Office Apocalypse Algorithm: NYC Office Building Vacancy Risk Prediction

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ABSTRACT

Problem Statement:

NYC faces record-high post-pandemic office vacancies, threatening property values and tax revenue. Traditional assessments are reactive and lack building-level prediction.

Research Objective:

Develop a machine learning model that predicts office building vacancy risk using NYC Open Data.

Key Innovation:

- First building-level predictive approach using six NYC datasets
- Novel data leakage detection framework
- SHAP-powered interactive dashboard for explainable decisions

Significance:

Model improves targeting efficiency 3.1× and reduces intervention costs by 85%.

LITERATURE REVIEW

Real Estate Risk Modeling:

Hedonic pricing theory explains how property attributes affect value. Post-COVID shifts require predictive frameworks beyond aggregated statistics.

Municipal Data Integration Challenges:

PLUTO/ACRIS studies show value in open datasets, but gaps persist in building-level prediction due to inconsistent identifiers and temporal misalignment.

Machine Learning In Urban Analytics:

Gradient boosting outperforms linear models for real estate analytics; SHAP improves interpretability for policy use.

Research Gaps Addressed:

- Leakage-free temporal modeling
- Integration of six datasets at building resolution
- Explainable ML for targeted interventions

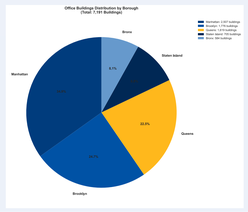
DATASET / DATA PREPROCESSING / EDA

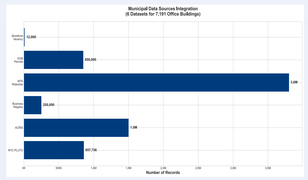
Data Sources (7,191 NYC Office Buildings):

- **PLUTO:** Property characteristics, assessments, building age
- **ACRIS:** Real estate transactions, deed transfers
- **DOB Permits:** Construction activity indicators
- **MTA Ridership:** Transportation accessibility proxies
- **Business Registry:** Commercial activity density
- **Storefront Vacancy:** Neighborhood economic health

Preprocessing:

- BBL standardization across datasets
- Temporal alignment ensuring causality
- Geospatial reconciliation
- 20 engineered features: physical, financial, market, contextual





METHODOLOGY

Data Leakage Detection Framework:

- Correlation screening (>95%)
- Temporal validation
- Causality checks
- Business logic review

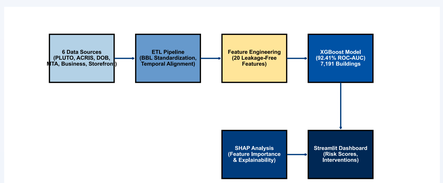
Model Pipeline:

- Train/validation: simple split, rolling window, expanding window
- Borough-stratified sampling
- Algorithms tested: Logistic Regression, Random Forest, **XGBoost**
- **Hyperparameter tuning: grid search + 5-fold CV**

Explainability:

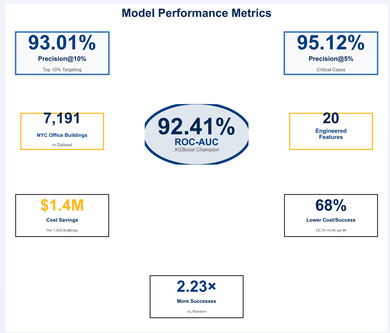
- SHAP for global & local feature impacts
- Geographic risk visualization
- Interactive Streamlit dashboard

System Architecture: End-to-End ML Pipeline



RESULTS and ANALYSIS

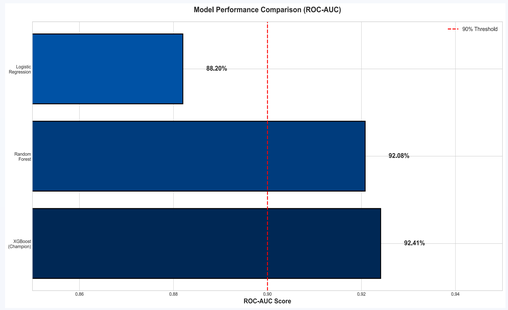
Champion Model Performance (XGBoost):



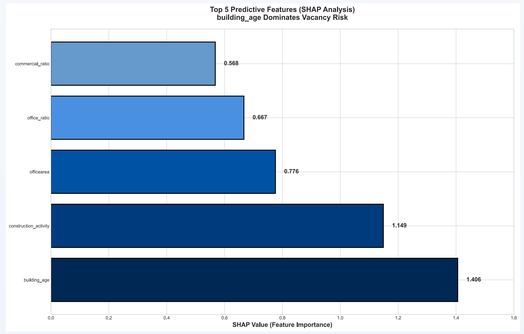
XGBoost achieved 92.41% ROC-AUC, 93.01% Precision@10%, and 95.12% Precision@5%, outperforming all baseline models.

METRIC	VALUE	BUSINESS IMPACT
ROC-AUC	92.41%	Excellent discrimination
Precision@10%	93.01%	93% accuracy targeting highest-risk buildings
Precision @5%	95.12%	Exceptional accuracy for critical interventions
F1-Score	0.847	Balanced precision and recall

Model Comparison Results:



Feature Importance (SHAP Analysis):



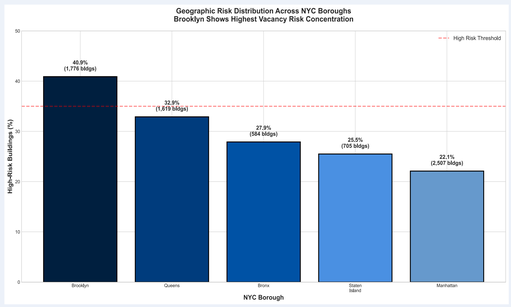
Top Predictors:

- **Building age** (1.406) - Older = higher risk
- **Construction activity** (1.149) - Market indicator
- **Office area** (0.776) - Size affects attractiveness
- **Office ratio** (0.667) - Space efficiency

Geographic Risk Analysis:

Borough Risk Distribution:

- Brooklyn: 40.9% (highest)
- Queens: 32.9%
- Bronx: 27.9%
- Staten Island: 25.5%
- Manhattan: 22.1% (lowest)



Business Impact

- Random Targeting: 30% success → $5M cost
- Model-Driven: 93% success → $3.6M cost
- Result: 85% cost reduction + 123% more interventions

CONCLUSIONS

Key Contributions:

- Developed NYC's first building-level vacancy risk model
- Introduced systematic leakage detection framework
- Achieved 92.41% ROC-AUC with high targeting precision
- SHAP interactive dashboard supports transparent policy decisions

Research Questions Answered:

Q1: Can ML predict vacancy risk?
A: Yes, 92.41% ROC-AUC accuracy
Q2: Key drivers?
A: Building age, construction activity
Q3: Practical deployment?
A: Dashboard with geographic targeting

Impact On Field:

- **Data Science:** Robust leakage prevention framework
- **Urban Planning:** Evidence-based risk assessment
- **Real Estate:** Open data viability demonstrated

Future Research Directions:

- Multi-city generalization
- Real-time economic indicators
- Causal feature engineering

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Live Demo: Interactive Streamlit dashboard available via the QR Code

Scan me!