INSY 662 – FINAL REPORT

POLITICAL CRIME PATTERNS IN MEXICO

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BACKGROUND

Between 2018 and October 1, 2024, **2,133 incidents of threats, murders, armed attacks, disappearances, and kidnappings against political figures** or facilities have been recorded during election periods in Mexico.

Organizations such as Data Cívica, México Evalúa, and Animal Político aim to gain a deeper understanding **of political-criminal violence**.

"crime one directed against a particular government or political system"

SECTION 01

PROJECT OBJECTIVE

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PROJECT OVERVIEW

THE MAIN QUESTION

How can past incidents of political violence and macroeconomic factors help predict future political crimes in Mexico?

THE OBJECTIVE

Predict the number and type of political crimes in Mexico by analyzing past violence against politicians and key macroeconomic factors.

THE IMPACT

- Identify patterns to forecast political crime trends.
- Develop a predictive model to reduce risks for political figures.
- Provide insights into socioeconomic factors contributing to political violence.

POTENTIAL STAKEHOLDERS

- Government and Public Officials
  - Law Enforcement Agencies
  - Policy Makers
- Political parties (Leaders, candidates, & campaign managers)
- Judicial Bodies (Prosecutors)
- Non-Governmental Organizations
- Journalists and Media Outlets
- General Public (citizens and community groups)

EXECUTIVE SUMMARY

What indicators are most effective in predicting political crime in Mexico? Our data was sourced from an organization called “Voting between Bullets” which aims to make voting fair without the influence of violence. We found it difficult to predict political violence due to the variability and the continuously evolving political landscape, however, it is core to democracy and the proper execution of the vote. With our research, we can best protect political figures and assist the proper, just, and peaceful undertaking of elections. The key insights we identified are as follows:

#1

MODEL

- Merge of Crime and economic data.
- KNN classification

#2

MAJOR POLITICAL PARTIES AT RISK

- National Action Party (PAN)
- Institutional Revolutionary Party (PRI)

#3

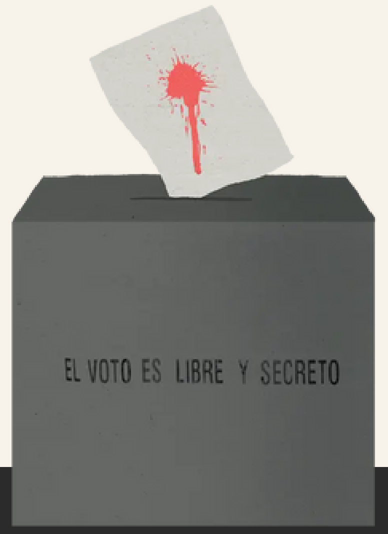
GENDER

- Both as threatened

SECTION 02

DATA EXPLORATION

DATA DESCRIPTION

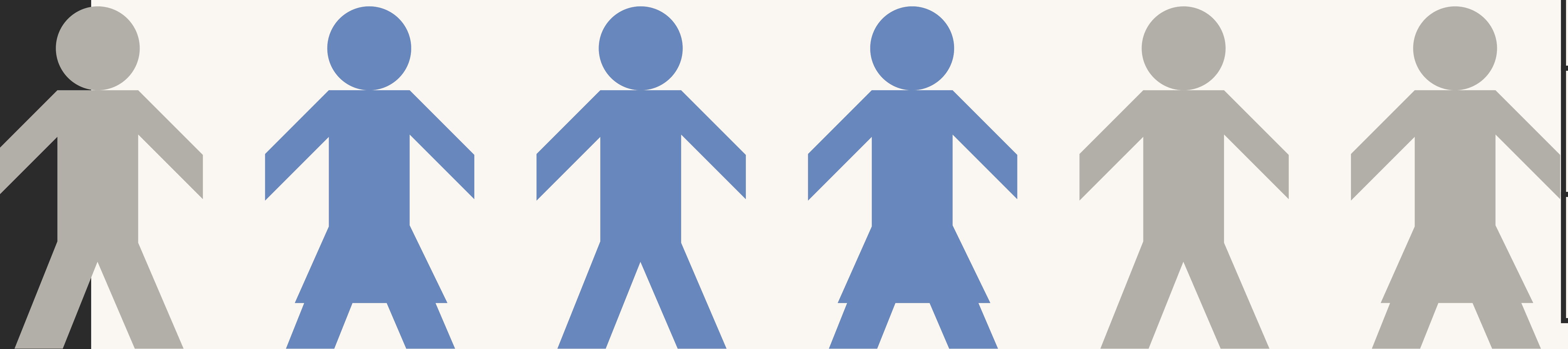


We utilized three distinct datasets to explore the relationship between political violence, demographic and economic factors:

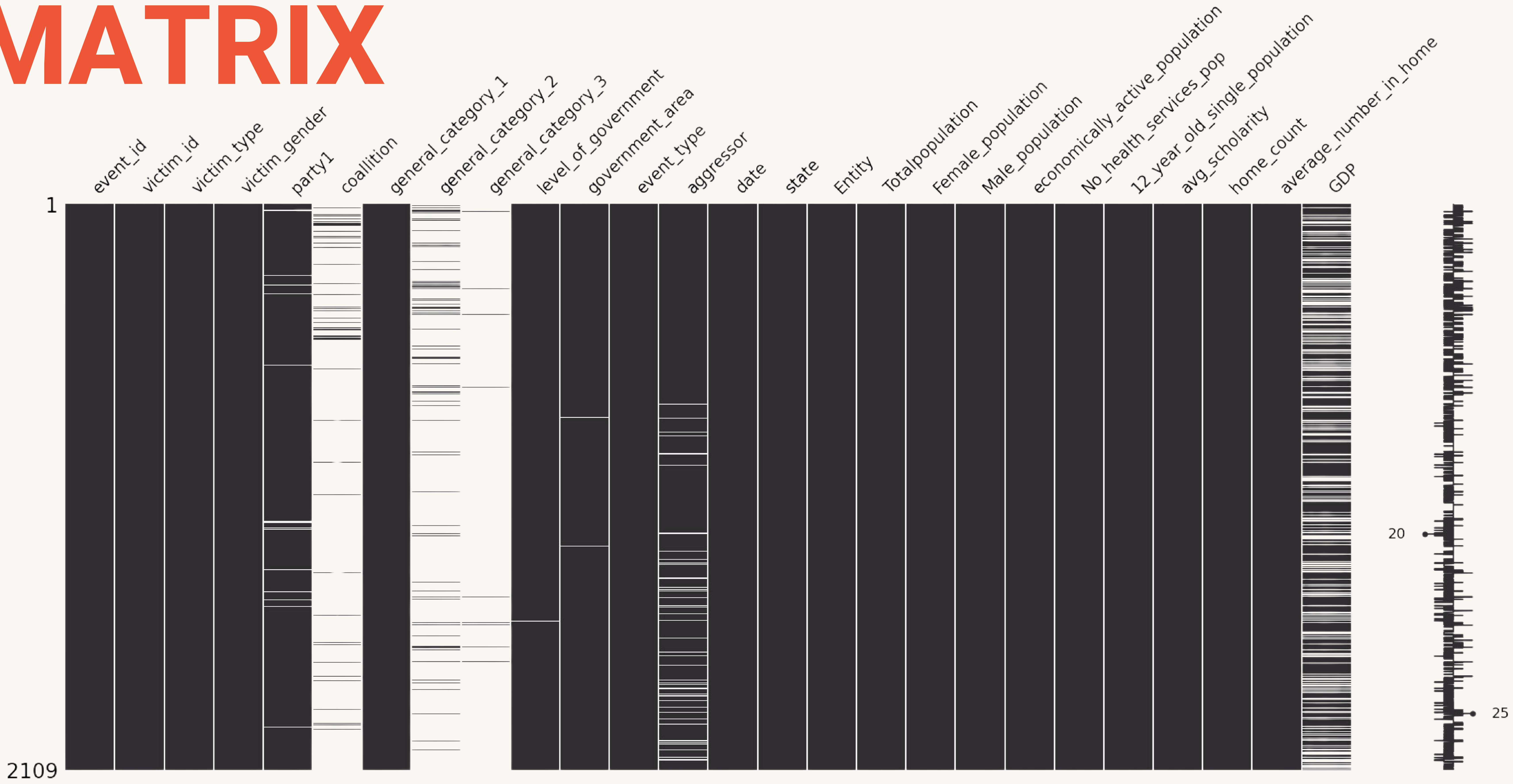
- **Political Violence:** Sourced from Datacivica, a non-profit data organization, this dataset includes information on various political crimes in Mexico between 2017 and 2024.
- **Economic Data:** Gross Domestic Product (GDP) information collected by Mexico's Central Bank (Banxico).
- **Demographic Data:** Provided by Mexico’s National Statistical Office, this dataset offers granular demographic details across different country regions like scholarity, gender, age, etc.

KEY VARIABLES

General Crime Data	Political Party Data	Demographic Data
Victim Name	Political Party	GDP
Victim Gender	General Category	Female Population
Event Type	Government Area	Health Service Availability
Victim Type	State	12 Year Old Proportion
		Average Scholarity
		Home Count
		Average Number In Home



PRE-PROCESSING MATRIX

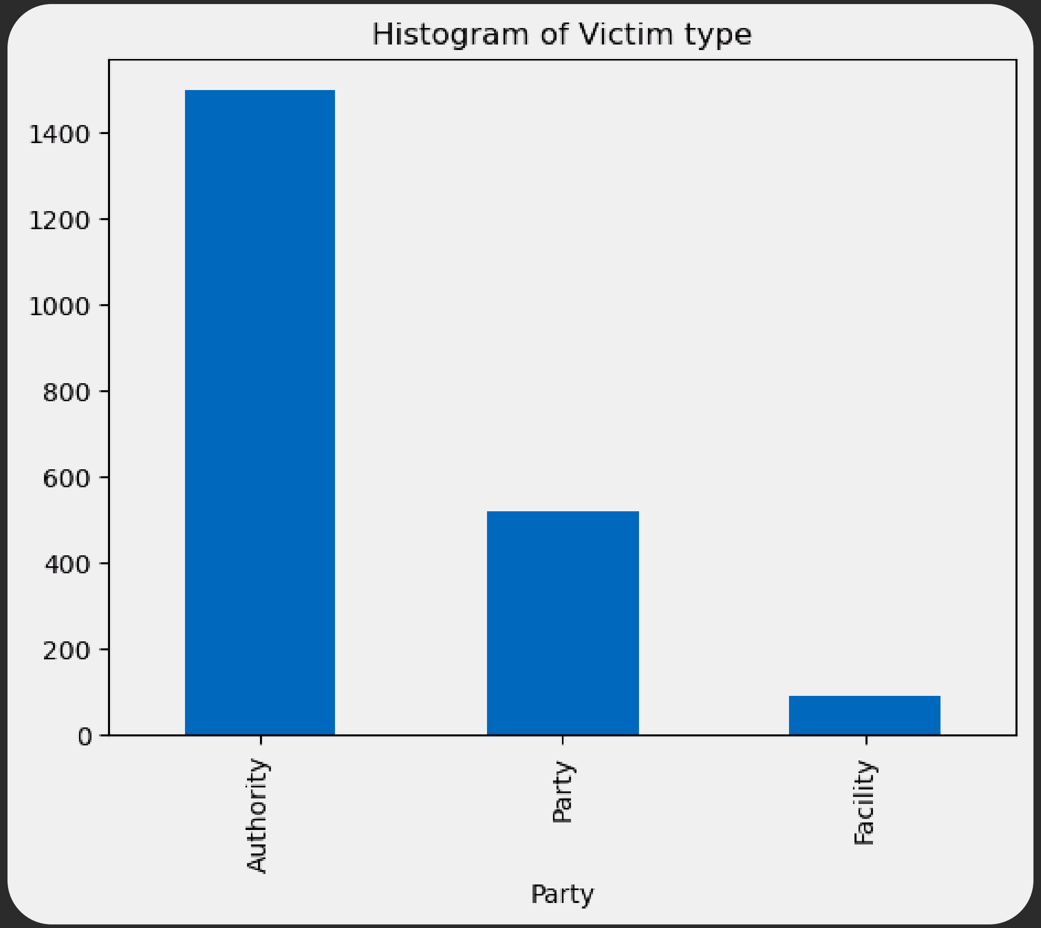


PREPROCESSING STEPS

1. **STANDARDIZE FORMATTING** — Rename columns and convert variables to consistent formats (e.g., English labels, numeric scales).
2. **DATA CLEANSING** — Remove duplicates and irrelevant identifiers that don’t contribute to analysis.
3. **HANDLE MISSING DATA** — Address missing values by removing null rows or imputing values using statistical techniques.
4. **DETECT OUTLIERS & NORMALIZE DATA** — Identify outliers using statistical methods and normalize data for consistent scaling.
5. **GAIN PRELIMINARY INSIGHTS** — Create frequency tables, histograms, and heat-maps to visualize data.

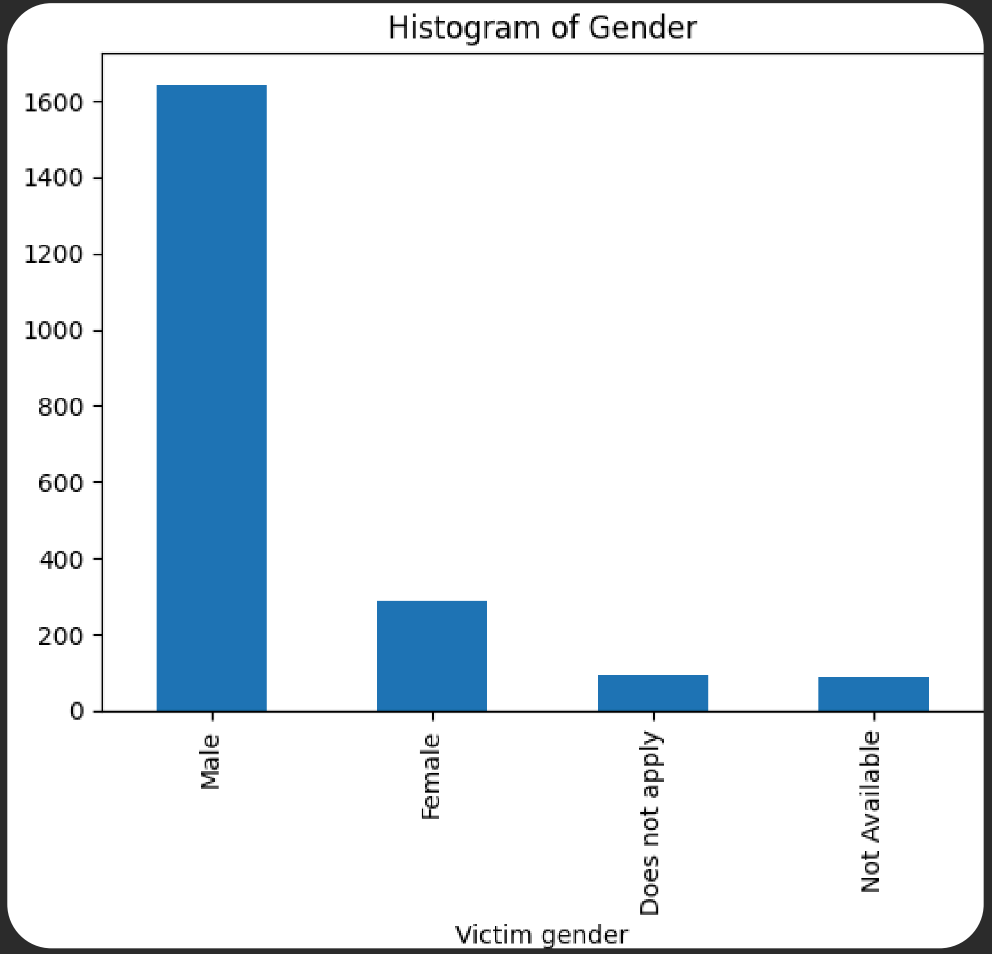
EXPLORATORY ANALYSIS I

VICTIM TYPE HISTOGRAM



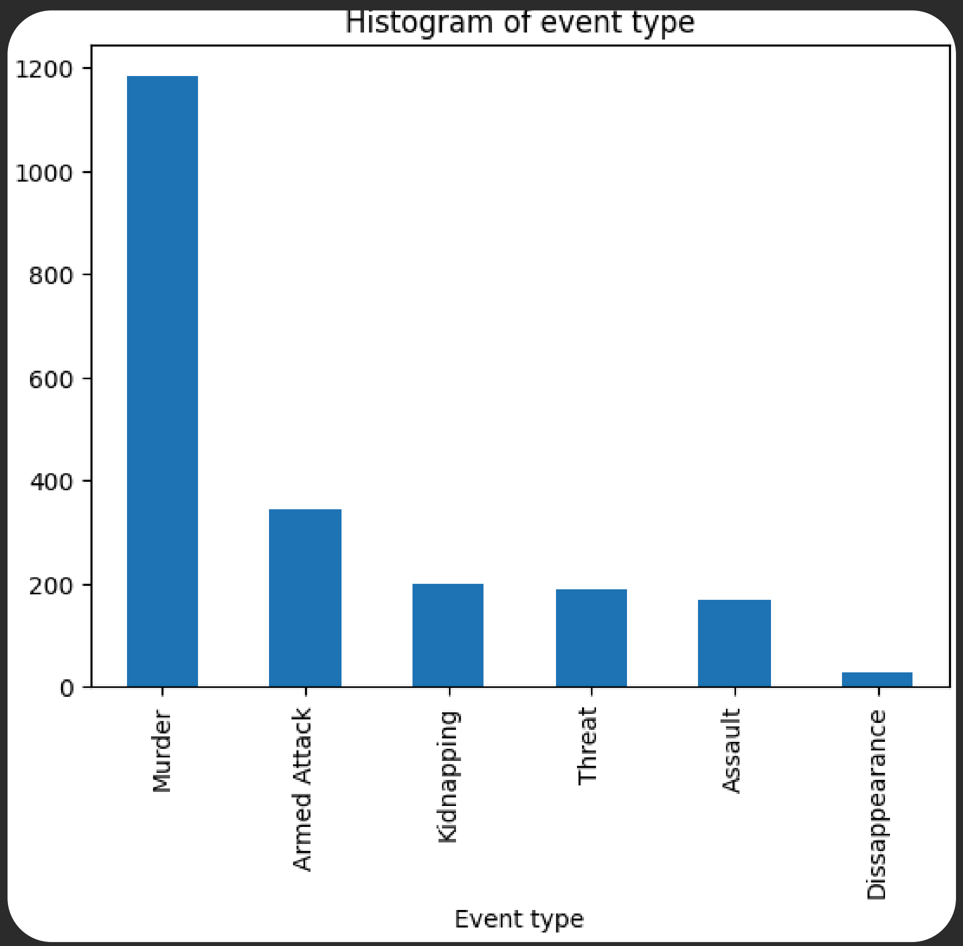
We can identify three main categories no further processing was considered.

GENDER HISTOGRAM



We stayed with three values; “not available” changed by the mode, “does not apply” respresents cadidates from the LBTQ++ community

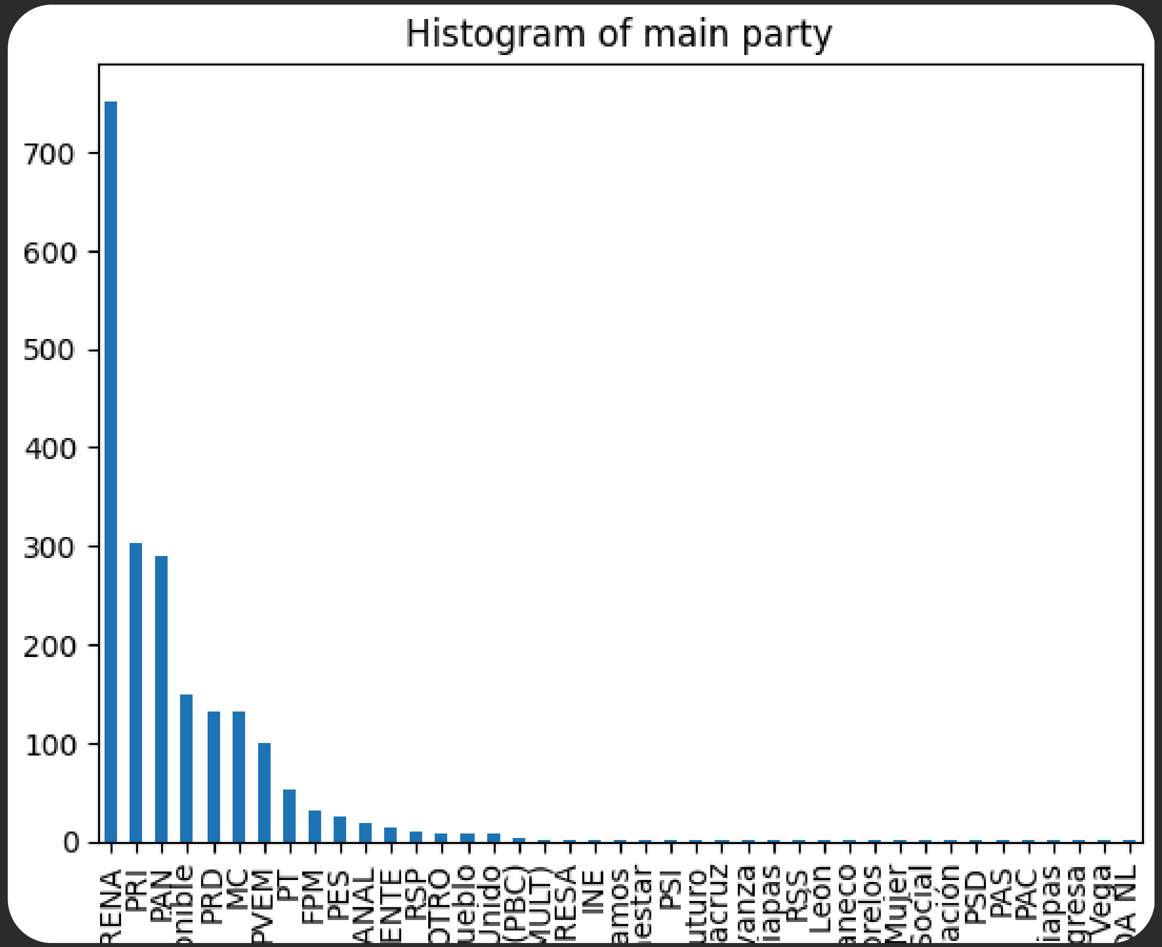
EVENT TYPE HISTOGRAM



We can identify six different categories and no further processing was considered.

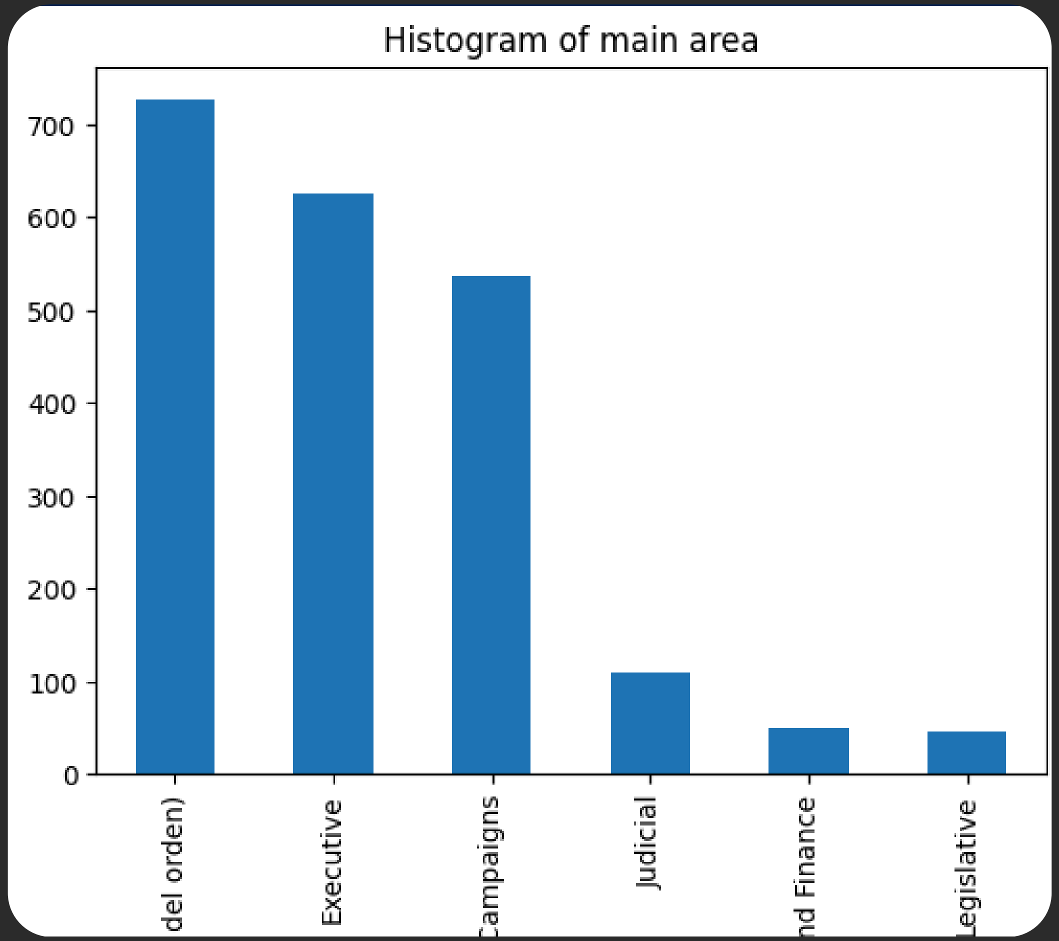
EXPLORATORY ANALYSIS II

MAIN PARTY HISTOGRAM



The data for the main party had a high level of granularity. We chose to group the top 10 parties while consolidating the remaining parties into an "Others" category.

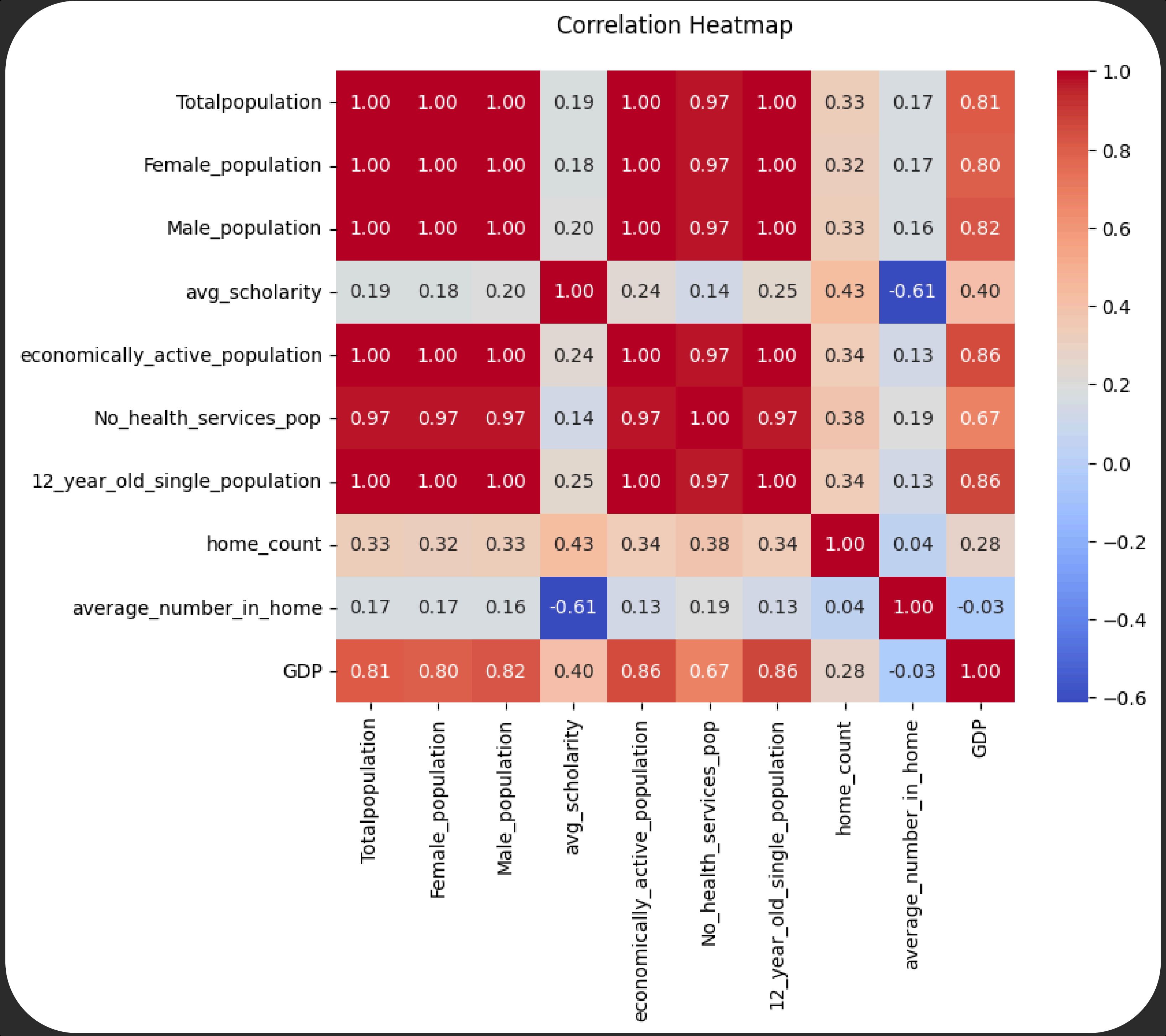
AREA HISTOGRAM



For the six categories in area, no further process was done.

CORRELATION MATRIX

- Some variables show a correlation of 1 due to overlapping population aggregations.
- Retained key variables: gender distribution, lack of access to health services, and total population.
- Omitted economically active population as it overlaps with GDP data.



POST-PROCESSING MATRIX

SECTION 03

MODEL BUILDING

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MODELING STEPS

We explored multiple models with various feature selection techniques. KNN without feature selection delivered comparable performance to other methods while being computationally efficient, making it the preferred choice for stakeholders.

#1

SCALING

Applied normal scaling to standardize the dataset for better model performance.

#2

FEATURE SELECTION

Utilized Decision Trees and Neural Networks to evaluate key features for analysis.

#3

MODEL TUNING

Focused on optimizing KNN clustering parameters to achieve the best results.

INITIAL MODELING

DATA SPLITTING

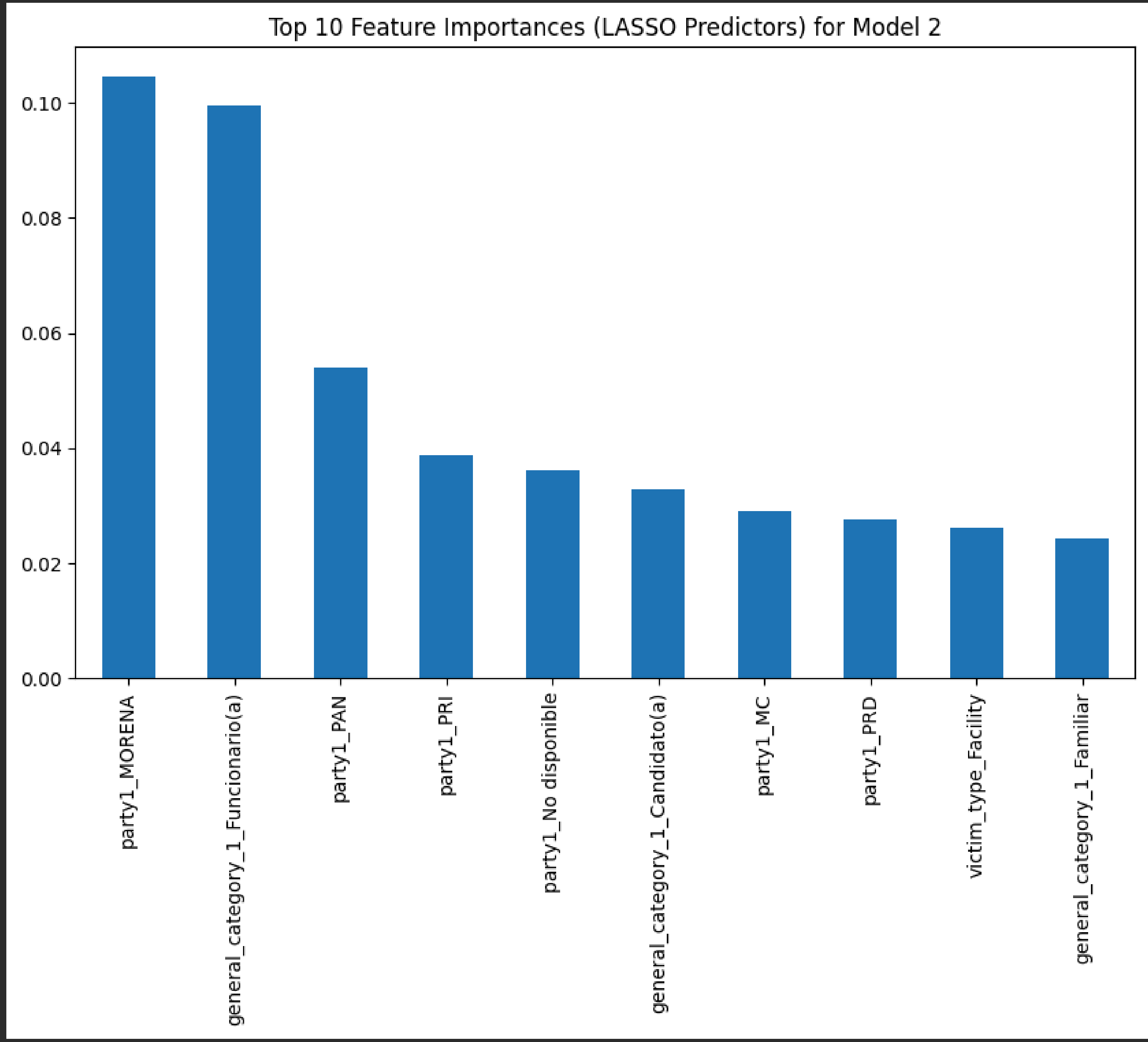
- Split the dataset into training (70%) and testing (30%) sets without scaling.

MODEL TESTING

- Trained three models on the raw data:
  - Random Forest Classifier
  - LASSO Regression
  - K-Nearest Neighbors (KNN)
  - Grid Search

MODEL EVALUATION

- KNN achieved the highest initial accuracy of 57%.



MODEL-TUNING

DATA SPLITTING

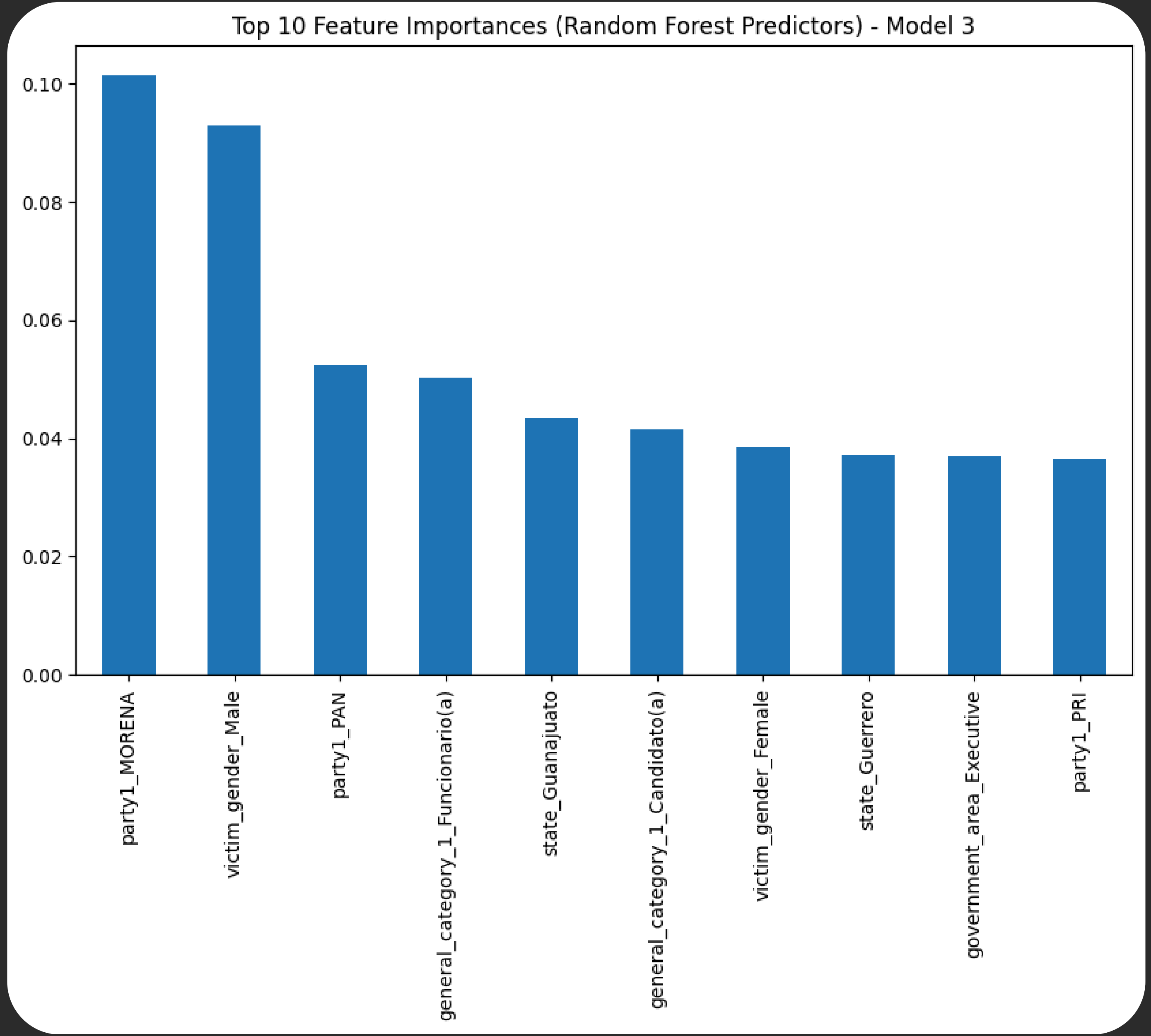
- Split the dataset into training (70%) and testing (30%) sets without scaling.

KNN TESTING WITH FEATURE SLECTION

- Trained 3 KNN models with features from:
  - Random Forest Classifier
  - LASSO Regression

MODEL EVALUATION

- **KNN no feature** selection and with random forest achieved the same accuracy of 65%.



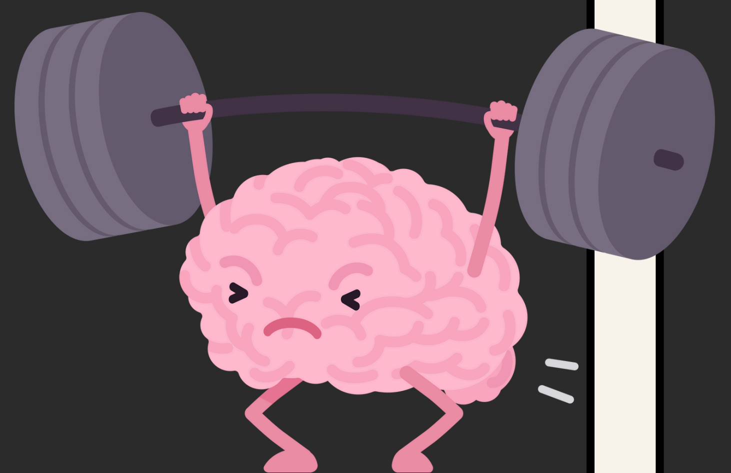
FEATURE SELECTION
TO BOOST PERFORMANCE

FEATURE SELECTION METHODS

- **LASSO Regression:** Eliminated less important features by shrinking coefficients to zero.
- **Random Forest Feature Importances:** Ranked features based on their contribution to the target variable.

RETRAINING MODEL

- Retrained the models using selected features from LASSO and Random Forest methods to improve efficiency and accuracy.



KNN WITHOUT FEATURE SELECTION

- Trained KNN on the original dataset without feature selection.

Key Observation:

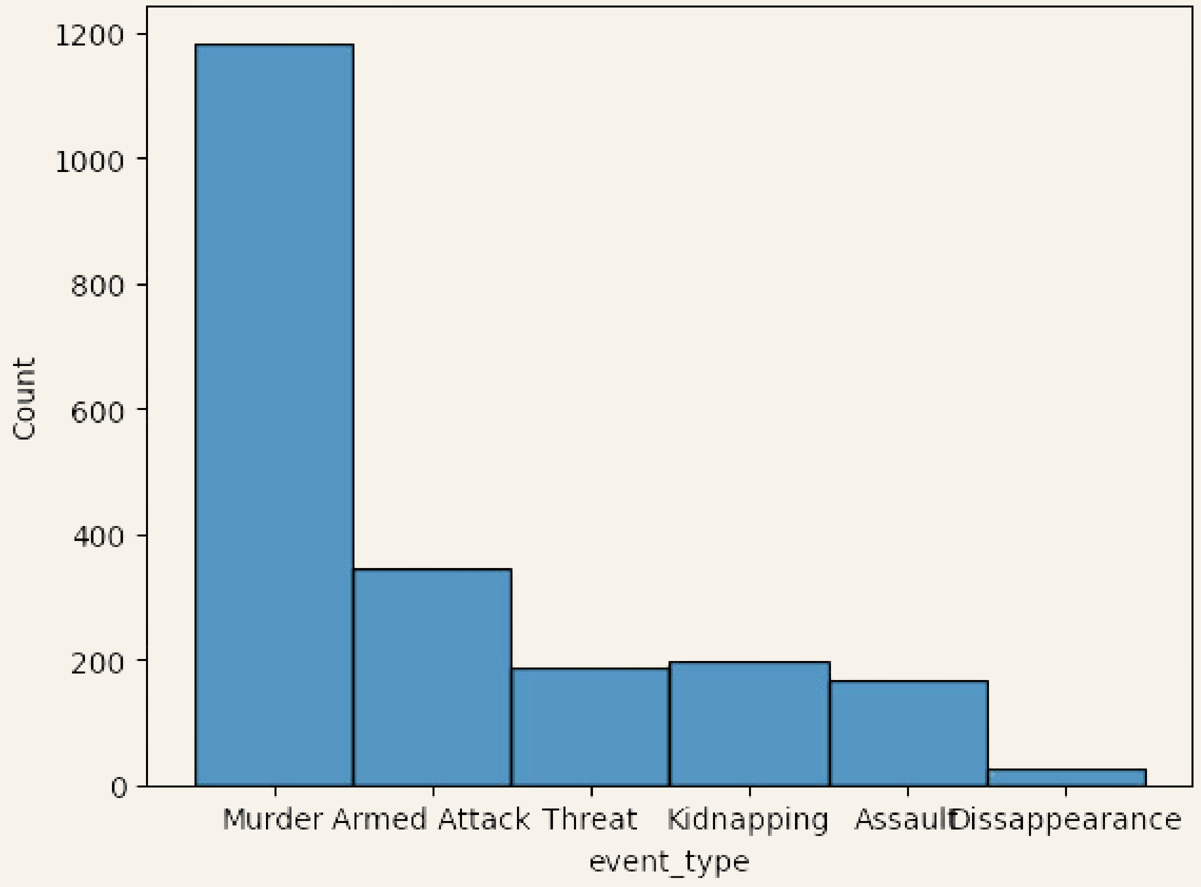
- KNN performed comparably to models using feature selection, making it a computationally efficient choice.

KNN MODEL

WITHOUT FEATURE SELECTION

- Significant misclassification persisted due to an imbalance in the target variable.
- Applied **SMOTE** to increase all non-murder categories to 350 data points each.

BEFORE




```
Test set accuracy: 0.6663479923518164
Classification Report:
              precision    recall  f1-score   support

           0       0.46      0.84      0.60       341
           1       0.59      0.62      0.60       167
           2       0.45      0.63      0.52        27
           3       0.50      0.64      0.56       198
           4       0.85      0.67      0.75      1172
           5       0.88      0.40      0.55       187

    accuracy                           0.67      2092
   macro avg       0.62      0.63      0.60      2092
weighted avg       0.73      0.67      0.68      2092
```

KNN MODEL

WITHOUT FEATURE SELECTION

- Significant misclassification persisted due to an imbalance in the target variable.
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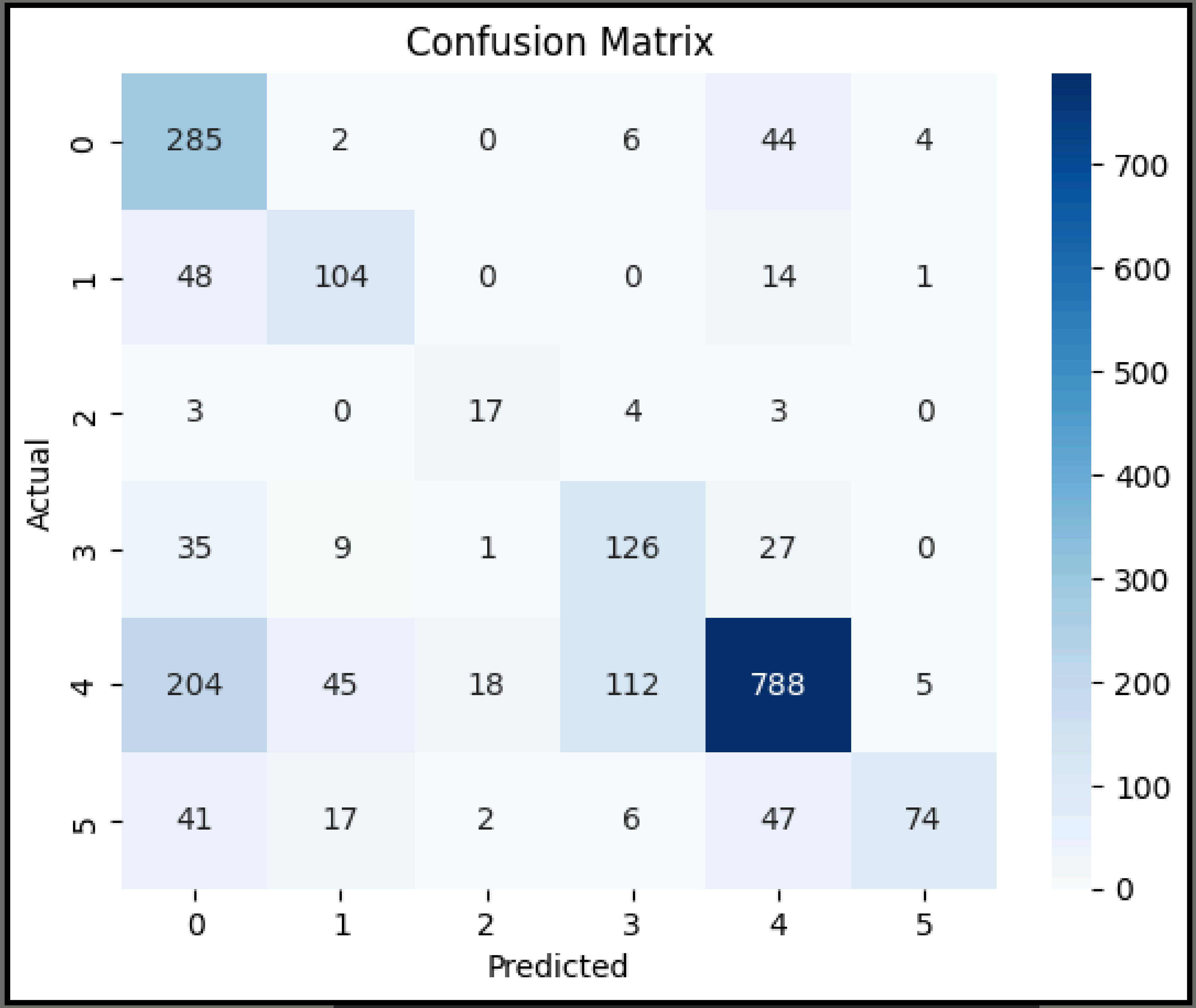


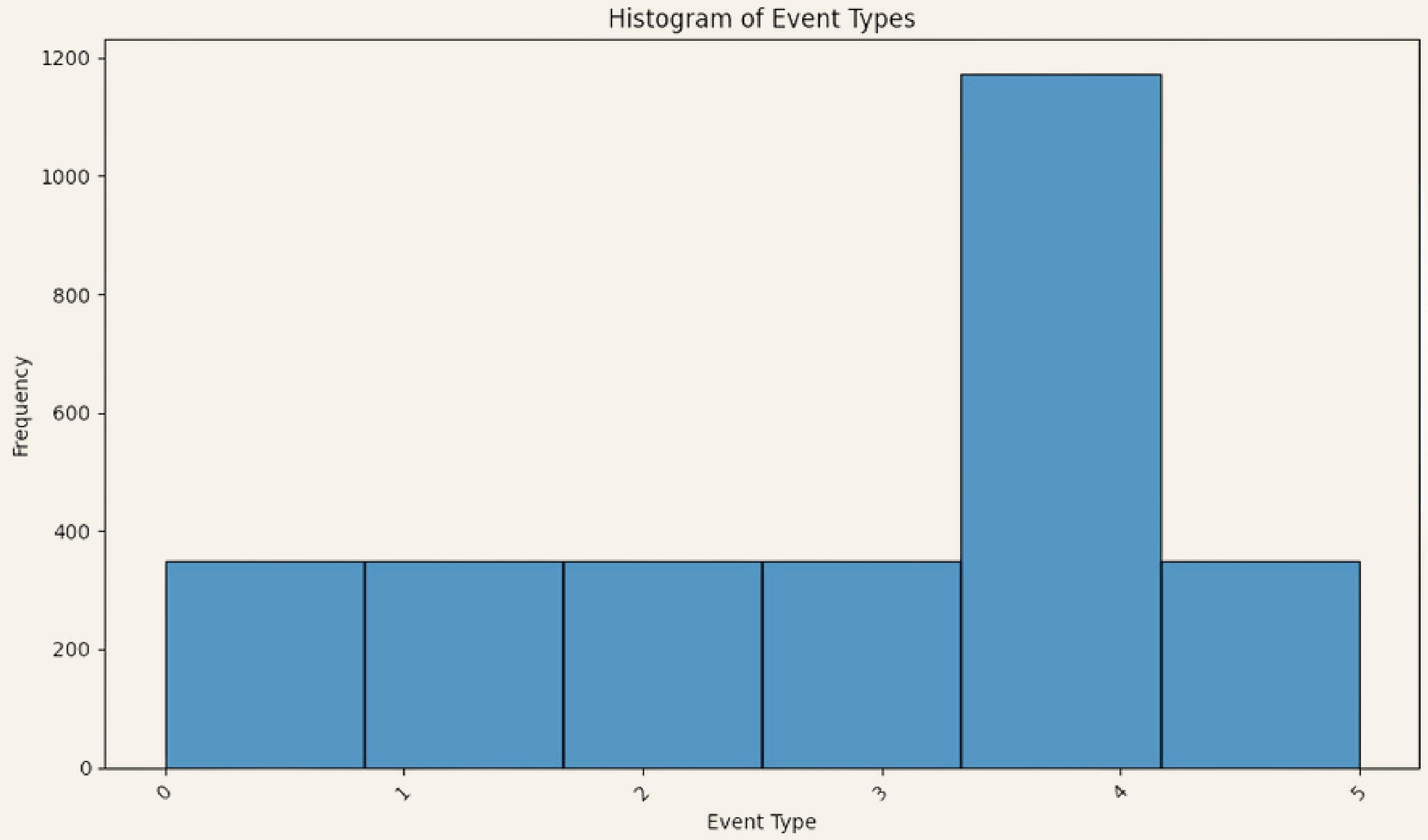
accuracy			0.67	2092
macro avg	0.62	0.63	0.60	2092
weighted avg	0.73	0.67	0.68	2092

KNN MODEL

WITHOUT FEATURE SELECTION

- Significant misclassification persisted due to an imbalance in the target variable.
- Applied **SMOTE** to increase all non-murder categories to 350 data points each.
- **Increased accuracy by 6%** and decreased misclassification.

AFTER




```
Test set accuracy: 0.7231348391512663
Classification Report:
              precision    recall  f1-score   support

           0       0.43      0.57      0.49       350
           1       0.68      0.69      0.68       350
           2       0.86      0.96      0.91       350
           3       0.76      0.60      0.67       350
           4       0.79      0.76      0.77      1172
           5       0.77      0.67      0.71       350

    accuracy                           0.72      2922
   macro avg       0.71      0.71      0.71      2922
weighted avg       0.73      0.72      0.73      2922
```

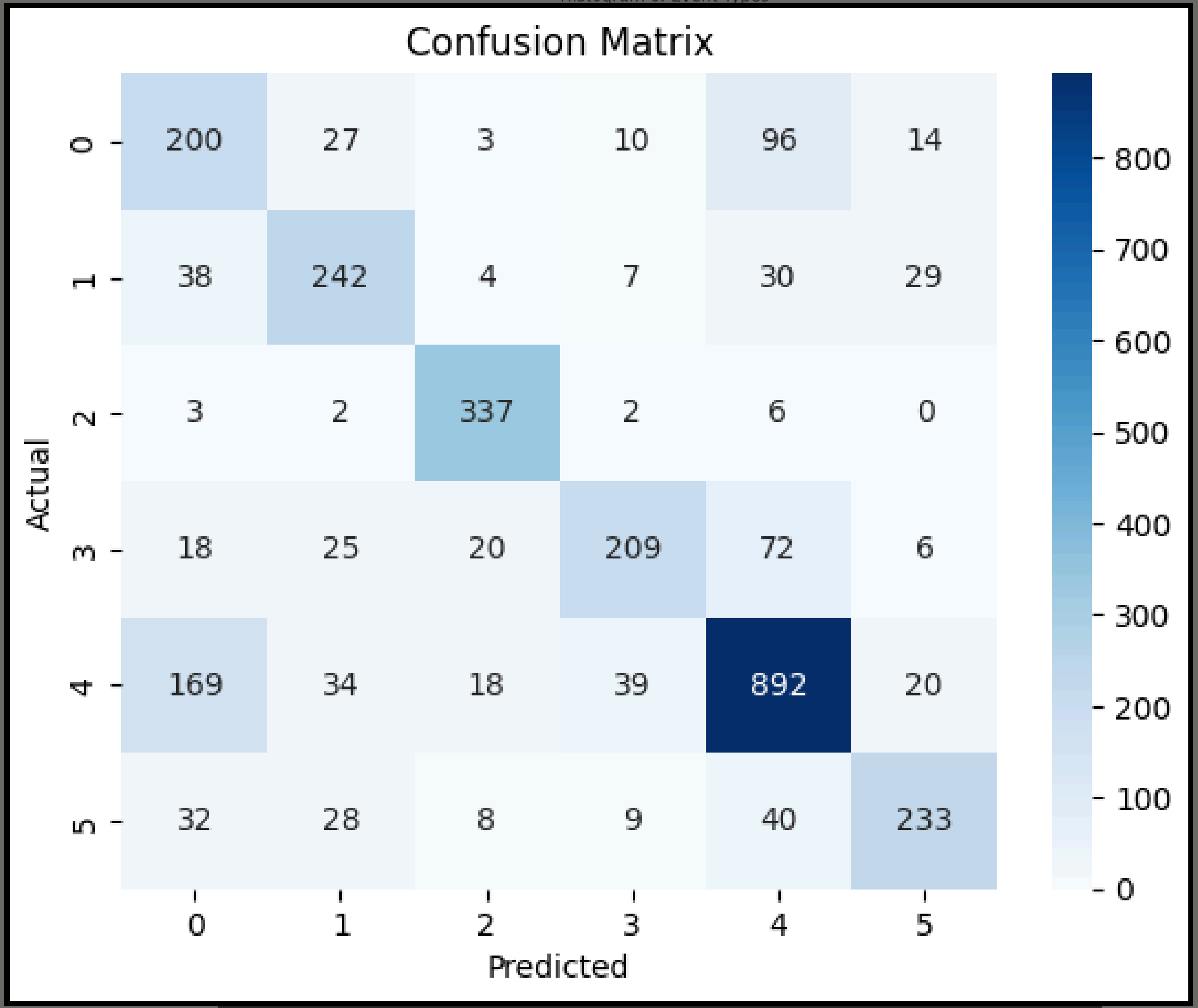
KNN MODEL

WITHOUT FEATURE SELECTION

- Significant misclassification persisted due to an imbalance in the target variable.
- Applied **SMOTE** to increase all non-murder categories to 350 data points each.
- **Increased accuracy by 6%** and decreased misclassification.

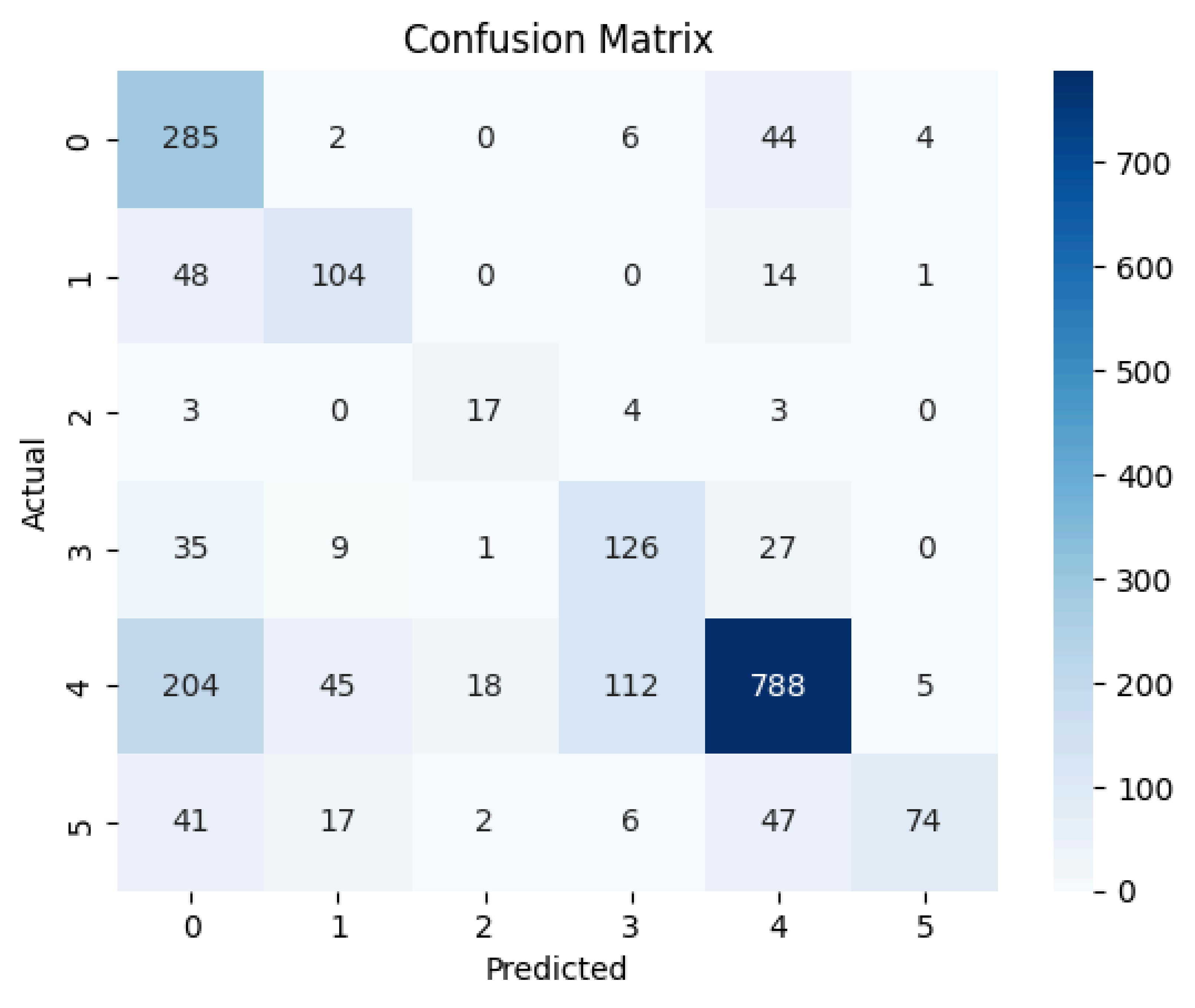
AFTER

Histogram of Event Types

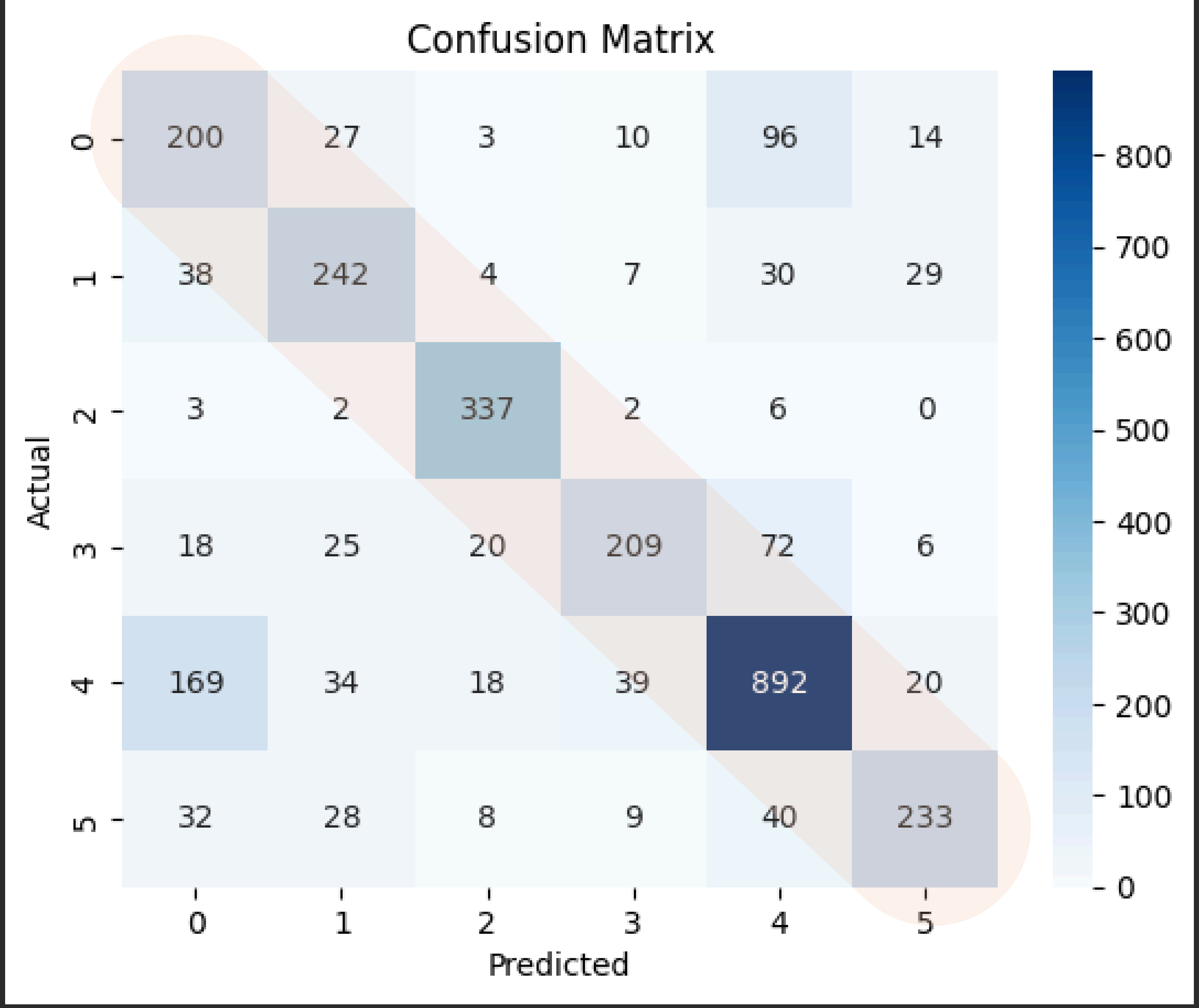


accuracy			0.72	2922
macro avg	0.71	0.71	0.71	2922
weighted avg	0.73	0.72	0.73	2922

BEFORE



AFTER



SECTION 04

RESULTS & CONCLUSION

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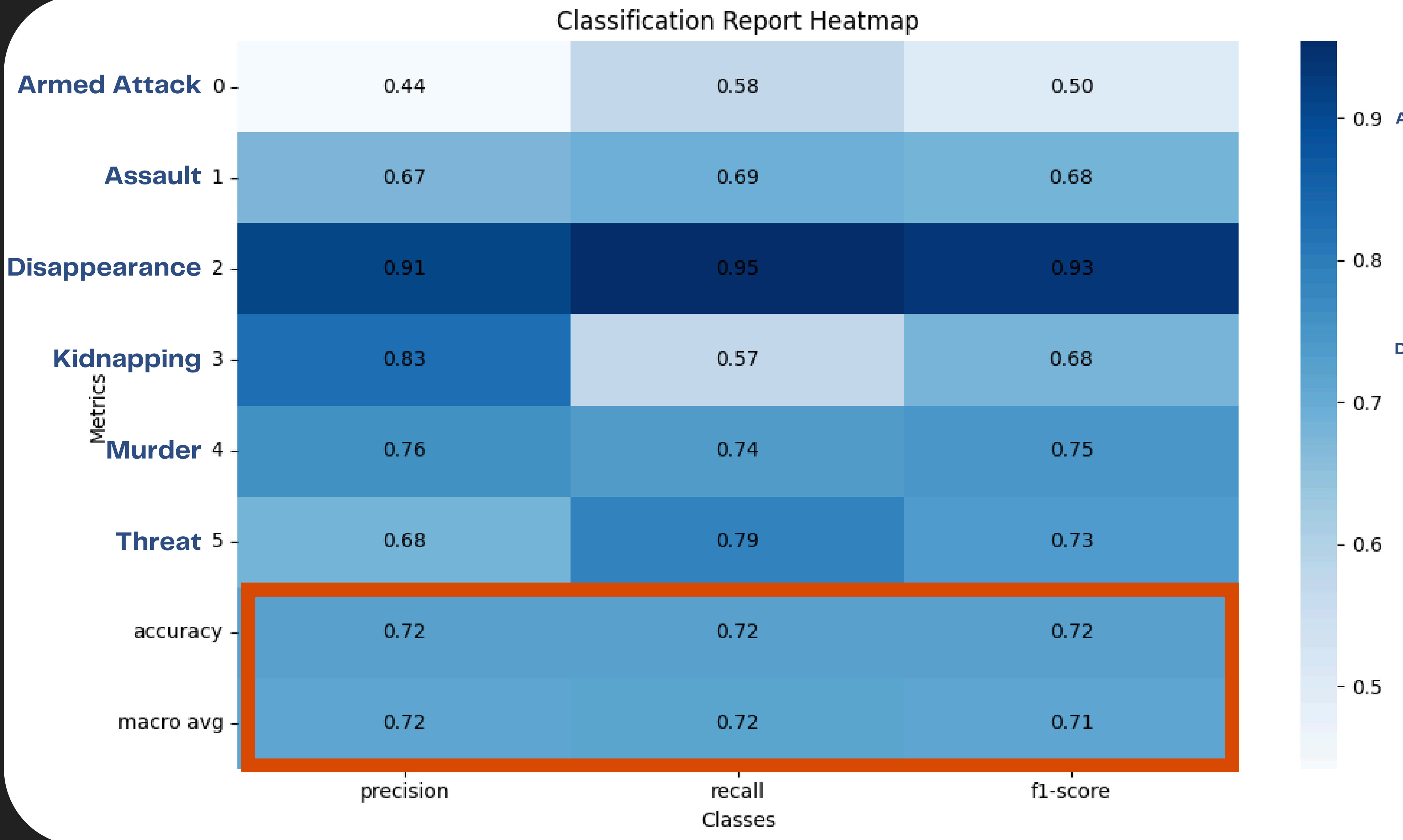
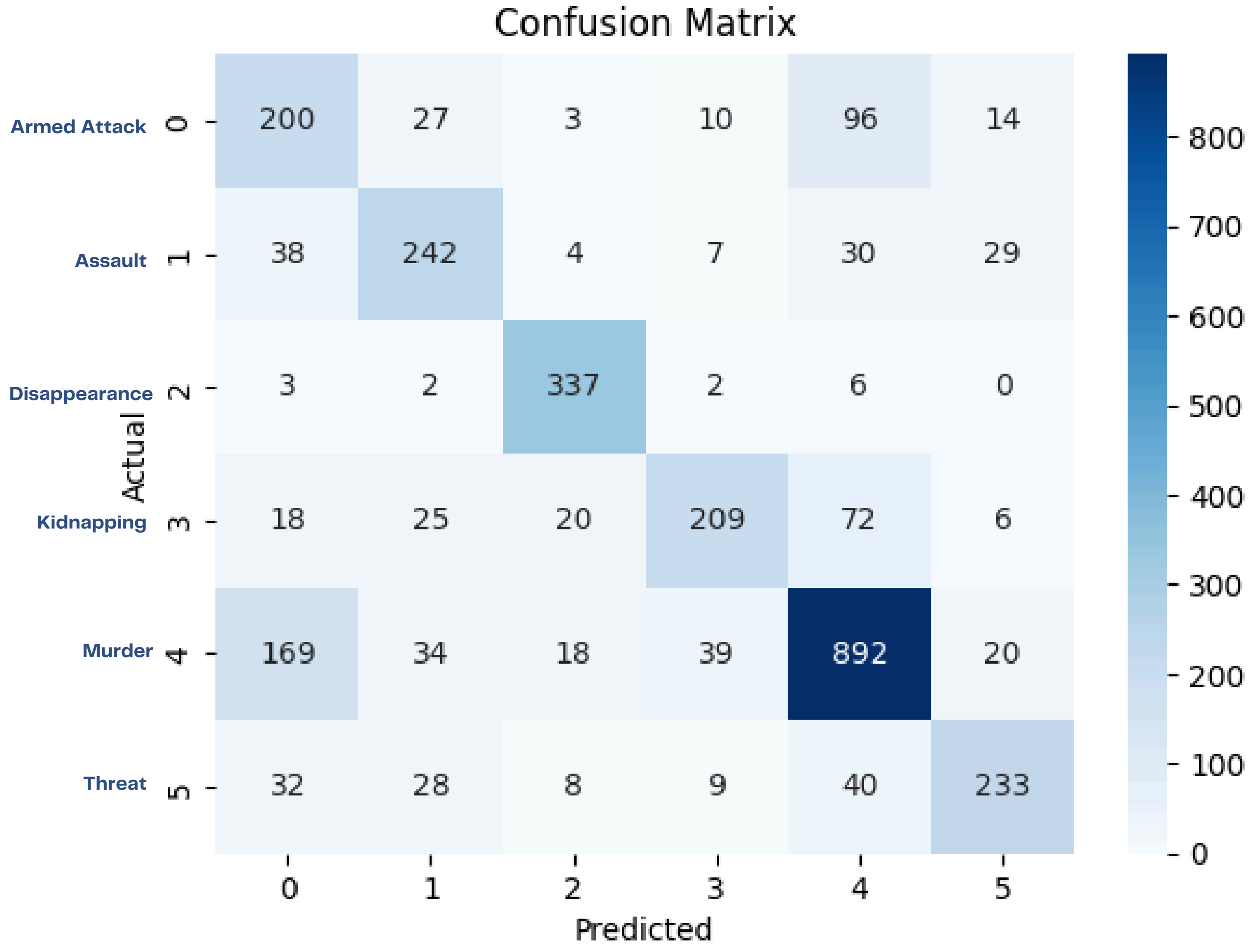
FINAL MODEL
KNN Model

Accuracy: 72%

```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

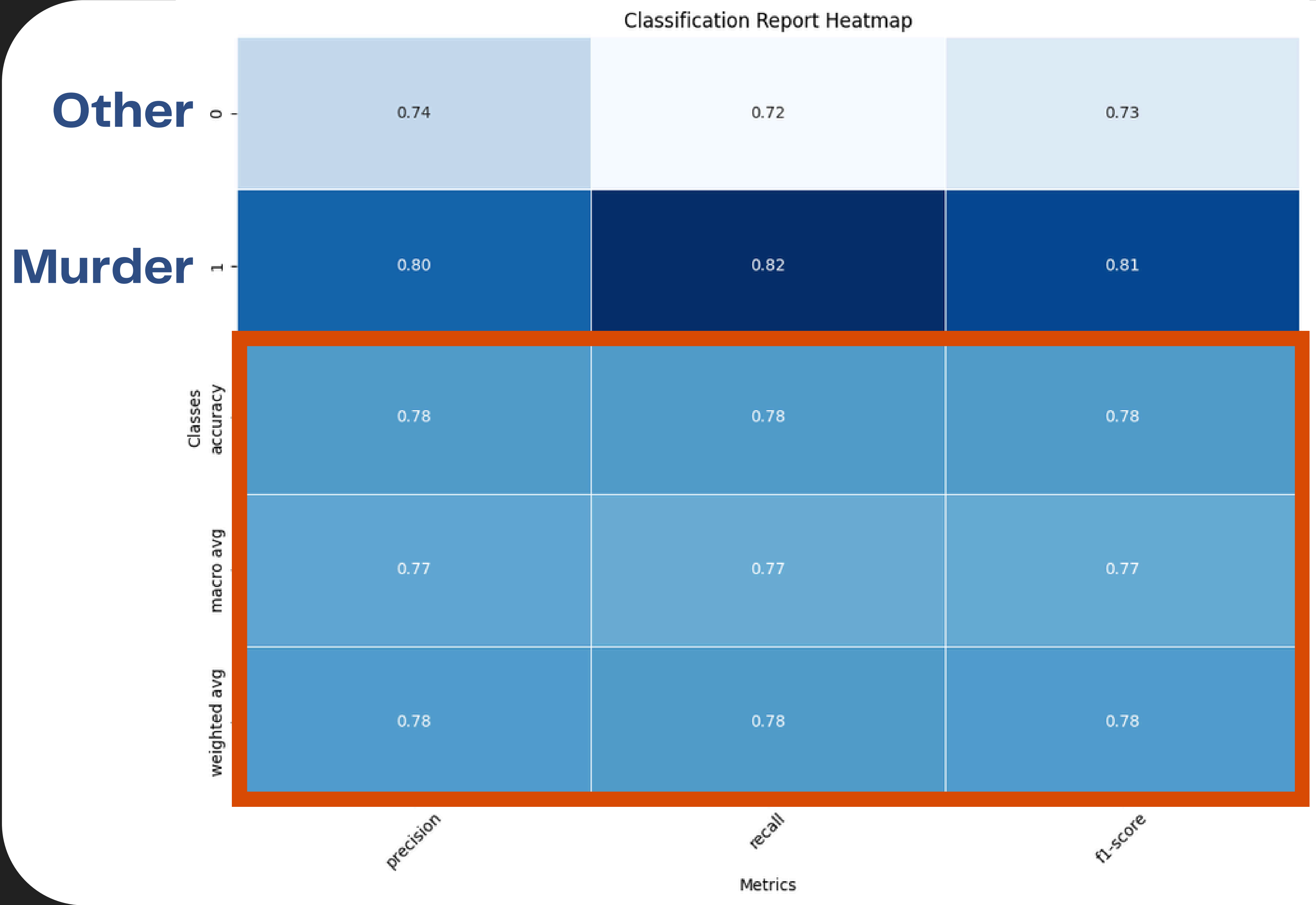


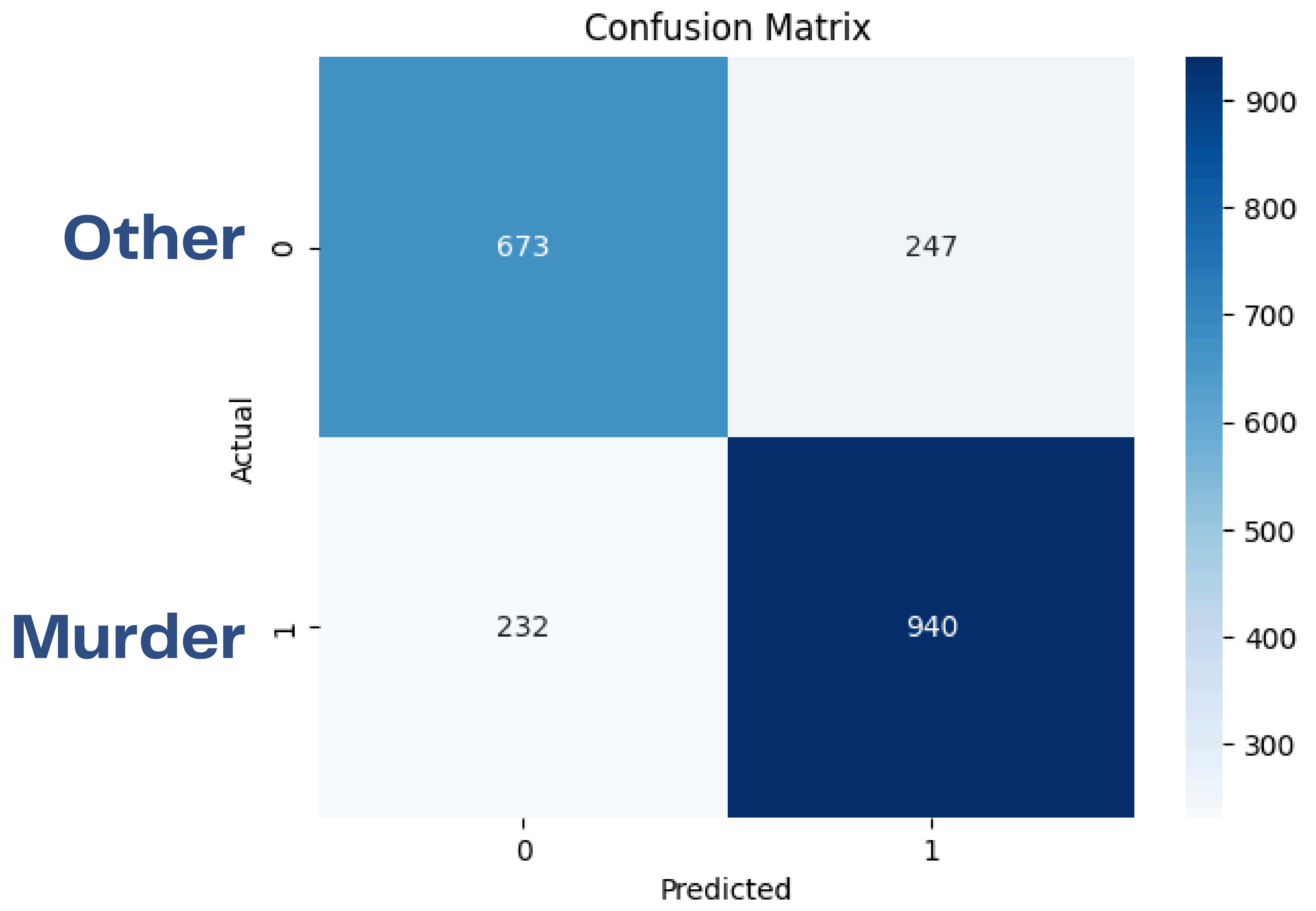


FINAL MODEL
KNN Model (BINARY)

Accuracy: 77%

```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```





FEATURE IMPORTANCE

STATE

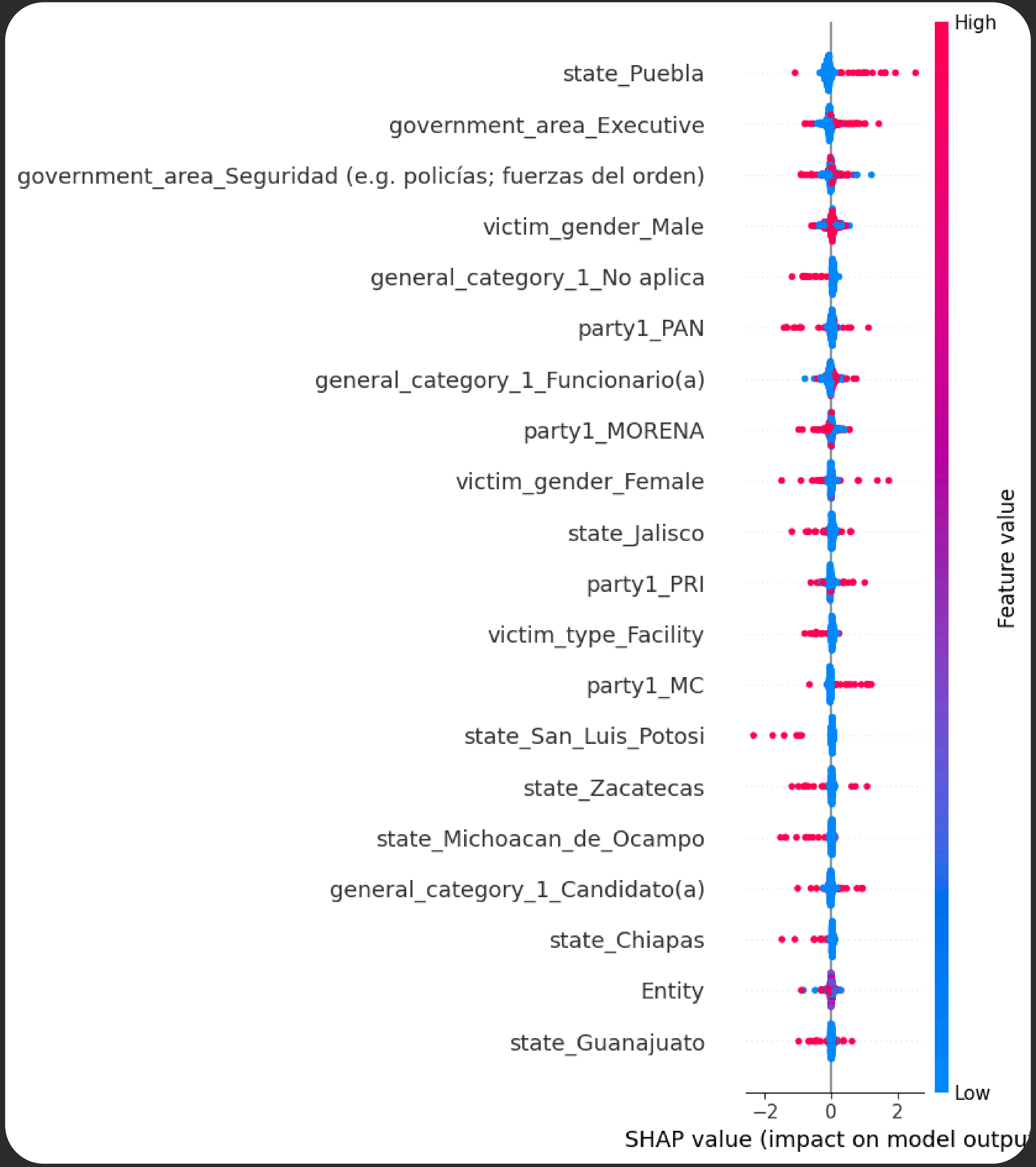
- Puebla
- Jalisco
- Zacatecas

DEMOGRAPHIC AT RISK

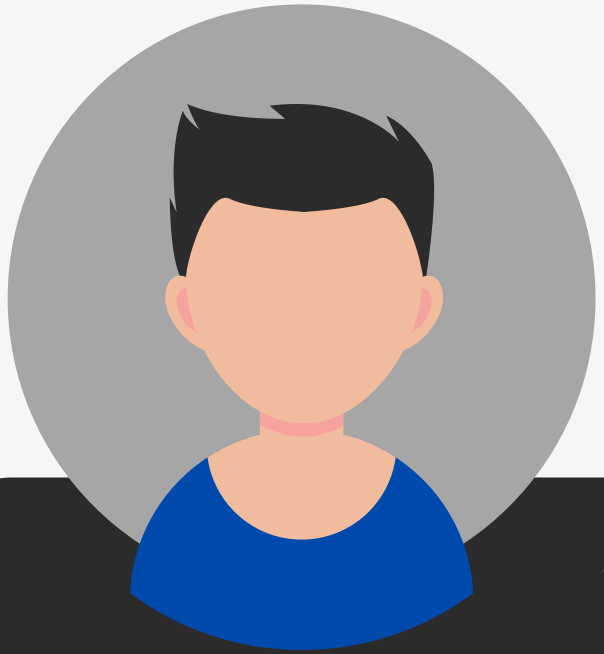
- Both Gender
- Executive
- Government official (Fonctionario)

PARTYS AT RISK

- National Action Party (PAN)
- Institutional Revolutionary Party (PRI)



SAMPLE PREDICTION



Victim Name: John Doe

Event Date: January 1, 2024

EVENT TYPE:
PENDING PREDICTION

Victim Type: *Authority*

Victim Gender: *Male*

Political Context:

- Party Affiliation: PRD (no coalition)
- First Political Office: Pre-candidate for PRI mayor of Atoyac
- Government Level: Municipal
- Government Area: Executive

Event Location:

- State: Guerrero
- Municipal: Atoyac de Álvarez
- INEGI Codes: State - 99999, Municipal - 99999

Demographics:

- Total Population: 1,000,000
- Male/Female Population: 500,000 each
- Economically Active Population: 600,000
- Population W/out Health Services: 200,000
- 12-Year-Old Single Population: 150,000

Socioeconomic Indicators:

- Average Scholarity: 8.5 years
- Homes Count: 250,000
- Average Household Size: 4.0
- GDP: $500,000

Victim Name: John Doe

Event Date: January 1, 2024

EVENT TYPE:
PREDICTION COMPLETE

Victim Type: *Authority*

Victim Gender: *Male*

DISAPPEARANCE

Political Cont

- Party Affili
- First Politic
  for PRI may
- Government Level: Municipal
- Government Area: Executive

Event Location:

- State: Guerrero
- Municipal: Atoyac de Álvarez
- INEGI Codes: State - 99999, Municipal - 99999

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Socioeconomic Indicators:

- Average Scholarity: 8.5 years
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FINAL TAKEAWAYS

MODELLING INSIGHTS

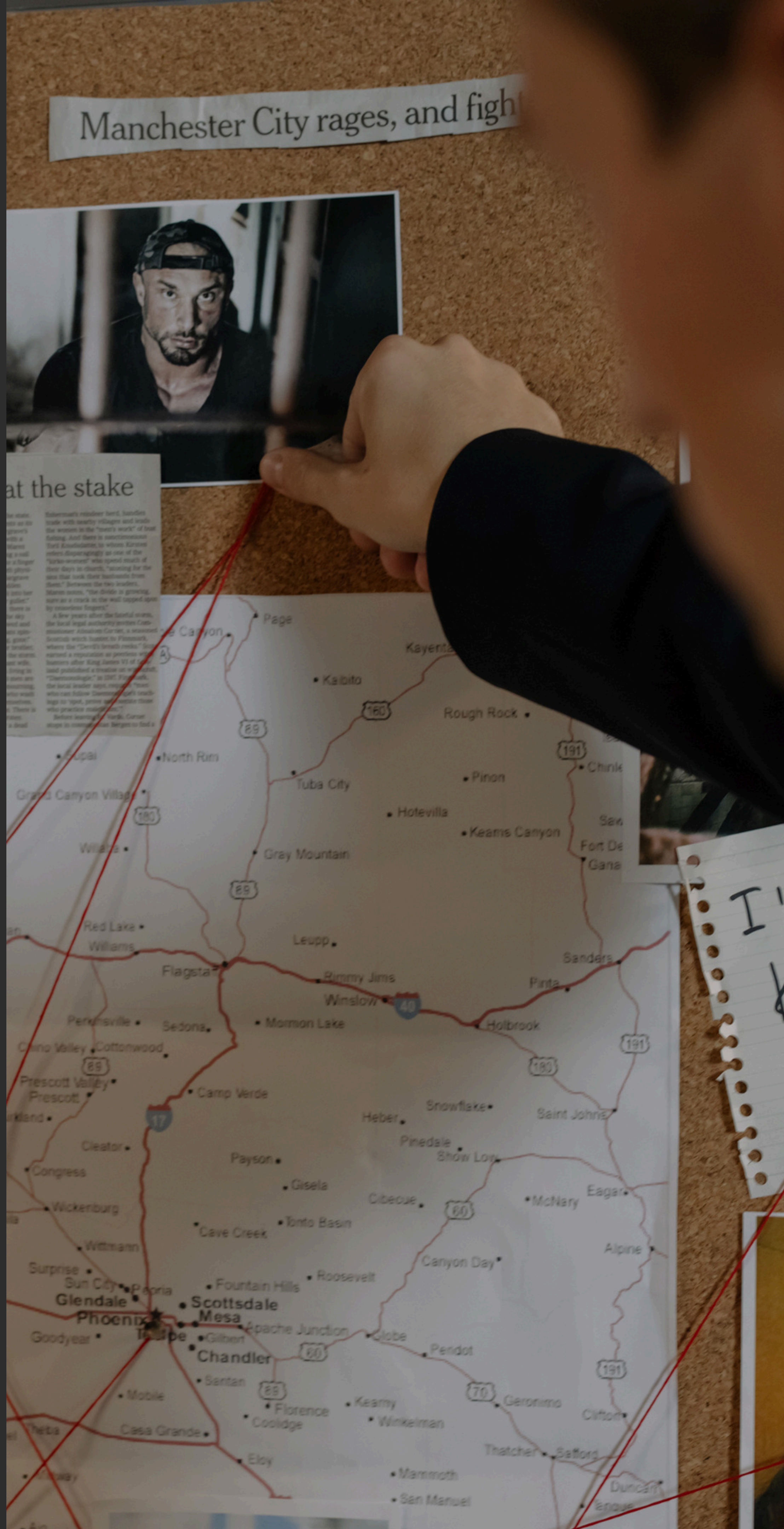
- Effective feature selection and optimization were crucial.
- Preprocessing and model tuning significantly improved performance.
- SMOTE addressed class imbalance effectively.

LIMITATIONS

- Assumes attacks; additional data could enhance model accuracy.

KEY VARIABLES

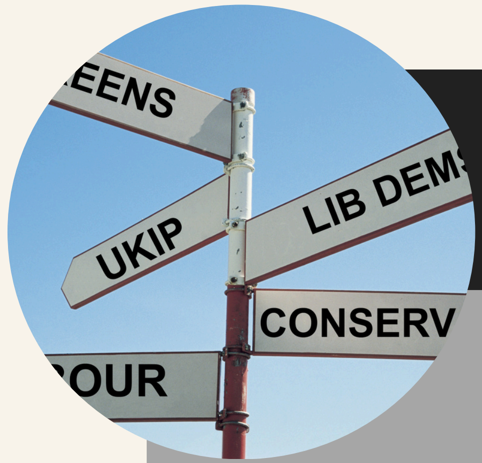
- Political party, state location, and individual roles were the most critical factors for predicting political violence.



SOCIETAL IMPACT

GOVERNMENT AGENCIES

Use model predictions to develop region-specific policies that counter political violence and address vulnerabilities exploited by organized crime.



POLITICAL PARTIES

Improve campaign security by identifying high-risk areas and providing tailored risk assessments.

LAW ENFORCEMENT

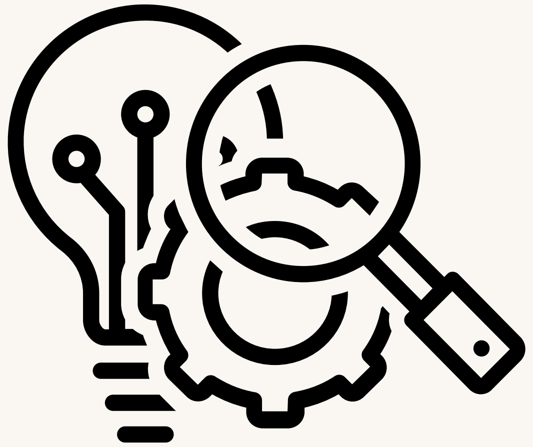
Focus resources on high-risk zones and threats while safeguarding political figures with personalized risk profiles.

POLICY MAKERS

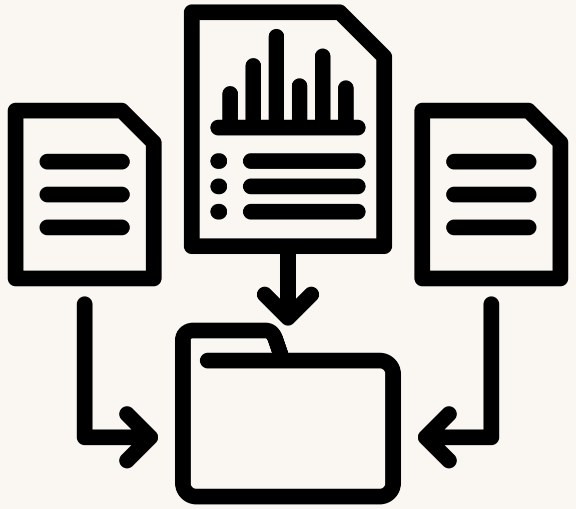
Tackle root causes like unemployment and instability through targeted policies to reduce crime and foster long-term stability.

FUTURE DIRECTIONS

Additional enhancements that can make our model more robust, actionable, and widely applicable.

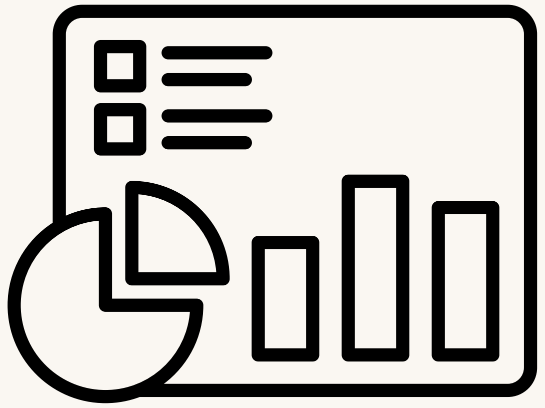


Improve Model Accuracy.



Enhance Law Enforcement Collaboration.

Broaden The Project Scope.
(unharmed politician)



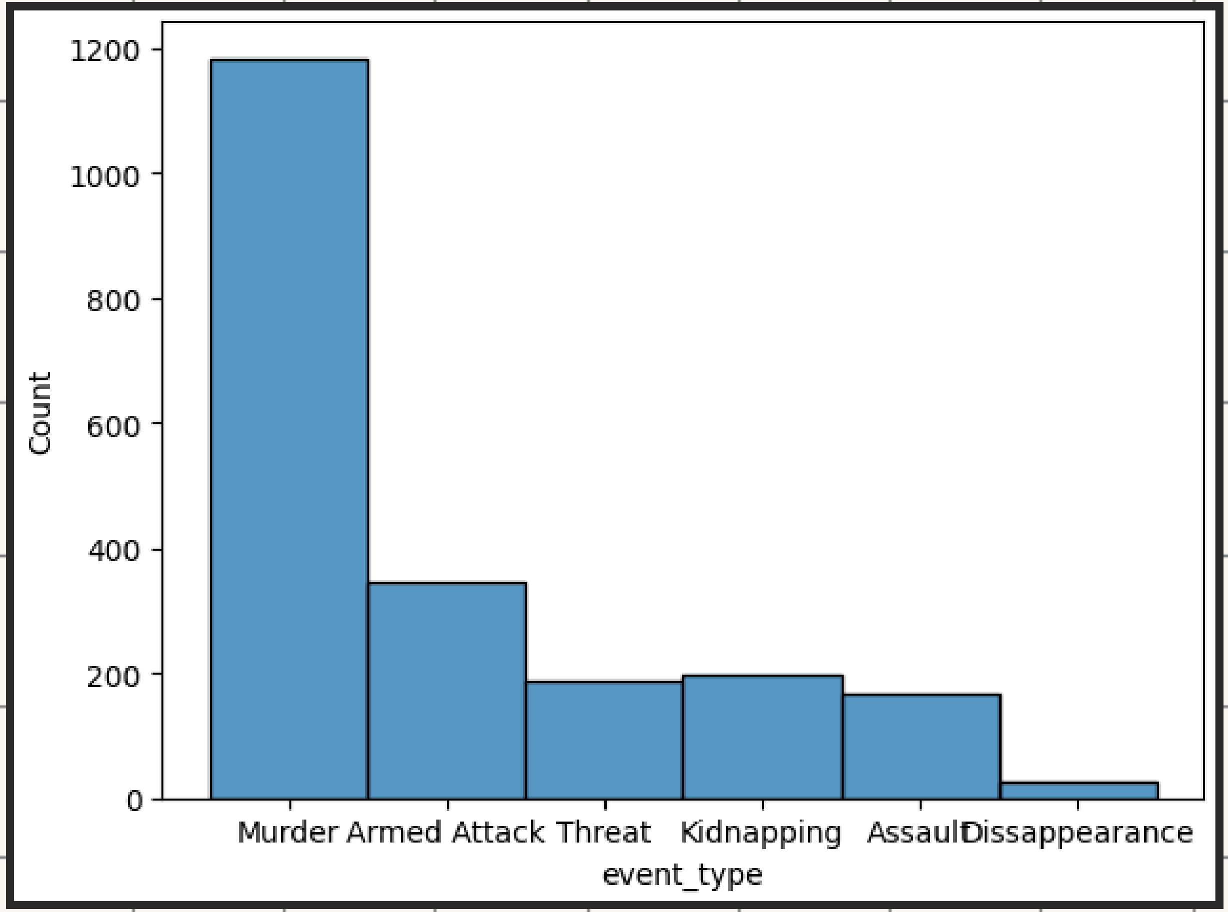
Integrate Explainability Tools.

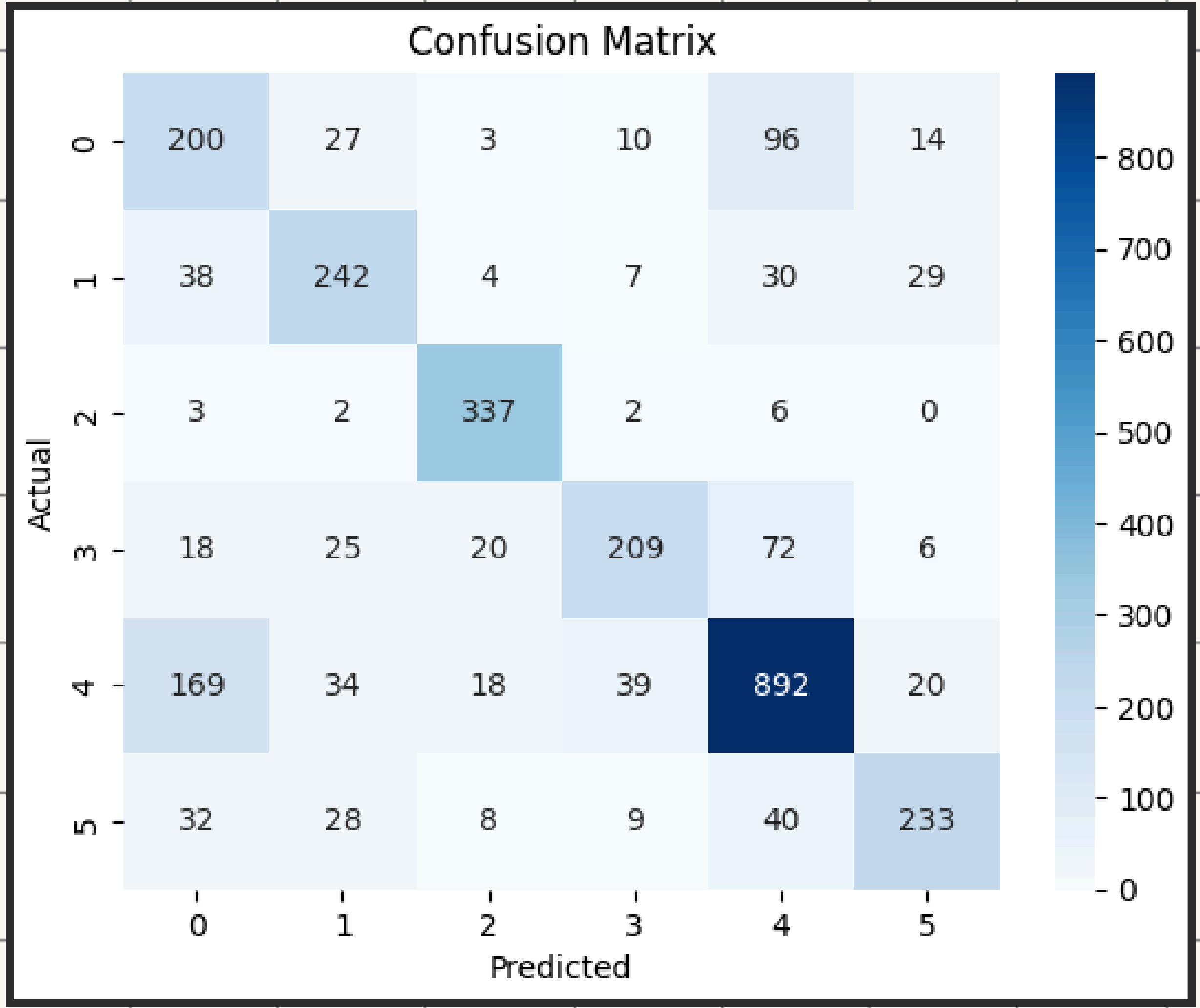
THANK YOU.

QUESTIONS & ANSWERS

APPENDIX

- **Selected KNN without feature selection.**
  - However there was still alot of misclassification.
    - Over-predicting 4 (Murder).
    - Caused by unbalanced amount of target variable.
  - Performed SMOTE to boost all non-murder to 350 data points each.
  - increased accuracy by 4% and decreased misclassification.
- Applying Permutation Importance.
  - Identified significant features affecting KNN.
  - Tested thresholds (0, 0.1, 0.001, 0.005, 0.0001).
  - Selected threshold of 0.001 for optimal results.
- **Final Model Evaluation**
  - **Retrained KNN with initially selected features.**
  - **Achieved accuracy of 72%, indicating significant improvement.**





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