Preemptive Spatial Prediction of Crime using Machine Learning Methods

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***Abstract*—Crime is one of the biggest problems, which our society is facing these days, and its prevention is important to make society a safe place to live in. Our study focuses on finding high-density criminal hotspots and the type of crime committed at a specific time. The paper analyzes the real-world dataset of Denver, Colorado. To determine the high-density criminal hotspot areas, we conducted Apriori and FP-growth algorithms to generate some interesting frequent patterns. Similarly, to predict the crime types at a specific time, we used several different algorithms such as Multi-Nomial Naive Bayes, Gaussian Naive Bayes, Decision Trees, Neural Network, and Multinomial Logistic Regression. The results of our paper show that Neural Network outperforms all other techniques in predicting the crime types at a specific time. Moreover, using Apriori and FP-growth algorithms we pinpoint high-density crime areas. Our results can help raise awareness among the people to avoid specific locations at a specific time, to avoid dangerous crimes. Furthermore, security agencies can utilize the results to predict future crimes at specific locations and times.**

1. Introduction

Crime is described as a peril that resentfully impacts the quality of life, social and economic growth of the nation and economy of any country. Crimes also affect the reputation of a country on an international scale and affect the economy of the nation by putting a financial burden on the government in hiring more security forces. It is the basic responsibility of the state to provide a safe environment for all citizens. Over the years, crime rates are increasing at a fast pace. To cater this issue, governing bodies are taking a lot of measures to reduce the crime growth. The very first measure is to increase the manpower of security agencies and deploy them at multiple locations. But, due to financial and resource constraints, it is technically impossible to deploy human resources everywhere. The second measure is to integrate gadgets such as security cameras at different locations for surveillance purposes. The issue with the measure is that it requires updating the entire infrastructure that is again dependent on time and has financial constraints.

Solving crime issue is a complex task that requires human physical efforts and intelligence for the processing of criminal data. Therefore, to reduce the crime rate, we are using some data mining approaches to determine high-density crime locations and the type of crime at a particular time. The predicted information can then be used by security agencies, to control the increasing crime rate with their limited resources. Also, it will raise awareness among the citizens about dangerous locations at a particular time.

To predict the type of crime and high-density criminal hotspots we input day, month, time, and location data to our model. Using this data, our model predict crime in certain area that will help make society a safer place to live.

1.1. Problem Formulation

Our research aims to make crime predictions in certain area using the features present in the real-world dataset of the city Denver, Colorado. The dataset is extracted from the official website of denver.gov.org. By using different machine learning and data mining algorithms such as Naive Bayes, Decision Trees, Apriori, Frequent-Pattern (FP) Growth, and Neural Networks (NN). We try to predict high-density criminal hotspots and the type of crime. By predicting what type of crime may occur next at a specific location with in a particular time can help security agencies to reduce crime rates and help them to take precautionary measures and stop the crime from happening.

Input to our models are 4-dimensional vector of features. Features include ”NEIGHBORHOOD_ID”, ”Day”, ”time”, ”Month” and output in 1-dimensional include ”OFFENSE_CATEGORY_ID”.

2. Related Work

The crime detection problem is a well-defined and well-known problem. A lot of work has been done relating to crime detection. For example, [1] explores models for predicting the frequency of several types of crimes by LSOA codes. Three algorithms are used from different categories of approaches: instance-based learning, regression, and decision trees. Results of this paper indicate that decision trees (M5P algorithm) can be used to reliably predict crime frequency in general. The shortcoming of this paper is that no work is done on the temporal patterns for particular areas, which can help detect the location of the crime.

Moreover, [2] highlights the importance of Machine Learning tools for law enforcement agencies to predict and solve crimes at a faster rate. It uses the technique of machine learning and data mining for crime prediction of Chicago crime data set. Six different algorithms are used: KNN, GaussianNB, MultinomialNB, BernoulliNB, SVC, Decision Tree. The accuracy of predicting the "type of crime" of KNN algorithms outperforms all others with 78.7. The shortcomings of this paper are that it does not provide details about the location information.

On the other hand, [3] consists of the application of various machine learning techniques that have been applied on crime data to monitor the impact of the economic crisis on the crimes that occurred in India. The machine learning models used in the paper are Decision Trees, Random Forest, Linear Regression, and Neural networks. These models have been used for analyzing crime data set instead of economic indicators like unemployment rate and GDP. Theft, Burglary, and Robbery are taken as the target variables. The vital difference of our model with this work is that this work is used to infer the effect of the unemployment rate and Gross District Domestic Product on theft, robbery, and burglary. These effects have been monitored across districts of various states in India. We want to solve the crime prediction problem without taking economic and social parameters as inputs. As an outcome, it has been found that out of all the four machine learning algorithms, Linear Regression outperformed the other algorithms and has the highest accuracy. The shortcoming of this paper is that the data set is not available and cannot be downloaded from the given link. The time complexity of none of the algorithms used in the paper is mentioned in the paper, which can help describe the efficiency of each algorithm.

In [4], authors discussed that different methods such as support vector machine, fuzzy theory, multivariate time series, and artificial neural network can be used to measure the performance of prediction methods. Paper discussed the limitations on these methods finding to provide an accurate prediction for the location of crimes as well as highlights the lack of capacity to analyze the high dimensional crime data at one platform which are gathered from different sources at different locations. [4] is theoretical and did not use any crime data-set to apply algorithms and visualize the frequent patterns.

In [5], two real-world datasets of USA states Denver in Colorado and Los Angeles in California. Machine learning algorithms are applied to find criminal hotspots in different areas in the states. Apriori Algorithm is used to extract all possible crime frequent patterns regardless of the committed crime type. In our research, we are using the same Denver dataset for pinpointing the high-density criminal hotspots and to determine the type of crime.

3. Dataset

In our study, we used the real-world crime data set from city of US named as Denver in state of Colorado. To build our data mining models, we combined our mining findings of Denver crimes dataset with its demographics information using Neighborhood names present in dataset as shown in 'Fig. 1". There are total 78 neighbours in complete dataset. We represent all neighbours in four different colors just to visualize the spread of neighbour areas.

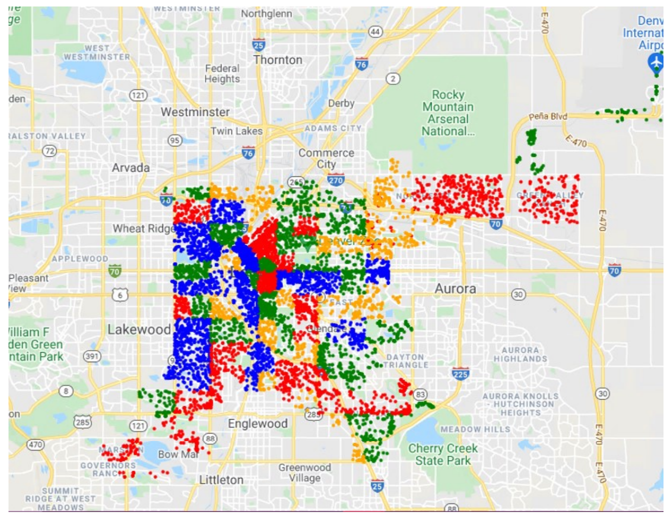

Figure 1. Map of Denver Neighborhoods

Dataset contains 467,150 instances and 19 attributes. It includes the crime incidents of Denver city from 2010-2015. The key attributes of this data set are mentioned in Table 1. To comprehend the data we performed different Exploratory Data Analysis (EDA) techniques on the data set. Along with that we apply some data pre-processing techniques to prepare data for training.

3.1. Data Pre-Processing

Firstly, we implemented Apriori and FP Growth algorithm to analyze the patterns in dataset and to predict the highly-dense criminal hotspots. Secondly, we did classification to predict the most likely type of crime happening at a certain time. For all of this our key features of the dataset are shown in Table I:

TABLE 1. TABLE I: DETAILS OF KEY ATTRIBUTES IN DENVER DATASET

Attribute	Data Type	Description
Offense Category ID	String	Name of offence category
First Occurrence Date	Date	Date of the event
Neighbourhood ID	String	Name of neighborhood
Is Crime	Boolean	Incident is crime or not

This dataset contains all incidents but we are only interested in those incidents in which value of ”IS_CRIME” is 1. So we filter out those incidents in which value of ”IS_CRIME” is 0. After this our dataset instances are reduced to 353,717 samples.

3.1.1. Data Cleaning

. There are some missing values in some attributes such as reported_date, last_occurance_date, and incident_address in the dataset. These are not our primary attributes so can ignore them for our model. Hence, we do not require any data cleaning.

3.1.2. Data Integration

. In our study we used ”FIRST_OCCURRENCE_DATE” and divided it into three different attributes named as: ”Month”, ”Day” and ”time”. In ”time” attribute we adopted military time system and took only hours part without paying attention to minutes and seconds.The time format is in 24hrs.

Furthermore, as discussed above we have 14 crime categories. Among all of these categories one category ”white-collar-crime” had very less samples so we discarded this category. We then worked on total of 13 crime categories which includes: ”aggravated-assault”, ”all-other-crimes”, ”arson”, ”auto-theft”, ”burglary”, ”drug-alcohol”, ”larceny”, ”murder”, ”other-crimes-against-persons”, ”theft-from-motor-vehicle”, ”sexual-assault”, ”robbery”, and ”public-disorder”.

3.1.3. Data Transformation

. In data transformation we realized that it is necessary to reduce the diversity of these two attribute- time and crime categories, values so we transformed our dataset into smaller number of groups. Initially time had 24 distinct values, which we transformed into 6 groups each group contains interval of 4 hours. Moreover, 13 crimes categories are grouped into 5 groups named as: ”Assault”, ”Drug Alcohol”, ”Other Crimes”, ”Public Disorder” and ”Theft”. After making groups it is converted into numerical format from 1-5 by using python library numpy and scikit-learn. Purpose of doing this is to to get more frequent patterns and to increase the model accuracy. Table 2 illustrate the data distribution after pre-processing.

3.2. Exploratory Data Analysis

To get the broader picture of dataset we did analysis on data to visualize it more clearly which helped to understand trends in data. Firstly, we did statistical data analysis on the categories of crimes. In ‘Fig. 2” x-axis shows the crime category and y-axis shows the total number of crimes in each crime category. Through this analysis, we came to know ”all-other-crimes” category has greater number of crimes while ”larceny”, ”public-disorder”, and ”theft-from-motor-vehicle” have almost same number of crimes. It made our model more bias toward those category which have greater number of crimes.

TABLE 2. ATTRIBUTES AFTER PRE-PROCESSING OF DENVER DATASET

Attribute	No of Distinct Values	Values
Offense Category ID	5	1:”Assault” 2:”Drug Alcohol” 3:”Other Crimes” 4:”Public Disorder” 5:”Theft”
Month	12	Month number in Integer
Day	7	Days of the week
Time	6	T1:”1am to 4:59am” T2:”5am to 8:59am” T3:”9am to 12:59pm” T4:”13pm to 16:59pm” T5:”17pm to 20:59pm” T6:”21pm to 0:59am”

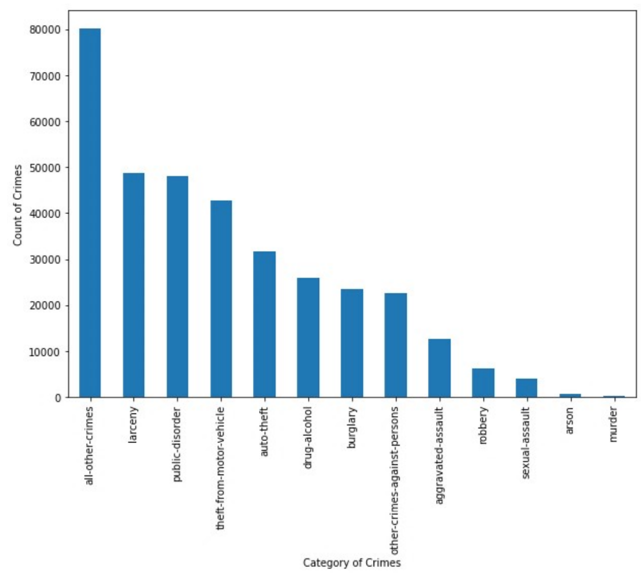

Figure 2. Count of each Crime Category

After applying data transformation, crime categories are divided into 5 distinct groups as shown in ‘Fig. 3”.

In ‘Fig. 4”, ‘Fig. 5”, and ‘Fig. 6”, total number of crimes are plot in each day, month, and group of hours. Moreover, we performed EDA on neighbourhoods to see which neighbour are more high density criminal hotspot by counting number of crimes in each neighbourhood as shown in ‘Fig. 7”

4. Techniques

We implemented the Bayes(Gaussian Naive Bayes & Multinomial Naive Bayes), Logistic Regression and Neural Networks for the classification purposes. For the extraction of frequent items, we used Apriori and FP-Growth algorithms. A brief overview of each algorithm is given below:

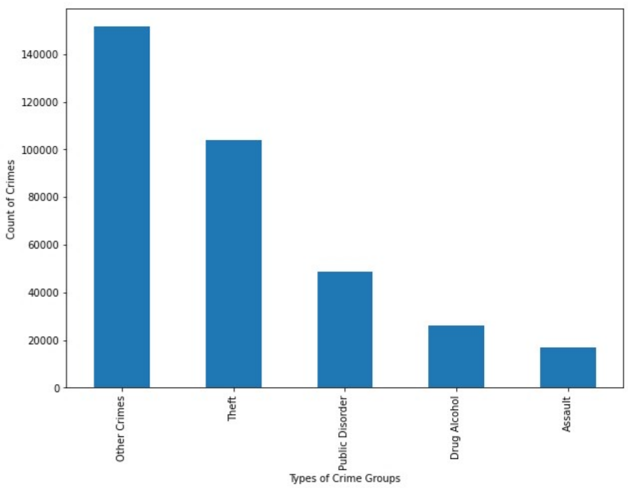

Figure 3. Count of each Crime Group

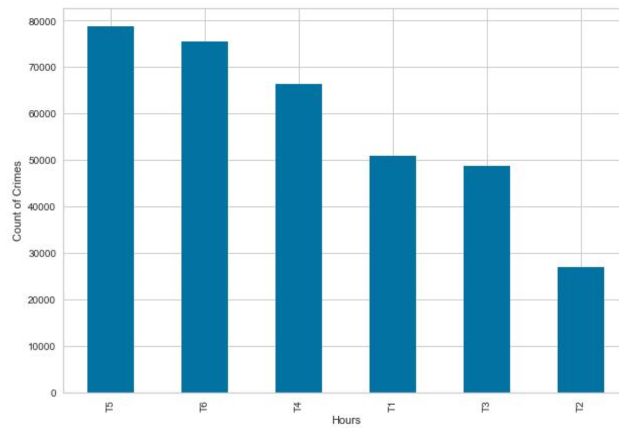

Figure 6. Count of Crimes in Hour Groups

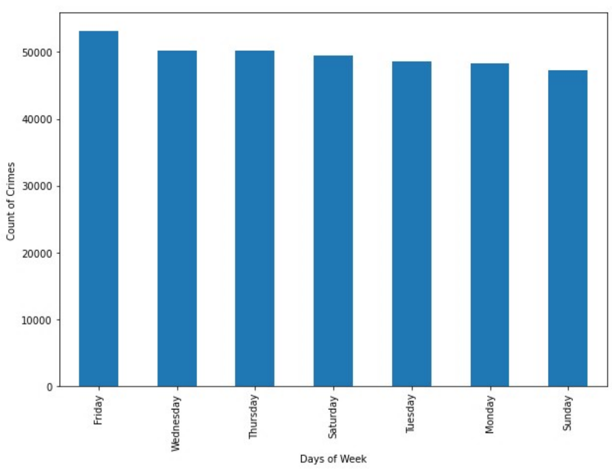

Figure 4. Count of Crimes on each Day

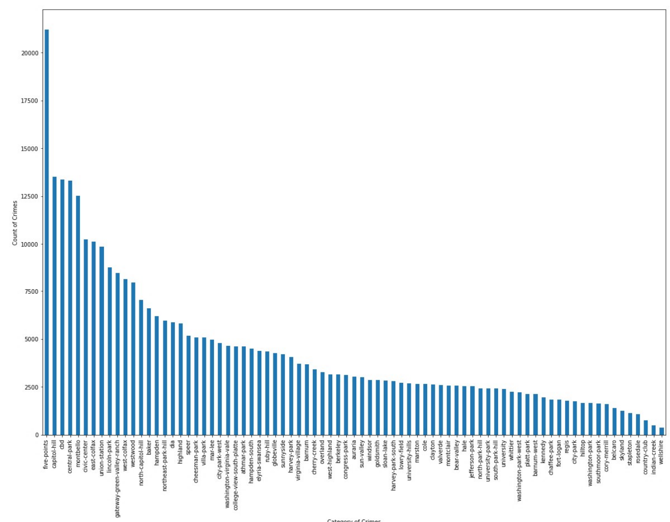

Figure 7. Count of Crimes in each Neighborhood

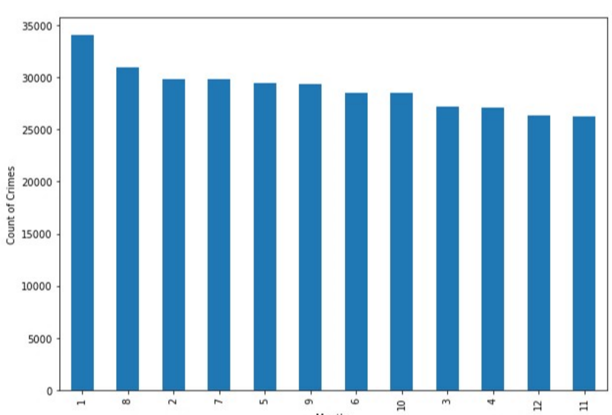

Figure 5. Count of Crimes in each Month

4.1. Decision Trees

It is a classification algorithm that won't require any training but on the basis of given attributes it returns tree-like model of decisions along with their possible consequences. It displays the tree as the conditional control statements on the basis of the features. It is less appropriate when we have many classes and less training data. It is also less suitable when we have continuous attribute. The tree generation is a computationally expensive task.
We used scikit-learn Decision Tree library to complete this task. We used k-folds approach and repeat the experiment for k=5 times. The average accuracy achieved was 38%. We kept changing the value of k and the model took 2 to 3 minutes per iteration.

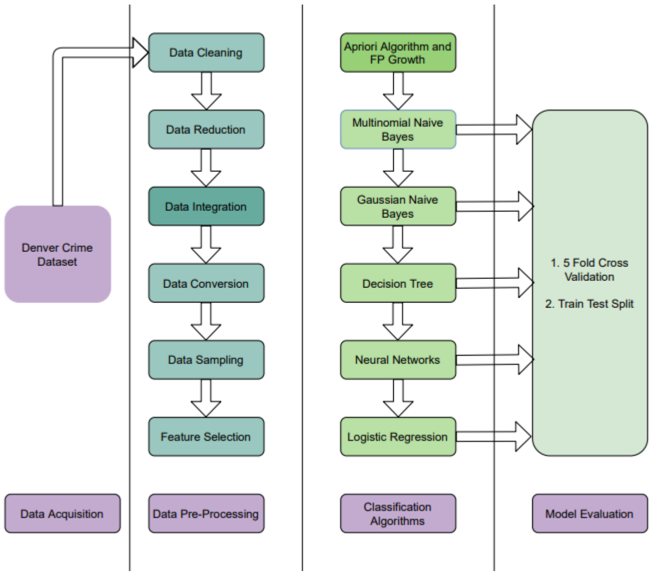

Figure 8. Flow Diagram of Proposed Methods

4.2. Bayes Classifier

The Bayes classifier operates in terms of Bayes Theorem as follows:

$$P(\theta|\mathbf{D}) = P(\theta)\frac{P(\mathbf{D}|\theta)}{P(\mathbf{D})}, \quad (1)$$

The key idea of the Bayes classifier is to find the θ that maximizes $P(\theta|D)$, which is the posterior probability of influence of the data on the prior probability which states to be $P(\theta)$ within this case. The prior probability provides us with a starting point and each train set acts as a candidate that helps to determine the probability of generated data. We can make use of Naive Bayes classifier which operates with an assumption that each feature in the training set can be independent of other features and we compute the posterior probability of the likely outcome.
We used scikit-learn Multinomial Naive Bayes and Gaussian Naive Bayes library to complete this task. We used k-folds approach and repeat the experiment for k=5 times. The average accuracy achieved for Gaussian NB was 43%. The average accuracy achieved for Multinomial NB was 38%. We kept changing the value of k and the model took 2 to 3 minutes per iteration.

4.3. Multinomial Logistic Regression

Logistic regression, known as the simplest form of neural network and is one of the discriminative classifiers. This classifier attempts to fit a linear model within the feature space much like regression, which can be misleading due to it's name but it has a slight twist. The train set can comprise of real valued data and we make use of a sigmoid function to squash the real data values into predefined binary values such as [0,1] or [-1, 1].

$$h_\theta(x) = \frac{1}{1 + e^{-}\theta^T x} \quad (2)$$

For multinomial logistic regression case, we used softmax activation instead of the sigmoid. We used L2 regularization as a penalty term in our model.

$$\text{Softmax}(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)} \quad (3)$$

Note that we keep a minimum predefined threshold(predefined by scikit-learn library in our case) to determine the classification of each train set. The key takeaway from this algorithm is that instead of predicting a class like within Bayes Classifier, we instead determined the probability of test point belonging to a particular class.
We used scikit-learn Logistic Regression library to complete this task. We used k-folds approach and repeat the experiment for k=5 times. The average accuracy achieved was 43.402%. We kept changing the value of k and the model took 2 to 3 minutes per iteration.

4.4. Neural Networks

A neural network is a series of algorithms that endeavors to recognize underlying relationships in a dataset through a process that mimics the way the human brain operates. The Neural networks can adapt to changing input resulting in the best possible results without needing to redesign the output criteria given that these can be used for both classification and regression problems. A neural network contains layers of interconnected nodes, each node is a perceptron and they are arranged in interconnected layers in a multi-layered perceptron (MLP). The input layer collects input patterns and the output layer outputs the signals to which input patterns may map. These may or may not comprise of a activation function, linear or non-linear, hidden layers fine-tune the input weights until the neural network's margin of error converges to the minimum. This fine-tuning is done by back-propagation using gradient descent. It is hypothesized that hidden layers extrapolate salient features in the input data that have predictive power regarding the outputs(i.e. feature extraction).
We used scikit-learn MLP library to complete this task. We used two hidden layers and one input and output layer. The learning rate was kept adaptive(initially 0.0001). We used SGD (stochastic gradient descent) to update weights of the model. The activation function 'RELU' is used in the hidden layers and 'softmax' in the output layers. We used k-folds approach and repeat the experiment for k=5 times. The average accuracy achieved was 44.9629%. We kept changing the value of k, learning rates and number of hidden layers and the accuracy achieved between 42-44%.

4.5. Apriori Algorithm

It is used for calculating frequent item-sets in the dataset. We gave threshold(minimum support probability and minimum confidence probability) to our model and it will return the association rules and frequent items in the dataset on the basis of given threshold. The algorithm followed an

iterative approach(level-wise search) where k+1 itemsets are find by using k-frequent itemsets using Cartesian product of sets. To improve the efficiency of level-wise generation of frequent itemsets, the algorithm assumens that all non-empty subsets of frequent itemset must be frequent. Hence one can conclude that, all supersets of an itemset will be infrequent if the itemset is itself infrequent.
We used python built-in library for this task and kept minimum thresholds for 0.001, 0.01 and 0.005.We need to transform the data using the 'Transaction Encoder' function for the pre-processing. It was observed that on changing threshold we got different frequent itemsets. A few samples of Apriori's output is given as:

TABLE 3. APRIORI ALGORITHM

Support	Itemsets
0.016	frozenset('T1', 'Five Points')
0.016	frozenset('T2', 'Five Points')
0.022	frozenset('T3', 'Five Points')
0.027	frozenset('T4', 'Five Points')
0.033	frozenset('T5', 'Five Points')

4.6. FP-Growth Algorithm

It is quite similar to Apriori algorithm but it discourage candidate generation by developing a tree using 'divide and conquer' strategy. It uses pattern fragment growth to mine the frequent patterns instead of genearting more and more candidates(as only few. It is a scalable mining algorithm for finding frequent itemsets. In case of large dataset, it is more efficient than the Apriori algorithm.
We used python built-in library for this task and kept minimum thresholds for 0.001, 0.01 and 0.005. We need to transform the data using the 'Transaction Encoder' function for the pre-processing. It was observed that on changing threshold we got different frequent itemsets. A sample output of FP-Growth algorithm's output for minimum support = 0.005 is given as:

TABLE 4. FP-GROWTH MODEL RESULTS

Support	Itemsets
0.00067	frozenset('T1', 'central-park','Sunday')
0.00055	frozenset('T1', 'central-park','Monday')
0.00056	frozenset('T1''central-park','Tuesday')
0.00046	frozenset('T1', 'central-park','Wednesday')
0.00056	frozenset('T1', 'central-park','Thursday')
0.00079	frozenset('T1', 'central-park','Saturday')

5. Experimental Evaluation and Comparisons

The primary purpose of this work is to classify 8 different types of crimes and established a future-oriented automated model. For evaluation of the models, we apply four evaluation criteria to judge their performance and accuracy. Firstly, we executed the k-fold cross-validation for five folds. Then we performed a train-test split method with 80% data for training and 20% data for testing. After that, we calculated the accuracy, recall, precision and F1 score of each classifier to compare which classifier performs better. Results of accuracy obtained at each fold is listed in table.

TABLE 5. RESULTS OF K-FOLD CROSS VALIDATION

Folds	Multi-NB	Gaussian-NB	Decision Tree	Neural Network	Logistic Regression
1	0.3835	0.4335	0.3785	0.4451	0.4343
2	0.3811	0.4336	0.3815	0.4501	0.4335
3	0.3826	0.4339	0.3831	0.4521	0.4336
4	0.3854	0.4337	0.3805	0.4510	0.4347
5	0.3815	0.4342	0.3815	0.4496	0.4341
Average	0.3828	0.4338	0.3810	0.4496	0.4340

Accuracy is defined as the measure to calculate the frequency of correctly labeled instances by the classifier. Accuracy measurements were done using the formula in equation (4)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

Precision is the measure of closeness of instances with each other and is calculated as per the formula in equation (5)

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

A recall is the measure of actual positive instances in the dataset that have been correctly classified as positive by the classifier. Recall measurements were done using the formula in equation (6)

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

F1-score is the harmonic mean of the precision and recall and is calculated using equation (7)

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{7}$$

where

- True Positive (TP): If the label is positive and the classification outcome is also positive.
- True Negative (TN): If the label is negative in the dataset and the classification outcome is also negative.
- False Positive (FP): If the data label is negative, but the classification outcome is positive.
- False Negative (FN): If the data label is positive in the dataset, but the classification outcome is negative.

We evaluated seven different models regarding different aspects. We used FP-Growth and Apriori algorithms to highlight the frequent patterns in the dataset. Apriori is a bottom-up and breadth first approach. Its main principle is

TABLE 6. CLASSIFICATION REPORT OF CLASSIFIERS

Classifier	Precision	Recall	F1-score
Multi-NB	0.3037	0.3816	0.1918
Gaussian-NB	0.3023	0.4342	0.2928
Decision Tree	0.3701	0.3815	0.2527
Neural Network	0.3253	0.4496	0.1871
Logistic Regression	0.3019	0.4341	0.1370

that if an item set is frequent then all of its subsets must also be frequent. It uses a level-wise approach where it generates patterns containing the first item, then the second item, then the third, and so on. The algorithm gets terminated when the frequent itemsets cannot be extended further. FP-Growth algorithm extracts the frequent itemset without the candidate generation and uses a depth-first approach. The algorithm first builds a compact data structure called FP-tree using the conditional pattern base from the database which satisfies the minimum support and then it extracts the frequent itemset from the FP-tree as shown in 'Fig. 9' and 'Fig. 10'.

Frequent Pattern	Minimum Support
T1, 'Five Points'	0.016
T2, 'Five Points'	0.016
T3, 'Five Points'	0.022
T4, 'Five Points'	0.027
T5, 'Five Points'	0.033
T1, 'Capitol Hill'	0.011
T2, 'Capitol Hill'	0.006
T4, 'Capitol Hill'	0.015
T5, 'Capitol Hill'	0.018
T1, 'CBD'	0.01
T2, 'CBD'	0.007
T3, 'CBD'	0.012
T4, 'CBD'	0.015
T5, 'CBD'	0.018
T6, 'CBD'	0.019
T3, 'Central Park'	0.006
T5, 'Central Park'	0.008
T1, 'Montbello'	0.01
T2, 'Montbello'	0.006
T3, 'Montbello'	0.01
T4, 'Montbello'	0.015
T5, 'Montbello'	0.017
T5, 'Montbello'	0.017

Figure 9. Apriori Results (frequent patterns) for Denver Crime Dataset

6. Conclusion and Future Work

In this project we predicted criminal hotspots and type of crime in those hotspots in certain time period. With the help of machine learning, it is easy to extract patterns and predict crime on huge amount of data. To get broader visualization of dataset, we did statistical data analysis. To learn patterns of most criminal hotspots, we used Apriori and FP growth algorithms. Moreover, for predicting crime type we apply Multinomial Naive Bayes, Gaussian Naive Bayes, Decision Trees, Logistic Regression, and Neural Networks. On Gaussian Naive Bayes and Neural Network our accuracies are 43.4% and 45.2%. In conclusion, these types of automated methods can open new ways of handling a sustainable and peaceful society in decreasing crimes for the developing and under-developed countries.

Sunday', 'T6', 'north-park-hill'	0.0002
Sunday', 'T5', 'north-park-hill'	0.0002
Sunday', 'T4', 'north-park-hill'	0.0001
Wednesday', 'T5', 'north-park-hill'	0.0002
Wednesday', 'T4', 'north-park-hill'	0.0002
Wednesday', 'T6', 'north-park-hill'	0.0002
Thursday', 'T5', 'north-park-hill'	0.0002
Thursday', 'T6', 'north-park-hill'	0.0002
Thursday', 'T4', 'north-park-hill'	0.0001
Tuesday', 'T6', 'north-park-hill'	0.0001
Tuesday', 'T5', 'north-park-hill'	0.0001
Tuesday', 'T4', 'north-park-hill'	0.002
Tuesday', 'T3', 'north-park-hill'	0.0001
Thursday', 'T5', 'lowry-field'	0.0002
Thursday', 'T4', 'lowry-field'	0.0002
Thursday', 'T6', 'lowry-field'	0.0002
Thursday', 'T3', 'lowry-field'	0.0001
Friday', 'T3', 'lowry-field'	0.0001
Monday', 'T3', 'lowry-field'	0.0001
Sunday', 'T3', 'lowry-field'	0.0001

Figure 10. FP Growth Results (frequent patterns) for Denver Crime Dataset

This research can be further extendable to more datasets and classification algorithms. The methods implemented in this paper is applicable only to the Denver dataset. It will be very interesting to see the performance and accuracy of the deployed methods on other countries dataset as well. Furthermore, if one can get more better and accurate results then crime prediction can be automated without any manual inspection.

References

[1] E. H. Ginger Saltos, *An Exploration of Crime Prediction Using Data Mining On Open Data*. IJITDM, 2017.

[2] S. R. Alkesh Bharati, *Crime Prediction And Analysis Using Machine Learning*. IRJET, 2018.

[3] J. k. J. H. Mamta Mittal, Lalit Mohan, *Monitoring the Impact of Economic Crisis on Crime in India Using Machine Learning*. Springer Link, 2018.

[4] R. A. Nurul Hazwani, Nor Azizah, *An Overview of Crime Prediction Methods*. ICT-ISPC, 2017.

[5] E. L. Tahani Almanie, Rsha Mirza, *Crime Prediction Based On Crime Types And Using Spatial And Temporal Criminal Hotspots*. IJDKP, 2015.