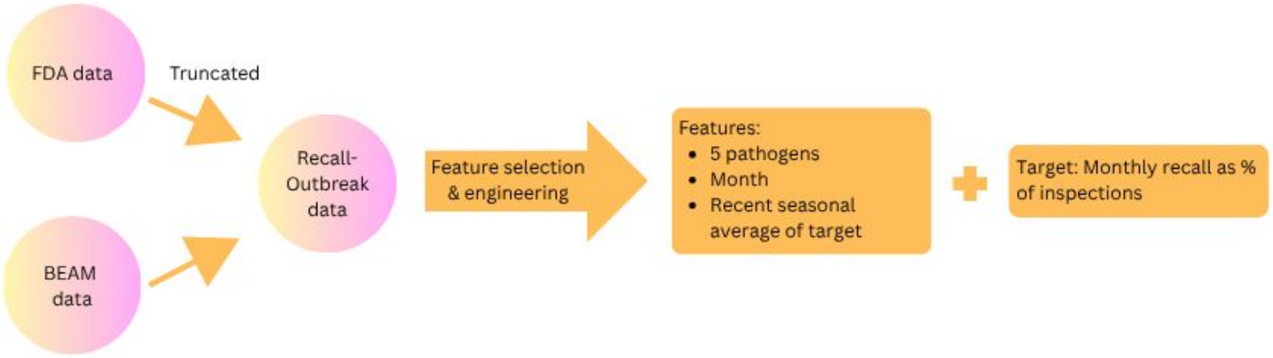
Feature selection & engineering

Features:

- State
- Days since inspection
- Inspection week
- Day
- Month
- Year
- Season
- Quarter
- Project Area
- Classification

Target: Recall classification
1: Recalled product
0: Non-recalled product

Future Work setup:



FDA data

Truncated

BEAM data

Recall-Outbreak data

Feature selection & engineering

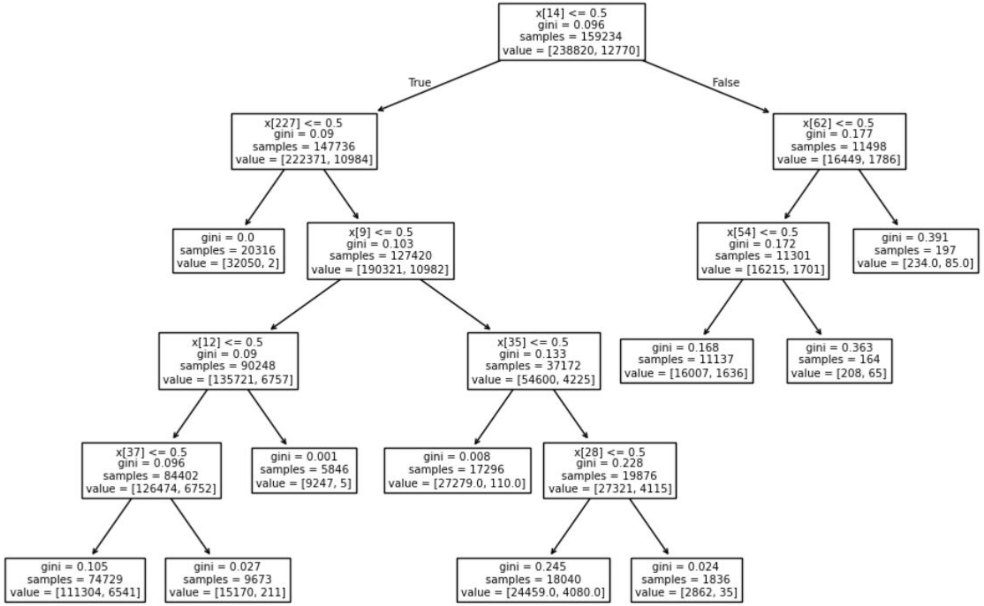
Features:

- 5 pathogens
- Month
- Recent seasonal average of target

Target: Monthly recall as % of inspections

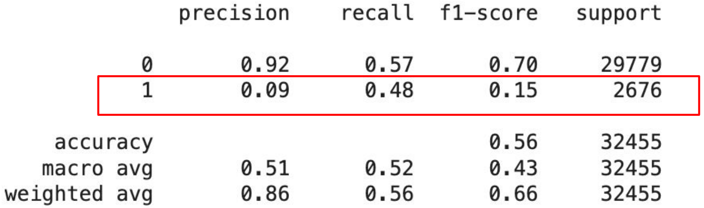
Random Forest Classification

- Model overview
  a. Use of thresholds
- Hyperparameter tuning
  a. Evaluation metric
- Final hyperparameter choice
  a. n_estimators = 100
  b. max_depth = 10
  c. class_weight = ‘balanced’



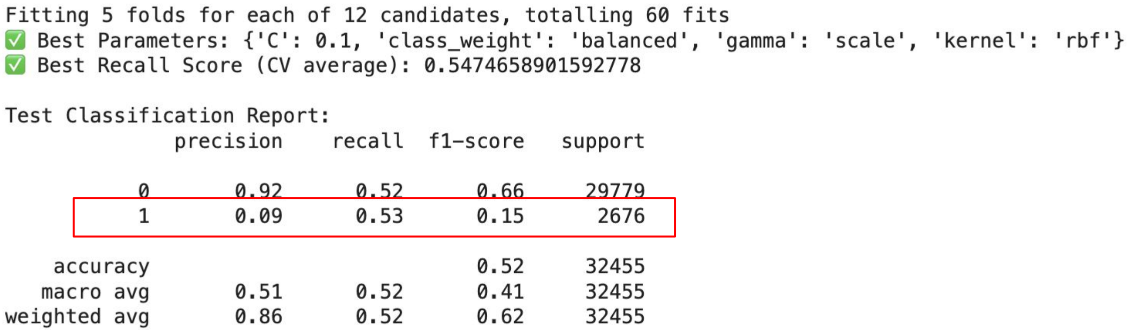
Support Vector Machine Classification

SVM
with class_weight = ‘balanced’



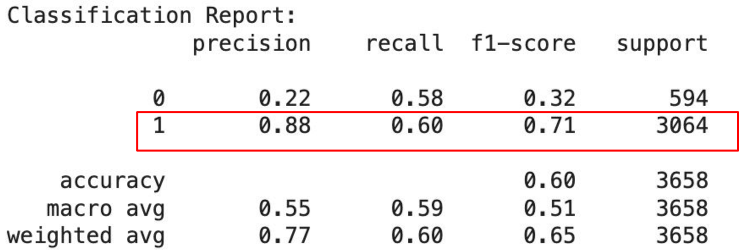
```
              precision    recall  f1-score   support

           0       0.92      0.57      0.70     29779
           1       0.09      0.48      0.15      2676

    accuracy                           0.56     32455
   macro avg       0.51      0.52      0.43     32455
weighted avg       0.86      0.56      0.66     32455
```

SVM
with class_weight = ‘balanced’; grid search for optimal parameters



```
Fitting 5 folds for each of 12 candidates, totalling 60 fits
✅ Best Parameters: {'C': 0.1, 'class_weight': 'balanced', 'gamma': 'scale', 'kernel': 'rbf'}
✅ Best Recall Score (CV average): 0.5474658901592778

Test Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.52      0.66     29779
           1       0.09      0.53      0.15      2676

    accuracy                           0.52     32455
   macro avg       0.51      0.52      0.41     32455
weighted avg       0.86      0.52      0.62     32455
```

SVM with class_weight = ‘balanced’; grid search for optimal parameters **on trimmed dataset**

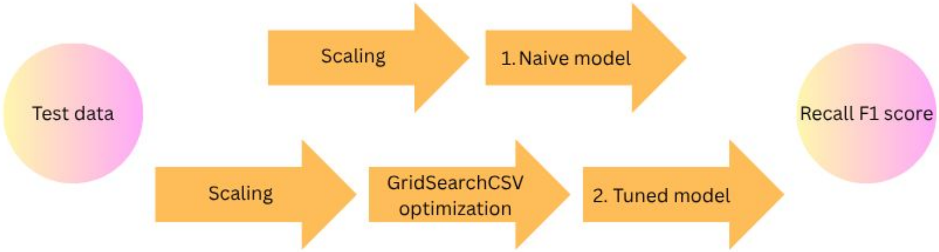


```
Classification Report:
              precision    recall  f1-score   support

           0       0.22      0.58      0.32       594
           1       0.88      0.60      0.71      3064

    accuracy                           0.60      3658
   macro avg       0.55      0.59      0.51      3658
weighted avg       0.77      0.60      0.65      3658
```

Model Selection

- Dummy (majority class) as baseline
- LR and RF F1 score improved by ~ 25%
- SVM still struggled to predict recalls

Model process



Test data

Scaling → 1. Naive model

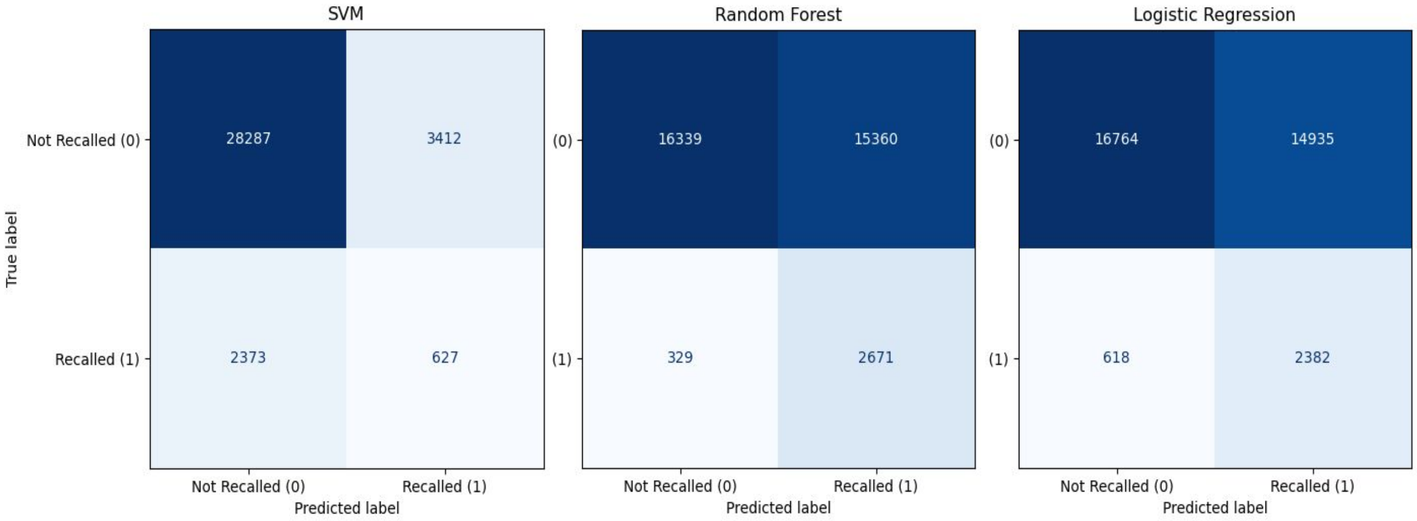
Scaling → GridSearchCSV optimization → 2. Tuned model

Recall F1 score

Conclusions:

- **Random forest** is our **chosen model** for its ability to predict recalls.
- **Predicting recalls is difficult** with current data especially due to imbalance.

Post optimization



SVM

True label	Predicted label: Not Recalled (0)	Predicted label: Recalled (1)
Not Recalled (0)	28287	3412
Recalled (1)	2373	627

Random Forest

True label	Predicted label: Not Recalled (0)	Predicted label: Recalled (1)
(0)	16339	15360
(1)	329	2671

Logistic Regression

True label	Predicted label: Not Recalled (0)	Predicted label: Recalled (1)
(0)	16764	14935
(1)	618	2382

Future Work

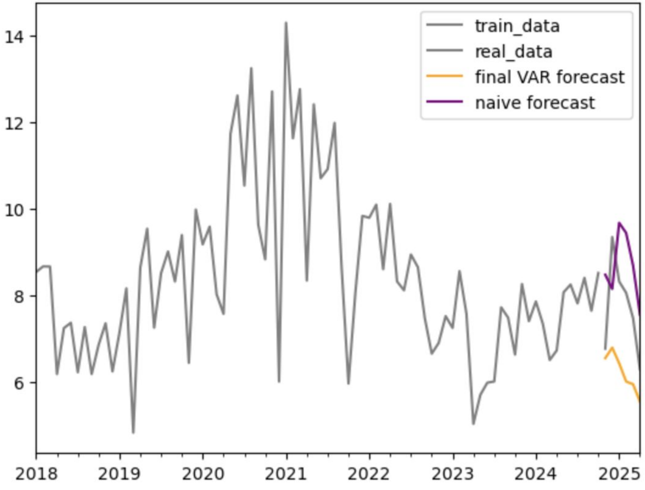
Predicting recall percentages in future months using a VAR (vector autoregression) model.

Variables used: recall percentage, numbers of outbreaks with 5 types of pathogens, recent seasonal average of recall percentage

Our current model only performs roughly as well as a baseline seasonal model.

Potential improvement:
Including more spatial information, climate reasons for recall, and by adding regularization.

Recall percentage by month


train_data
real_data
final VAR forecast
naive forecast