CRIME CASE RESOLUTION PREDICTION ANALYSIS REPORT

LAPD DATA 2020-2025

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EXECUTIVE SUMMARY

This project developed a machine learning model to predict crime case resolution outcomes using Los Angeles Police Department data from 2020-2025. The XGBoost model successfully classifies cases into three categories with strong performance on minority classes despite severe class imbalance (80% Unsolved vs. 10% Solved by Arrest vs. 10% Solved Exceptionally). The model achieves 71% overall accuracy while maintaining balanced performance across all classes, providing valuable insights for law enforcement resource allocation.

PROJECT OVERVIEW

BUSINESS PROBLEM

Law enforcement agencies need to optimize limited investigative resources by identifying cases with the highest probability of being solved. Traditional methods rely on officer experience and manual assessment, which can be inconsistent and time-consuming.

TECHNICAL CHALLENGE

- **Severe class imbalance**: 80% Unsolved vs. 20% Solved cases
- **High-dimensional data**: 400+ features after engineering
- **Complex feature relationships**: Non-linear patterns in crime data
- **Data quality issues**: Missing values and inconsistent reporting

SOLUTION APPROACH

Developed a machine learning pipeline that processes raw crime data, engineers meaningful features, and builds predictive models to classify case resolution outcomes with balanced performance across all categories.

DATA DESCRIPTION

DATASET CHARACTERISTICS

- **Source**: Los Angeles Police Department (LAPD)
- **Time Period**: January 2020 - December 2025
- **Total Records**: 1,004,991 crime incidents
- **Geographic Coverage**: Entire City of Los Angeles

KEY VARIABLES

- **Temporal Features**: Date reported, date occurred, time of occurrence
- **Geographic Features**: Latitude, longitude, police precinct codes
- **Crime Characteristics**: Crime codes, modus operandi (MO) codes, weapon involvement
- **Victim Information**: Age, gender, descent
- **Target Variable**: Case status (Unsolved, Solved by Arrest, Solved Exceptionally)

DATA QUALITY ASSESSMENT

- **Missing Values**: Handled through strategic imputation and removal
- **Data Leakage**: Identified and removed problematic features (Weapon Used Cd)
- **Consistency**: Standardized categorical codes and temporal formats

METHODOLOGY

DATA PREPROCESSING

Temporal Processing

- Calculated time-to-report differentials
- Created time-of-day bins and day-of-week features
- Handled datetime inconsistencies

Geographic Processing

- Latitude/Longitude validation and cleaning
- K-means clustering (50 clusters) for spatial patterns
- Police precinct area mapping

Feature Engineering

- **MO Code Embeddings**: Converted free-text MO codes to learned vector representations
- **Crime Complexity**: Created crime_count from multiple crime code fields
- **Victim Demographics**: Encoded categorical variables with appropriate scaling

MODEL DEVELOPMENT

Algorithms Tested

- **Neural Network with Embeddings**: Architecture: Input layers for structured data + MO code embeddings; Result: Failed due to class imbalance (predicted only majority class)
- **XGBoost (Tuned)**: Parameters: max_depth=4, learning_rate=0.05, subsample=0.7; Result: Good performance but slightly over-regularized
- **XGBoost (Standard)**: Parameters: Default settings with class weighting; Result: Selected as best performer - optimal balance

Class Imbalance Handling

- **Class Weighting**: Inverse proportional weighting
- **Evaluation Metrics**: Focus on F1-score and recall for minority classes
- **Validation**: Stratified sampling and cross-validation

EVALUATION FRAMEWORK

- **Primary Metric**: Macro F1-score (balance across all classes)
- **Secondary Metrics**: Class-wise precision, recall, and support
- **Validation Approach**: 80/20 stratified train-test split
- **Error Analysis**: Confusion matrix and classification reports

RESULTS ANALYSIS

MODEL PERFORMANCE COMPARISON

Metric	Neural Network	XGBoost (Tuned)	XGBoost (Standard)
Overall Accuracy	80%	70%	71%
Unsolved F1-Score	0.89	0.82	0.83
Solved by Arrest F1-Score	0.00	0.33	0.35
Solved Exceptionally F1-Score	0.00	0.45	0.47
Macro Avg F1-Score	0.30	0.54	0.55

SELECTED MODEL PERFORMANCE (XGBOOST STANDARD)

	precision	recall	f1-score	support
Unsolved	0.95	0.74	0.83	160,575
Solved by Arrest	0.28	0.49	0.35	18,088

	precision	recall	f1-score	support
Solved Exceptionally	0.35	0.69	0.47	22,336
accuracy			0.71	200,999
macro avg	0.53	0.64	0.55	200,999
weighted avg	0.82	0.71	0.75	200,999

KEY INSIGHTS

1. **Unsolved Cases**: High precision (95%) indicates reliable negative predictions
2. **Solved Cases**: Moderate recall (49-69%) captures majority of solvable cases
3. **Precision-Recall Tradeoff**: Willingness to accept false positives to avoid missing solvable cases
4. **Feature Importance**: Weapon data, crime type, and response time are strongest predictors

BUSINESS IMPACT

OPERATIONAL BENEFITS

1. **Resource Optimization**: Identify 49-69% of potentially solvable cases automatically
2. **Case Prioritization**: Focus investigative resources on high-probability cases
3. **Performance Benchmarking**: Establish data-driven baselines for solve rates
4. **Pattern Recognition**: Identify factors that contribute to case resolution

PRACTICAL APPLICATIONS

- **Daily Case Triage**: Prioritize new cases based on solvability predictions
- **Resource Allocation**: Assign detectives and resources more effectively
- **Performance Monitoring**: Track solve rates across different crime types and areas
- **Training Tool**: Educate officers on factors that influence case resolution

LIMITATIONS AND CHALLENGES

TECHNICAL LIMITATIONS

1. **Precision on Solved Cases**: 28-35% precision indicates many false positives
2. **Class Imbalance**: Despite techniques, minority class performance remains challenging
3. **Data Quality**: Reliance on accurate and consistent police reporting
4. **Temporal Changes**: Crime patterns may evolve, requiring model retraining

PRACTICAL CONSIDERATIONS

1. **Ethical Implications**: Avoid automated decisions that might affect investigations
2. **Human Oversight**: Recommendations should support, not replace, expert judgment
3. **Implementation Costs**: Integration with existing systems requires resources
4. **Change Management**: Officer adoption and trust in predictive tools

RECOMMENDATIONS

IMMEDIATE ACTIONS

1. **Implement XGBoost Model**: Deploy for case prioritization and resource planning
2. **Focus on High-Recall Predictions**: Prioritize catching solvable cases over precision
3. **Human-in-the-Loop**: Use predictions as advisory input for experienced detectives
4. **Monitor Performance**: Establish ongoing evaluation of model predictions vs. outcomes

FUTURE IMPROVEMENTS

1. **Feature Engineering**: Incorporate additional data sources (demographic, economic)
2. **Model Refinement**: Experiment with advanced techniques for imbalanced data
3. **Real-time Deployment**: Integrate with case management systems for live predictions
4. **Explainability**: Develop tools to explain model predictions to officers
5. **Regular Retraining**: Establish process for periodic model updates with new data

CONCLUSION

The crime prediction model successfully addresses the challenge of imbalanced classification in law enforcement data. By achieving 49-69% recall on solved cases while maintaining 95% precision on unsolved cases, the model provides practical value for police departments seeking to optimize investigative resources. The selected XGBoost model offers the best balance of performance and interpretability, making it suitable for deployment as a decision-support tool.

While precision on solved cases requires improvement, the model represents a significant step toward data-driven policing strategies. With proper implementation and ongoing refinement, this approach has the potential to enhance investigative efficiency and ultimately contribute to higher case resolution rates.

APPENDICES

- Data Dictionary
- Code Repository
- Validation Details
- Ethical Considerations Framework