## Ahsanullah University of Science and Technology

Department of Computer Science and Engineering



CSE4250 | Thesis-II

**Group No 3903** 

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# Development of Machine Learning Models for Crime Prediction using Historical Data

1. Predicting Crime Using Time and Location Data (2019) Yuki, Jesia & Sakib, Md. Mahfil & Zamal, Zaisha & Habibullah, Khan & Das, Amit

The major aim of this study was to expect which category of crime is most probably to take place at a detailed time and places in Chicago.

## Algorithms:

- Decision Tree
- Random Forest
- Bagging
- AdaBoost
- ExtraTree Classifier

## Dataset:

• Chicago Crime Dataset (over 16 years)

| Algorithm     | Accuracy |
|---------------|----------|
| Random Forest | 95.99%   |
| Decision Tree | 99.88%   |
| AdaBoost      | 74.78%   |
| Bagging       | 99.92%   |
| Entra Tree    | 91.10%   |

2. Building a Learning Machine Classifier with Inadequate Data for Prediction (2017) Nguyen, Trung & Hatua, Amartya & Sung, Andrew

A crime predicting method which forecasts the types of crimes that will occur based on location and time.

## Algorithms:

- Support Vector Machine
- Random Forest
- Gradient Boosting
- Multilayer Neural Network

## Dataset:

- Portland Police Bureau (PPB)
- Public Government Source American FactFinder

| Algorithm                 | Accuracy |
|---------------------------|----------|
| Support Vector Machine    | 67.095%  |
| Random Forest             | 67.088%  |
| Gradient Boosting         | 76.42%   |
| Multilayer Neural Network | 50.2%    |

## 3. Crime Analysis Through Machine Learning (2018)

Suhong Kim , Param Joshi, Parminder Singh Kalsi, and Pooya Taheri

This paper investigates machine-learning-based crime prediction.

## Algorithms:

- K-Nearest Neighbor
- Boosted Decision Tree

## Dataset:

• Vancouver Police Dataset

| Algorithm             | Accuracy |
|-----------------------|----------|
| K-Nearest Neighbor    | 39%      |
| Boosted Decision Tree | 44%      |

# 4. Crime Prediction and Analysis Using Machine Learning(2018)

Bharati and D. S. RA

## Algorithms:

- K-Nearest Neighbor
- Gausian Naive Bayes
- Multinomial Naive Bayes
- Bernouli Naive Bayes
- SVC
- Decision Tree

| Algorithm               | Accuracy |
|-------------------------|----------|
| K-Nearest Neighbor      | 78.91%   |
| Gausian Naive Bayes     | 64.60%   |
| Multinomial Naive Bayes | 45.60%   |
| Bernouli naive Bayes    | 31.35%   |
| SVC                     | 31.35%   |
| Decision Tree           | 78.60%   |

## 5. Crime Prediction Using Spatio-Temporal Data(2020)

S. Hossain, A. Abtahee, I. Kashem, M. M. Hoque, and I. H. Sarker

## Algorithms:

- Decision Tree
- K-Nearest Neighbor
- Random Forest

## Dataset:

• San Francisco PD Crime Dataset (over 16 years)

| Algorithm             | Accuracy | Log Loss |
|-----------------------|----------|----------|
| Decision Tree         | 31.17%   | 3.312    |
| KNN (N=50)            | 28.50%   | 5.04     |
| KNN (N=500)           | 27.91%   | 2.62     |
| Random Forest (T=10)  | 31.22%   | 2.34     |
| Random Forest (T=50)  | 31.70%   | 2.28     |
| Random Forest (T=100) | 31.71%   | 2.28     |

Steps for developing any machine learning models:

- Data Collection
- Data Preprocessing
- Feature Extraction
- Classification Strategy



# **Possible Sources**

# Bangladesh<br/>PoliceBangladesh<br/>Newspapers

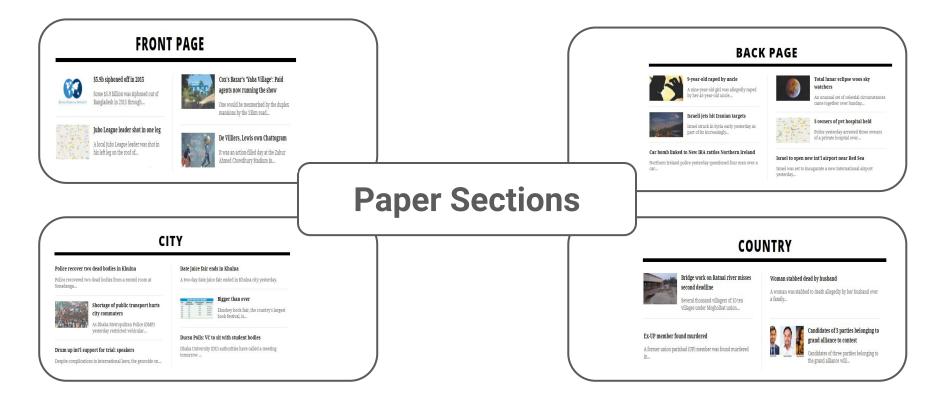
# **Data Collection**

# **Selected Source**



- Gathering crime headlines and links
- Extracting the informations

# **Data Collection**

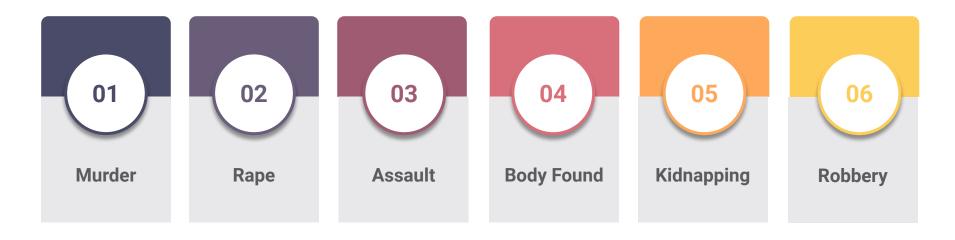


# **Selection of Crimes**

| Narcotics                | 112549 |
|--------------------------|--------|
| Woman & Child Repression | 16253  |
| Theft                    | 5561   |
| Murder                   | 3830   |
| Smuggling                | 4501   |
| Theft                    | 5561   |
| Kidnapping               | 444    |
| Robbery                  | 562    |
| Assault                  | 811    |

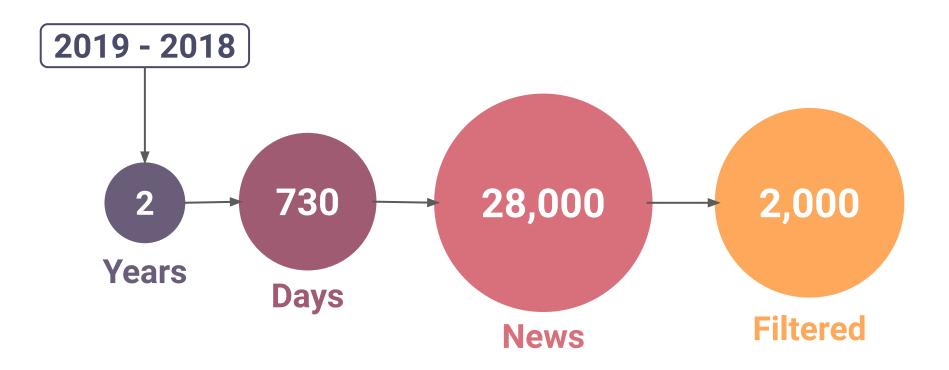
# Mostly Occurred in Bangladesh (2018)

# **Selection of Crimes**



# **Rationality for Newspaper**

# **Data Collection - Manual**



# **Data Collection - Manual**

## **BACK PAGE**

#### Two workers killed

Two workers were killed in a landslide at an illegal stone quarry...



#### One killed as AL men clash

A man was killed and at least two others were injured in a clash...



#### Einstein vs Modi

The organisers of a major Indian science conference distanced...

#### WikiLeaks tells journos 140 things not to say about Assange

WikiLeaks on Sunday advised journalists not to report 140 different...



#### RMG workers' wage demo continues

Vehicles start to move on the busy Airport Road in Dhaka after the...



#### 30...

Of a polls observer group

Schoolgirl murdered after 'rape' An eight-year-old girl was killed after being "raped" in Gabtala...

#### UN observers welcome to Xinjiang, with conditions: China

An EC-registered organisation which observed the December

China said yesterday it would welcome UN officials to the restive...



#### Myanmar asks army to crush Rakhine rebels

Myanmar government leader Aung San Suu Kyi yesterday discussed...



Accident News (False Positive)

British citizen of Bangladesh origin found dead in rehab

2

A Bangladesh-born UK citizen on Sunday was found dead in front of a...



#### e News

Murder News

-

News out side of Bangladesh (false Positive)

12:00 AM, June 12, 2018 / LAST MODIFIED: 12:06 AM, June 12, 2018

# Schoolboy found dead

## Our Correspondent, Pirojpur

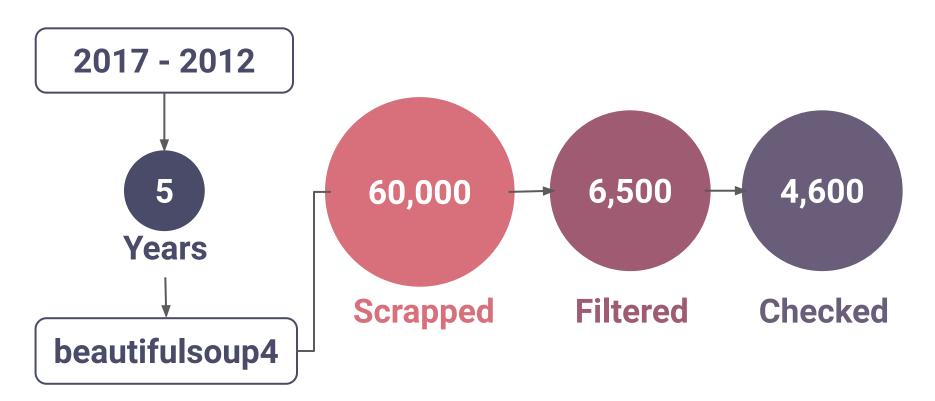
A schoolboy was found dead in Bhandaria upazila of the district on Sunday.

The deceased was Yamin Hossain Hridoy, 14, son of Md Shahjahan Hawlader of Darulhuda village, and a Class VIII student of Pasharibuniya High School in the upazila.

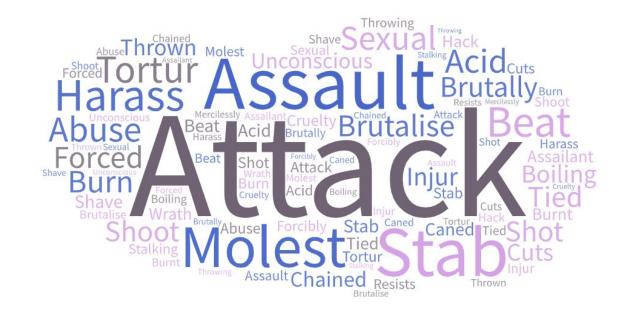
The victim's father Shahjahan said Yamin went to sleep at a decorator shop of one of his relatives on Saturday night and did not return home.

Later, locals found the body floating on a ditch near the shop on Sunday evening and informed police.

# **Data Collection - Scrapped**



# **Data Collection - Scrapped - Filtering**



□ Filtering crime news from scrapped news link with most frequent keywords

# **Data Collection - Scrapped - Filtering**



□ Filtering crime news from scrapped news link with most frequent keywords

# **Data Collection - Scrapped - Filtering**



Removing redundant news based on keyword not related to crime

brother Akah and Habib's son Humayun.

#### Country 1. News Date 7. Victim Age Youth kills uncle, lands in jail Ş **Our Correspondent, Mymensingh** 8. Victim's Address 2. Criminal Approach Sun Apr 7, 2019 12:00 AM Last update on: Sun Apr 7, 2019 12:06 AM man was stabbed to death allegedly by his nephew in Monipur Ghat area of Kishoreganj town on Friday evening. 3. Relation between 9. Criminal Age Victim and Criminal The victim was day labourer Habibur Rahman Habib, 55, son of Abdur Rashid of Brahmankandi in Sadar upazila. 10. Motive behind the 4. Incident Place Quoting locals, Officer in Charge of Kishoreganj Model Police Station Abu Crime. Bakar Siddiq said there had been a feud between Habib and his nephew Shamim Ahmed Akash, 23, son of Dulal Mia, over killing of Akash's sister-in-5. Incident Time law Rawshan Ara in 2017. Both Habib and Dulal are stepbrothers, police said. 6. Victim Profession A case was lodged, accusing Rawshan's husband Hazrat Ali, his parents,

Since the murder, Akash and his brother Hazrat had been blaming Habib for implicating them in the case and the feud had been prevailing, said the OC.

Over the feud, Akash stabbed Habib when he was having tea at a stall of Monipur Ghat. Habib died on the spot.

Hearing screams, local people rushed to the spot and caught Akash redhanded. Later he was handed over to police. 11

On information, police recovered the body and sent it to Kishoreganj General Hospital for autopsy.

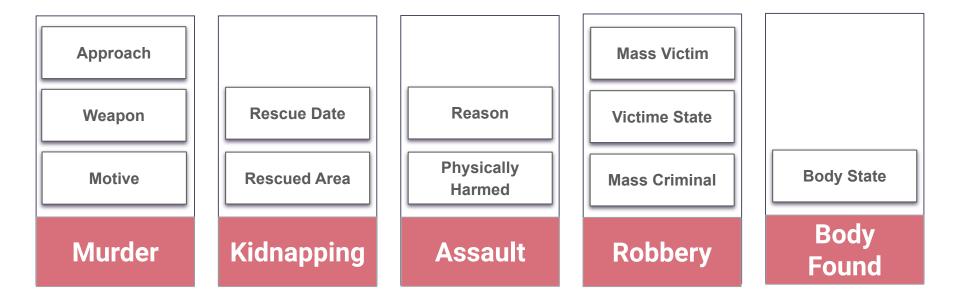
The victim's wife, Kalpana Akter, lodged a case with the police station, accusing Akash.

Akash was produced before a Kishoreganj court that sent him to jail yesterday.

**11. If Criminal Arrested** 

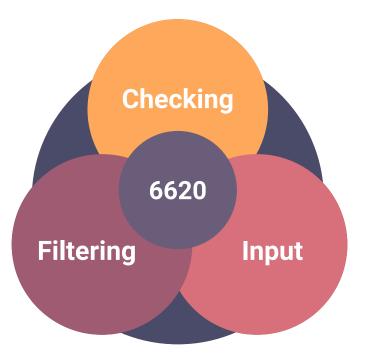


## **Common Features**

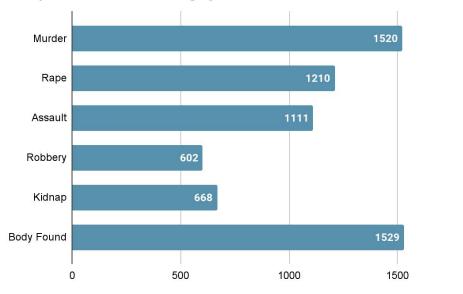


## **Category Special Features**

# **Obtained Dataset**



Data points in each crime category



2000

# **Data Preprocessing**

## **Incident Place Formatting Raw Separating Formatted Replacing with Official Location Name** Location Location Regular Expression

Correcting Inaccurate Location Mapping Specific Places to Corresponding Upazilla Mapping Places from Municipal Area

# **Incident Date**

- Manually formatted the dates of different forms, such as -Friday, yesterday, the day before, before an event, etc.
- Python module "**Datetime**" used to extract day number, week day, week number, etc.

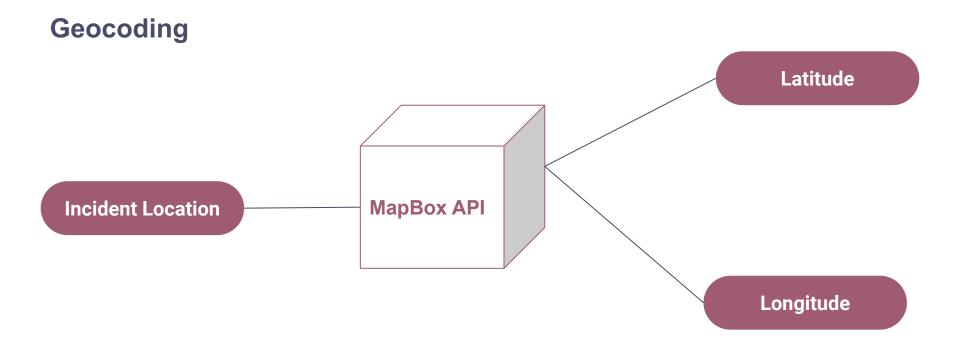
# **Data Preprocessing**

# **Incident Time**

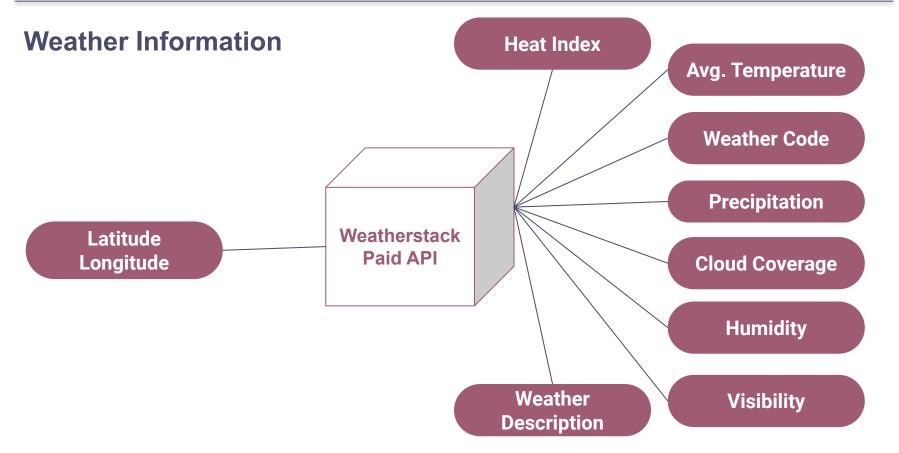
Determines certain part of the day.

| Time frames     | Part of the day |
|-----------------|-----------------|
| 6 am - 11:59 am | Morning         |
| 12 pm - 3:59 pm | Noon            |
| 4 pm - 5:59 pm  | Afternoon       |
| 6 pm - 7:59 pm  | Evening         |
| 8 pm - 5:59 am  | Night           |

# **Feature Engineering - Feature Addition**



# **Feature Engineering - Feature Addition**



## Data Adjustment

- Precision of latitude and longitude ranged from 6 to 8 digits in floating point precision.
- Latitude and longitude values were rounded to the nearest six digit floating point precision.

## Weather

- Contained in six features: precipitation, humidity, visibility, cloud cover, heat index, and average temperature in the json format.
- The values of all features were converted to Int and Float.

## **Unique Values, Floating Numbers and Sequentiality**

- Categorical
  - Few unique values
  - Contains character, string, integers
- Numerical
  - Significant amount unique values
  - Contains integers, floating point numbers

## Date

- Using Python's "Datetime" module, the incident date was converted to a Datetime Object.
- Year, Month, Day, Weekday were extracted from this Datetime object

## Season

• Season is another categorical feature.

Hot: March-May.

Rainy: June-October.

Winter: November-February.

## Weekend

• This feature returns: True and False depending on weekdays - Friday and Saturday.

## Correlation of the Weather Features



## Weather features were grouped into three categories:

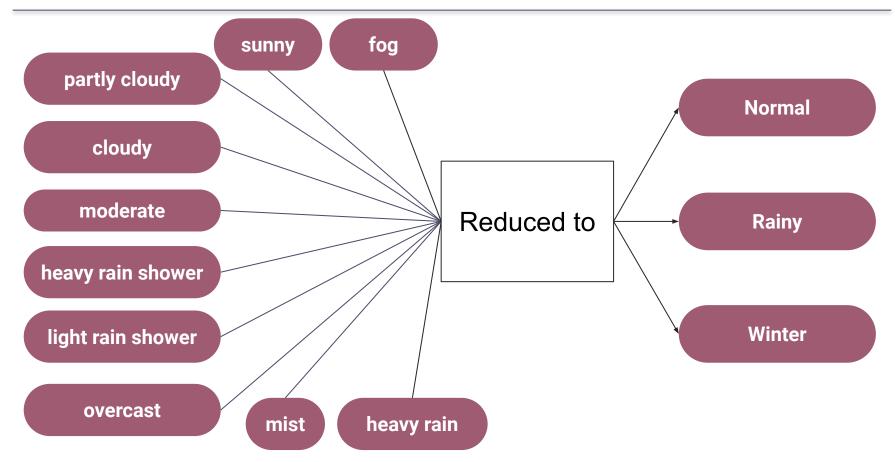
- Average Temperature and Heat Index.
- Cloud Cover and Humidity.
- Visibility and Precipitation.

## Importance of Weather Feature:

- Feature importance was calculated before choosing one from each category.
- Min-Max normalization was used for this purpose.

## **Importance of Weather Features**

| Feature             | Importance |
|---------------------|------------|
| Cloud Cover         | 0.258      |
| Humidity            | 0.206      |
| Precipitation       | 0.202      |
| Heat Index          | 0.166      |
| Average Temperature | 0.134      |
| Visibility          | 0.031      |



#### **Converting Features from Numerical to Categorical**

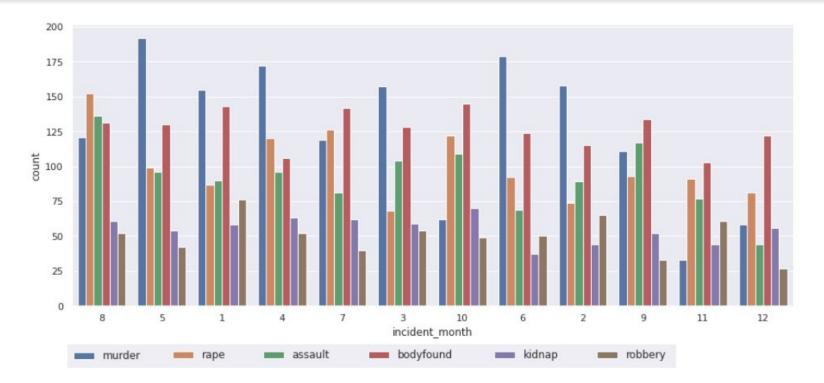
Precipitation

| Intensity        | Precipitation Rate               |
|------------------|----------------------------------|
| No Rain          | rate = 0.0                       |
| Light Rain       | 0.0 <rate <2.5<="" td=""></rate> |
| Moderate<br>Rain | 2.5 <rate <10<="" td=""></rate>  |
| Heavy Rain       | 10 <rate <50<="" td=""></rate>   |
| Violent Rain     | 50 <rate< td=""></rate<>         |

| Cloud Cover            |                 |  |  |  |
|------------------------|-----------------|--|--|--|
| Туре                   | Cloud Cover     |  |  |  |
| Clear                  | cover < 10      |  |  |  |
| Scattered 10 < cover < |                 |  |  |  |
| Broken                 | 50 < cover < 90 |  |  |  |
| Overcast               | 90 < cover      |  |  |  |

#### Shade Temperature (Celsius) Normal below 26 26 - 32 Cautious Extreme Cautious 33 - 41 42 - 54 Danger Extreme Danger over 54

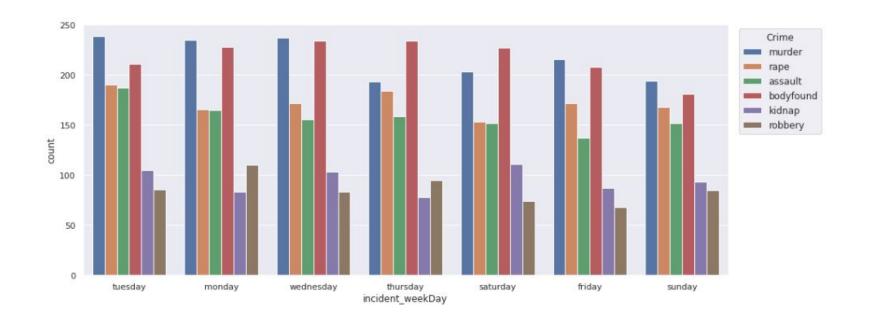
#### Heat Index



Crime Count Per Month

| Class | Months | Frequency Order                                    |
|-------|--------|--|
| 1     | 8      | Rape >Assault >Body Found >Murder >Kidnap >Robbery |
| 2     | 5      | Murder >Body Found >Rape >Assault >Kidnap >Robbery |
| 3     | 1,2    | Murder >Body Found >Assault >Rape >Robbery >Kidnap |
| 4     | 4      | Murder >Rape >Body Found >Assault >Kidnap >Robbery |
| 5     | 7      | Body Found >Rape >Murder >Assault >Kidnap >Robbery |
| 6     | 3      | Murder >Body Found >Assault >Rape >Kidnap >Robbery |
| 7     | 10     | Body Found >Rape >Assault >Kidnap >Murder >Robbery |
| 8     | 6      | Murder >Body Found >Rape >Assault >Robbery >Kidnap |
| 9     | 9      | Body Found >Assault >Murder >Rape >Kidnap >Robbery |
| 10    | 11     | Body Found >Rape >Assault >Robbery >Kidnap >Murder |
| 11    | 12     | Body Found >Rape >Murder >Kidnap >Assault >Robbery |

Crime Frequency Order on Months



Crime Count Per Weekday

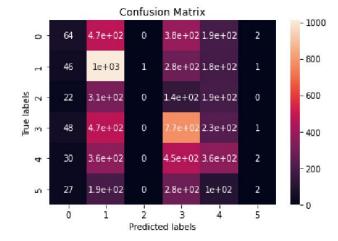
| Class | Weekdays                             | Frequency Order                                    |
|-------|--------------------------------------|--|
| 1     | Tuesday, Wednesday<br>Friday, Sunday | Murder >Body Found >Rape >Assault >Kidnap >Robbery |
| 2     | Monday                               | Murder >Body Found >Rape >Assault >Robbery >Kidnap |
| 3     | Thursday                             | Body Found >Murder >Rape >Assault >Robbery >Kidnap |
| 4     | Saturday                             | Body Found >Murder >Rape >Assault >Kidnap >Robbery |

Crime Frequency Order on Weekdays

### **Distance: Incident area, District, Division**

- Distance between the incident area and the corresponding District city was added to the dataset.
- Distances between the District city and the corresponding divisional city were introduced to the dataset.
- Haversine formula was used to calculate distance from latitude and longitude.

#### **Logistic Regression**

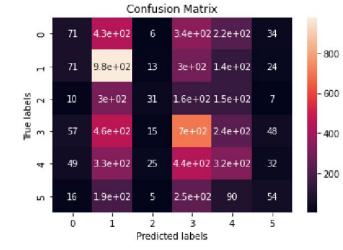


| Crime      | Precision | Recall | <b>F1</b> | Accoracy |
|------------|-----------|--------|-----------|----------|
| Assault    | 0.27      | 0.06   | 0.10      |          |
| Body Found | 0.36      | 0.66   | .047      | 37.97    |
| Kidnap     | 0.00      | 0.00   | 0.00      |          |
| Murder     | 0.33      | 0.51   | 0.40      |          |
| Rape       | 0.29      | 0.30   | 0.30      |          |
| Robbery    | 0.25      | 0.00   | 0.01      |          |

Confusion Matrix for Logistic Regression

Performance of Logistic Regression

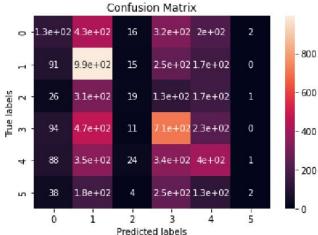




| Crime      | Precision | Recall | F1   | Accuracy |
|------------|-----------|--------|------|----------|
| Assault    | 0.26      | 0.06   | 0.10 | 36.00    |
| Body Found | 0.36      | 0.64   | 0.46 |          |
| Kidnap     | 0.33      | 0.05   | 0.08 |          |
| Murder     | 0.32      | 0.46   | 0.38 |          |
| Rape       | 0.28      | 0.27   | 0.27 |          |
| Robbery    | 0.27      | 0.09   | 0.14 |          |

Confusion Matrix for Naive Bayes

Performance of Naive Bayes



| - 800 | Crime      | Preci |
|-------|------------|-------|
|       | Assault    | 0.2   |
| - 600 | Body Found | 0.3   |
|       | Kidnap     | 0.2   |
| - 400 | Murder     | 0.3   |
|       | Dana       | 0.0   |

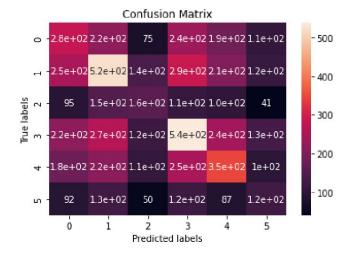
**SVM** 

| Crime      | Precision | Recall | <b>F1</b> | Accuracy |
|------------|-----------|--------|-----------|----------|
| Assault    | 0.28      | 0.12   | 0.17      | 8        |
| Body Found | 0.36      | 0.65   | 0.47      | 38.12    |
| Kidnap     | 0.21      | 0.03   | 0.05      |          |
| Murder     | 0.35      | 0.47   | 0.40      |          |
| Rape       | 0.31      | 0.33   | 0.32      |          |
| Robbery    | 0.33      | 0.00   | 0.01      |          |

Confusion Matrix for SVM

Performance of SVM

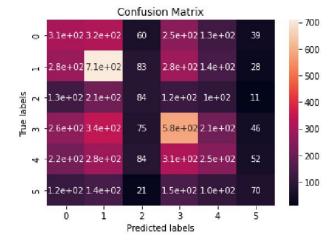




| Crime      | Precision | Recall | <b>F1</b> | Accuracy |
|------------|-----------|--------|-----------|----------|
| Assault    | 0.25      | 0.25   | 0.25      |          |
| Body Found | 0.36      | 0.35   | 0.36      | 34.74    |
| Kidnap     | 0.24      | 0.24   | 0.24      |          |
| Murder     | 0.35      | 0.35   | 0.35      |          |
| Rape       | 0.28      | 0.28   | 0.28      |          |
| Robbery    | 0.20      | 0.22   | 0.21      |          |

Confusion Matrix for Decision Tree

Performance of Decision Tree

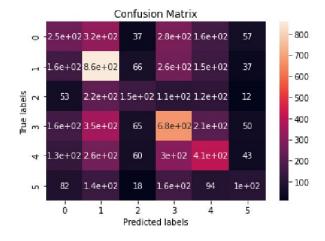


#### KNN

| Crime      | Precision | Recall | <b>F1</b> | Accuracy |
|------------|-----------|--------|-----------|----------|
| Assault    | 0.23      | 0.28   | 0.25      |          |
| Body Found | 0.35      | 0.46   | 0.40      | 33.05    |
| Kidnap     | 0.21      | 0.13   | 0.16      |          |
| Murder     | 0.34      | 0.38   | 0.36      |          |
| Rape       | 0.26      | 0.21   | 0.23      |          |
| Robbery    | 0.28      | 0.12   | 0.17      |          |

Confusion Matrix for KNN

Performance of KNN



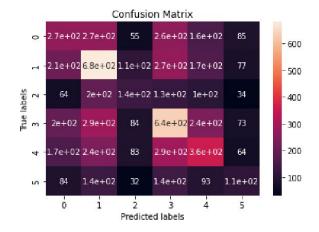
#### **Random Forest**

| Crime      | Precision | Recall | <b>F1</b> | Accuracy |
|------------|-----------|--------|-----------|----------|
| Assault    | 0.30      | 0.23   | 0.26      |          |
| Body Found | 0.40      | 0.56   | 0.46      | 40.33    |
| Kidnap     | 0.36      | 0.21   | 0.27      |          |
| Murder     | 0.38      | 0.45   | 0.41      |          |
| Rape       | 0.34      | 0.32   | 0.33      |          |
| Robbery    | 0.33      | 0.17   | 0.23      |          |

Confusion Matrix for Random Forest

Performance of Random Forest

### **Extra Tree**

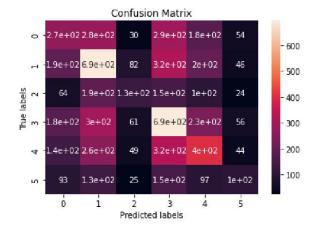


| Crime      | Precision | Recall | <b>F1</b> | Accuracy |
|------------|-----------|--------|-----------|----------|
| Assault    | 0.28      | 0.26   | 0.27      |          |
| Body Found | 0.37      | 0.43   | 0.40      | 36.60    |
| Kidnap     | 0.28      | 0.22   | 0.24      |          |
| Murder     | 0.36      | 0.42   | 0.39      |          |
| Rape       | 0.31      | 0.28   | 0.29      |          |
| Robbery    | 0.25      | 0.19   | 0.21      |          |

Confusion Matrix for Extra Tree

Performance of Extra Tree

### Adaboost

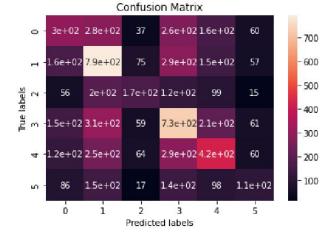


Crime Precision Recall **F1** Accuracy Assault 0.27 0.30 0.24 **Body Found** 0.52 0.380.44 Kidnap 0.42 0.17 0.24 39.57 Murder 0.37 0.42 0.49 0.35 Rape 0.37 0.34 0.23 Robbery 0.37 0.16

Confusion Matrix for Adaboost

Performance of Adaboost





| Crime      | Precision | Recall | <b>F1</b> | Accuracy |
|------------|-----------|--------|-----------|----------|
| Assault    | 0.34      | 0.27   | 0.30      | 41.50    |
| Body Found | 0.40      | 0.52   | 0.45      |          |
| Kidnap     | 0.40      | 0.26   | 0.32      |          |
| Murder     | 0.40      | 0.48   | 0.44      |          |
| Rape       | 0.37      | 0.35   | 0.36      |          |
| Robbery    | 0.30      | 0.18   | 0.23      |          |

Performance of XGBoost

Confusion Matrix for XGBoost

#### **Comparative analysis**

| Algorithm           | Accuracy |  |
|---------------------|----------|--|
| Logistic Regression | 37.97    |  |
| Naive Bayes         | 36.00    |  |
| SVM                 | 38.12    |  |
| Decision Tree       | 34.74    |  |
| KNN                 | 33.05    |  |
| Random Forest       | 40.33    |  |
| Extra Tree          | 36.60    |  |
| AdaBoost            | 39.57    |  |
| XGBoost             | 41.50    |  |

### **Conclusion and Future Works**

### Limitations

- Only 6600 criminal records in this dataset.
- Only those crimes that were reported in the newspaper were gathered.
- It was difficult to collect socioeconomic data.
- The dataset is imbalanced. From 2019 to 2012, there were approximately 600 kidnap and robbery criminal records available. However, around 1500 murder criminal records were added during the same time period.

### **Conclusion and Future Works**

### **Future Works**

- Collection of more criminal records in this dataset.
- Inclusion of human trafficking, narcotics, smuggling, and other criminal records.
- Fine-tuning and more customization of applied models.
- Exploration of algorithms like CatBoost, LogitBoost, LGBM, Bagging, etc.
- Handling missing values in other ways, such as by clustering them or making predictions based on dataset.
- Balancing the dataset with oversampling and undersampling techniques.

### Recommendation





# Closing

