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Crime Link Prediction Across Geographical Location Through Multifaceted Analysis: A Classifier Chain Temporal Feature-Data Frame Joins

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Abstract

Crime link prediction across geographical locations is vital for law enforcement to uncover hidden connections between crimes spanning different areas. Traditional methods often fail to capture the complexity and temporal dynamics of crime data, limiting their predictive power. This research introduces a novel approach to enhance crime link prediction by leveraging a multifaceted analysis that integrates multiple inputs and outputs. A classifier chain transformation is used for sequential multi-label classification, capturing interdependencies between crime types across locations. This method facilitates a comprehensive understanding of crime patterns over time. Experiments conducted on a South African Police Services (SAPS) crime dataset demonstrate the proposed model's superior performance compared to state-of-the-art methods, achieving precision, recall, F1-score, and accuracy of 0.98, 0.99, 0.99, and 98.99%, respectively. This research aims to contribute to the crime link prediction models, offering a more nuanced and robust framework for forensic experts and law enforcement.

A. Introduction

Crime is an inevitable and persistent problem that brings negative outcomes to society [1]. It has been reported that more than 400,000 people lose their lives to homicide globally each year, with 80% of the victims being under 50 years old [2]. This makes homicide one of the leading causes of death among young adults [1]. In addition to the enduring physical and psychological harm inflicted on victims, crime also places a financial burden on governments, increasing spending on law enforcement and justice services [3]. To enhance public safety and support urban sustainability, a swift police response is essential whenever authorities are notified of criminal activities. In this context, crime link prediction becomes critical, as it helps analyze the behavioral or physical traits of crimes and assesses the likelihood of connections or patterns among them based on historical data.

As crime data is a type of spatial-temporal event data, some effective data mining techniques have been proposed to explore the spatial and temporal features of crimes to improve the crime prediction accuracy. In recent years, several methods such as Deep Reinforcement Learning (DRL) [4], Time Evolve Deep Reinforcement Learning Criminal Network Analysis (TDRL-CAN) [4], logistic regression analysis [5], Katz score [6], agent-based model [7], and regression-based on probabilistic models [1] have been used in crime link prediction to resolve issues related to inaccurate prediction [5]. The dynamic nature of crime has restricted the effectiveness of these conventional methods. Additionally, these methods fall short revealing hidden criminal connections between criminal activities that transcend geographical locations in real-world implementation. It is imperative to develop a model with temporal features to reveal the relationships between criminals' activities across geographical locations.

Based on the dynamisms in the nature of crime, evidence have shown that there is a strong correlation between criminal activities and the geographical areas where they occur. With the growing amount of data available from various sources, it has become possible to combine multi-source information to improve crime link prediction [8]. For instance, research in [9] integrates different resources by structuring them as graph-based data and merging the resulting graph representations. However, by using the auxiliary data solely as input features for each region, this approach does not fully capture the influence of individual factors within the detailed urban data, leading to a significant loss of contextual information.

While previous studies investigated the connection between crime and locations, they did not explicitly address the factors leading to criminal behaviors [10]. Some methods with attention mechanisms may distinguish the temporal effect on crime prediction, but the analysis on more specific factors (such as period, days of the week, population, and seasonality) is left untouched, hindering improved performance accuracies of some of the methods. For instance, during the festive periods there is high tendency of crime occurrences since most people might be far away from their home [11].

To improve the crime link prediction accuracy and create preventive warning to security operators, this study proposes a novel approach to advance the prediction of crime links between geographical locations using a leveraging multifaceted analysis. This methodology integrates multiple inputs and outputs, employing a classifier chain transformation to enhance predictive accuracy for crime link prediction purposes. Several chains of ML classifiers are used to train the extracted multiple inputs data with temporal features and the Decision Tree classifier which produced the better result are taken into consideration. Hence, the method is suitable for the crime link prediction across geographical locations. Most of the prior research focused on using historical data directly on machine learning, they do not differentiate influence of multifaceted information on crime link prediction accuracy.

Drawing upon the provided background information, this study raises the following inquiry: How can a new chain classifier framework, integrating temporal data frame joins for link prediction across geographical locations be developed? The proposed method is developed with the consideration of the above-mentioned gaps and the associated research question, which led to the following contributions:

- The development of a new framework that integrates multiple inputs and outputs, employing a classifier chain transformation with the application of data frame joins on temporal features, facilitating a comprehensive understanding of crime patterns over time. This offers an innovative approach to enhance the performance of link prediction between two geographical locations. It thereby enhances the overall security measures.
- Detailed experimental evaluations of the new model benchmark with related state-of-the-art prediction models, using publicly available Africa-based and Canada-based crime data to predict possible links between crime types between two geographical locations. This research proves the proposed framework's superiority over the alternatives by demonstrating its improved performance and dependability.
- This research identifies some temporal features derived from the research findings in forensics, added to the existing baseline crime dataset, to improve the performance of the link prediction systems. The results demonstrate significant optimization of the prediction performance after including temporal features.
- The deployment of the proposed model for forensic experts and law enforcement agency systems to predict crime links across geographical locations alleviates the problem of static crime data visualization.

The remainder of this paper is arranged in the following order: Section 2 provides a review of the existing related techniques and the theoretical background of the proposed model. Section 3 presents a detailed explanation of the classifiers; Section 4 discusses various experiments and evaluations of the model. The concluding remarks are shared in Section 5.

B. Related Works

Different research has been conducted on crime link prediction in the literature. The summary of existing crime link prediction methods in terms of the problem addressed, the method used, the result obtained, and their limitations are presented in Table 1.

Table 1. Summary of related works on crime link prediction

Citations	Problem Addressed	Method Used	Result Obtained	Limitations
[6]	Noisy and incomplete criminal network information in Sicilian Mafia Organization.	Katz score link prediction is used.	Findings suggest the soundness of the link prediction is relatively high provided that only a limited amount of knowledge about the connection is hidden or missing	The approach could not handle heterogeneous criminal networks from different locations.
[7]	Test effect of four policy scenarios on recruitment of organized crime.	A novel agent-based model drawing on theories of peer effects, social embeddedness of organized crime, and the general theory of crime is developed.	The simulation generates realistic outcomes, with relatively stable organized crime membership and crime rates.	The findings show that the case studies are limited in their generality.
[4]	Prediction of hiding or missing links in criminal networks which represents possible interactions between individuals over time	The Deep Reinforcement Learning (DRL) is used	The predictive accuracy of the DRL model trained on the temporal data is significantly better than other ML models used.	The prediction of negative links has not been precise which could be attributed to the small dataset used.
[5]	Examine the crime scene behaviour to assess the level of predictive accuracy of linking crimes based on their offending characteristics	Logistic regression analysis is used.	The results obtained outline the potential that foraging domestic burglary offenders display distinct behaviours from other forms of offenders	The result of the data is subjectively judged and hence it includes false positive and omitted false-negative decision results.
[1]	Distinguished between linked and unlinked crime with burglaries, commercial robberies, and car thefts	The regression-based and probabilistic models were used.	The results show the regression model gives an accuracy of 0.903 for robbery and 0.820 for car thefts.	The unsolved criminal cases were not used in the implementation

One can see that the existing literature regarding crime link predictions has become apparent from the limitations. Previous research has contributed immensely but often lacked comprehensive and advanced approaches to deal with the intricacies of integrating multiple inputs and outputs, facilitated by a classifier chain transformation and data frame joins on temporal features to enhance the predictive accuracy of crime linkages between two geographical locations. The theoretical background used in this research is explained in folowing sections.

Support Vector Machine (SVM)

A support vector machine is one of the supervised algorithms that can be used for classification problems [12], [13]. SVM is used to find an appropriate region that contains most of the data drawn from an unknown probability distribution (non-linear class problem) and place a linear boundary between the classes.

$$f(x) = sign(w.x) + b \tag{1}$$

where w is the weight, x is the input data of dimension, and b is a bias. The optimal hyperplane separating the data can be obtained as a solution to the optimization problem as in equation (2).

$$minimize(w) = \frac{1}{2}\|W\|^2 \tag{2}$$

k-Nearest Neighbor (k-NN)

k-NN is a supervised machine learning algorithm that can be used for both classifications as well as regression problems [14],[15]. However, in this research k-NN is used for the classification problem. k-NN is based on the minimum distance from the query instances to all training samples to determine the k-NN, which spans the entire input space as in equation (3).

$$d(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2} \tag{3}$$

Prediction of the query instances is taken as the majority votes of the k-NN. The idea is that any point x is likely to be like those points about x. The choice of the parameter value k is critical, but k-NN is advantageously robust to uncertainty or noisy training samples.

Decision Tree (DT)

The decision tree is a supervised learning algorithm that can be used for classification and regression problems [16], [17]. In this research, DT is used as a classification problem. DT classifies an instance by filtering down a tree from the root to a leaf node, which provides the classification of the instance. Entropy and information gain are the two most common criteria used in the implementation of the DT model as in equations (4) and (5).

$$Entropy\ (X) = \sum_i^c p(x_i) log_2\, p(x_i) \tag{4}$$

$$Gain(X, H) = entropy(X) - entropy(X, H) \tag{5}$$

where X is the random variable with x_i and $p(x_i)$ is the probability of the variable, $Gain\ (X, H)$ denotes the information gain of attribute H, entropy (H) signifies the sample set of information on entropy and entropy (X, H) represents the information entropy of attributes. The subsequent section gives a detailed explanation of the proposed methodology used in this research.

C. Research Method

The investigation in this research employs an experimental research design. This study makes use of experimental data to back up positive claims about gaps and contributions in Section 1. The following sections show the experimental procedures used for the implementation. In this study, PHYTON was the implementation software used. The South African Police Services (SAPS) and Canadian crime dataset repository supplies [17].

Experimental procedure

In this study, the image data is acquired from publicly available South African Police Services (SAPS) and Canadian crime dataset repositories. The data is passed through data pre-processing to remove noise or any unwanted artefacts. The pre-processed data is fed to the data engineering where temporal features are extracted from the crime dataset. The extracted features are passed to the classifier chain for training and crime link prediction purposes. For the reader to comprehensively understand, the stages used in the experimental procedures for the crime link prediction are illustrated in Figure 1.

Stage 1: Data Acquisition

In this experiment, the crime data used is obtained from publicly available South African Police Services (SAPS) and Canadian crime datasets [18]. These datasets contain historical information of criminals which are in Comma Separated Values (CSV) format. To improve the performance of the proposed method, the acquired crime dataset is directed to the data pre-processing stage for further processes, where unnecessary noise and artefacts are removed.

Data Pre-Processing

Data pre-processing has become a regular operation in data analysis for computational efficiency [19]. To perform the data pre-processing stages used in this research, the data is pre-processed through the feature scaling techniques used to convert independent features that are present in the data to a fixed range using the normalization technique as discussed in the following sub-section.

Data Normalization

Normalization is a scaling approach in which features are re-scaled so that the data can fall within the range of zero and one [20],[21]. The normalized form of each feature is computed as in equation (6).

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{6}$$

where X' is the normalized features, X is the input data features, X_{min}= minimum value of the feature, and X_{max}= maximum value of the feature. The raw data is then transformed into a meaningful dataset. This is then loaded to the data engineering stage for further processes.

Stage 3: Data Engineering

To enhance the crime link prediction accuracy, the temporal features such as the month, time, days of the week, seasonality, modus Operandi, and weather are added through the extraction of the data information such as time, days of the week, the population of the region etc., which are extracted from different sources to improve the prediction performances of the classifiers. The crime features extracted/selected in this research consist of crime month, time, crime type, and crime locations.

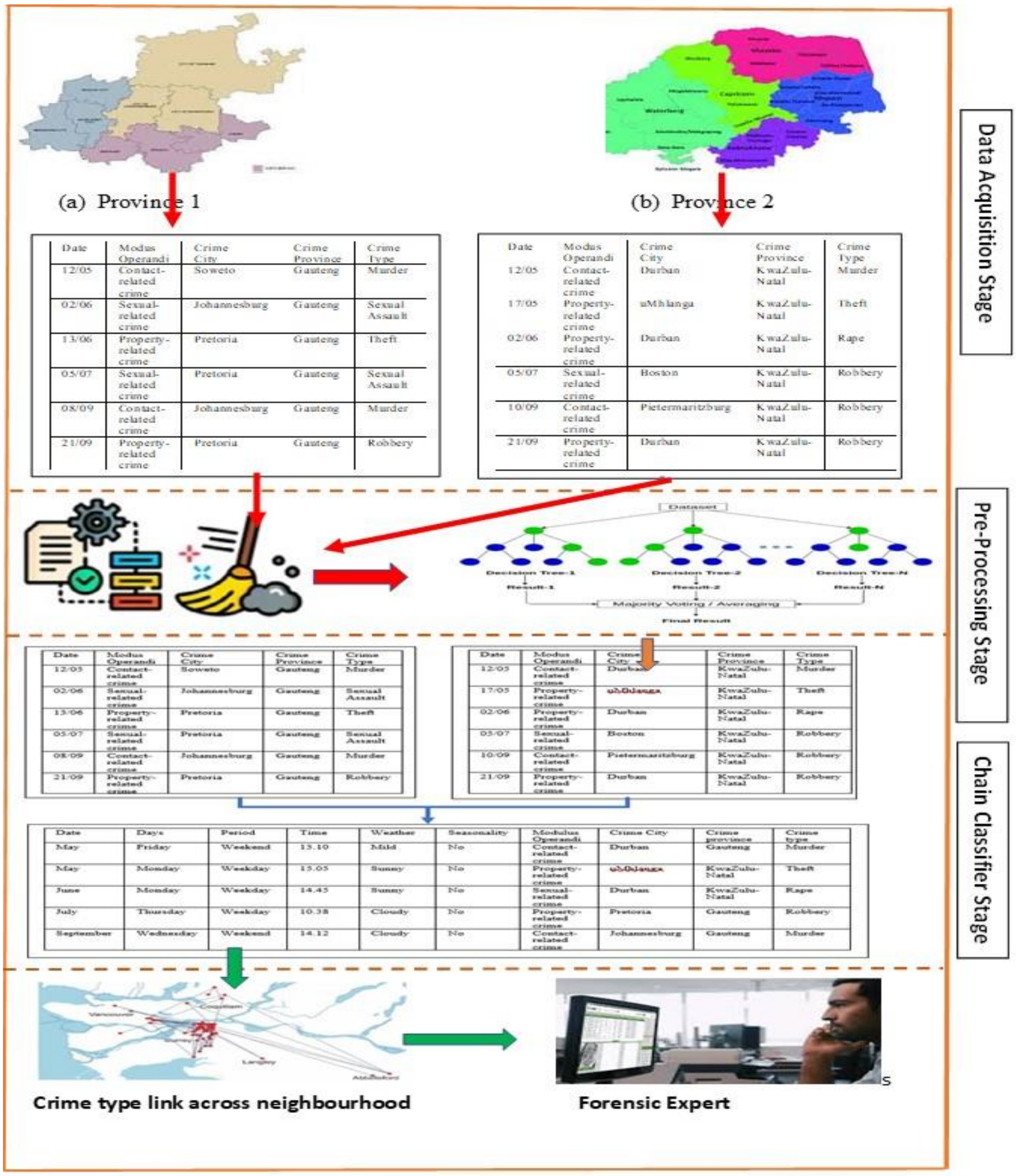
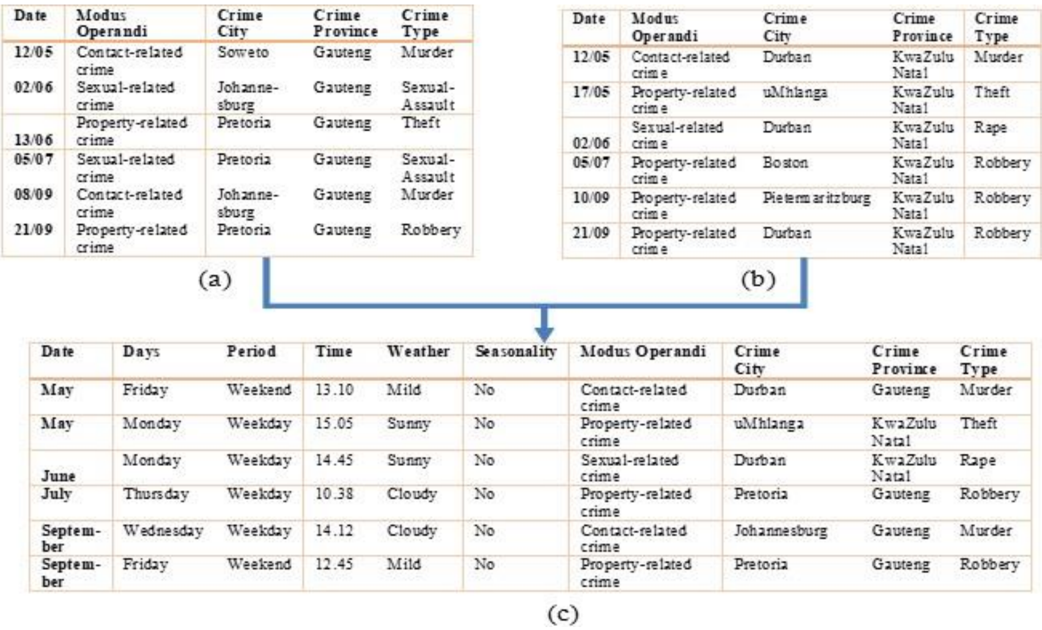


Figure 1. System framework for prediction of possible crime link between geographical locations

Features Extraction

To improve the crime link prediction model, the crime data frame data join is employed as shown in Figure 2. Figure 2(a) shows the original crime dataset from one province and Figure 2(b) indicates the crime dataset from neighboring province. Figure 2(c) shows the result when the data frames of the two provinces are left inner-joined to merge the crime data with the temporal features column, based on the date.



Date	Modus Operandi	Crime City	Crime Province	Crime Type
12/05	Contact-related crime	Soweto	Gauteng	Murder
02/06	Sexual-related crime	Johanne-sburg	Gauteng	Sexual-Assault
13/06	Property-related crime	Pretoria	Gauteng	Theft
05/07	Sexual-related crime	Pretoria	Gauteng	Sexual-Assault
08/09	Contact-related crime	Johanne-sburg	Gauteng	Murder
21/09	Property-related crime	Pretoria	Gauteng	Robbery

(a)

Date	Modus Operandi	Crime City	Crime Province	Crime Type
12/05	Contact-related crime	Durban	KwaZulu Natal	Murder
17/05	Property-related crime	uMhlanga	KwaZulu Natal	Theft
02/06	Sexual-related crime	Durban	KwaZulu Natal	Rape
05/07	Property-related crime	Boston	KwaZulu Natal	Robbery
10/09	Property-related crime	Pietermaritzburg	KwaZulu Natal	Robbery
21/09	Property-related crime	Durban	KwaZulu Natal	Robbery

(b)

Date	Days	Period	Time	Weather	Seasonality	Modus Operandi	Crime City	Crime Province	Crime Type
May	Friday	Weekend	13.10	Mild	No	Contact-related crime	Durban	Gauteng	Murder
May	Monday	Weekday	15.05	Sunny	No	Property-related crime	uMhlanga	KwaZulu Natal	Theft
June	Monday	Weekday	14.45	Sunny	No	Sexual-related crime	Durban	KwaZulu Natal	Rape
July	Thursday	Weekday	10.38	Cloudy	No	Property-related crime	Pretoria	Gauteng	Robbery
Septem-ber	Wednesday	Weekday	14.12	Cloudy	No	Contact-related crime	Johannesburg	Gauteng	Murder
Septem-ber	Friday	Weekend	12.45	Mild	No	Property-related crime	Pretoria	Gauteng	Robbery

(c)

Figure 2. Crime dataset from (a) one province, (b) original data from another province and (c) inner left data frame joins with temporal features for both provinces

Model Training, Testing and Evaluation Metrics

The dataset is divided into training and testing groups. A cross-validation technique is used to test the model, with 90% of the dataset designated for testing and the remaining 10% for training. This is because training and testing datasets need to be appropriate representations of interaction between crime types and locations. Overfitting and bias were prevented by repeating this procedure. Different machine-learning techniques were employed to test the trained method.

Building Model by Classifier Chain with Algorithmic Development and Mathematical Analysis

Algorithm 1 consists of a multi-label chain classifier with multiple class labels to a single instance. A multi-label dataset is denoted as $D = \{X^{(i)}, Y^{(i)}\}_{i=1}^{N}$ consisting of N samples. Each i^th instance $X^{(i)}$ is associated with a label vector $Y^{i} = [Y_1^{(i)}, \dots Y_L^{(i)}]$; there are L elements corresponding to the class label and each element$y_j^{(i)} \in \{linked, not\ linked\}$ of the jth concept of the instance. A multi-label model is tasked with providing predictions $\hat{Y} = [\hat{Y}_1, \dots \hat{Y}_L]$ for any given test instance $\hat{X}$ for the prediction, the classifier chains (RF, k-NN, SVM, GBM, and DT) are applied to the test instances. The prediction process can be mathematically expressed as shown in equation (7).

$$\begin{aligned} \hat{Y}_1 &= h_1(X) \\ \hat{Y}_2 &= h_2(X, \hat{Y}_1) \\ &\;\;\dots\dots \\ \hat{Y}_L &= h_L(X, \hat{Y}_1, \hat{Y}_2, \dots \hat{Y}_{L-1}) \end{aligned} \tag{7}$$

where $\hat{Y}$ represents the predicted crime type for the i^{th} geographical location.

Each ML classifier h_i is trained using the transformed input crime feature matrix X' of the geographical location, which includes the original features X joined with temporal features of the next location and the previously predicted crime type $\hat{Y}_i$. The best ML classifier in each location is deployed for predicting the crime type to be linked.

Figure 3 displays the pseudo-code used to create a classifier chain model for crime link prediction across geographical locations implementation. After integrating multiple inputs and outputs, facilitated by a classifier chain transformation and data frame joins on temporal features. The best classifiers with the best prediction capability were ultimately selected to form the proposed method.

Algorithm 1: Classifier Chain for Prediction of Crime Link across Geographical Location

Input $D = \{(X1, y1), (X2, y2), \ldots, (Xn, yn)\}$, M = number of iterations, $\psi(y, f)$ = choice of the loss function, $h(x, \theta)$ = base-learner, F
Output = predicted class y

```
// Support Vector Machine
construct k in SVM model
use equation (1)- (4) to generate the i* hyperplane
test sample x_test is assigned the class label using equation (28)

// Decision Tree
GenDecTree(Sample S, Features F)
if stopping_condition(S,F) = = true then
   Leaf = CreateNode()
   leafLabel = classify (S)
return leaf
root = createNode()
   for each value v ∈ V:
      S_v = {S | root test_condition(s) = V and S ∈ S}
      child = TrueGrowth(S_v, F)
      add child as descent root and label the edge ( {root→child} as V)
return root
// k-Nearest Neighbor
  for (x',l') ∈ S do
        compute the distance d(x, X') as in equation (5)
     endfor
   sort the |S| distance by increasing order
   count the number of occurrences of each class l_j among the k nearest neighbor
   assign to x the most frequent class
// Gradient Boost Algorithm
initialize f_0 with constant
   for t = 1 to M do
     compute the negative gradient g_t(x)
       fit a new base-learner function h(x, θ_t)
         find the best gradient descent step-size ρ_t
update the function estimate: f_t ← f_{t-1} + ρ_t h(x, θ_t)
endfor
// Random Forest
Function RandomForest(D, F)
p ← ∅
 for i ∈ 1,..., k do
      p_i = RandomizedTreeLearn(D^(i), F)
       p ← p ∪ {p_i}
   endfor
return H
Function RandomizedTreeLearn(D, f)
at each node:
   f ← very small subset of F
split the best feature of F
Split the tree iteratively until one leaf node is attained and the tree remains completed
   return y
end
```

Figure 3. Classifier chain model pseudo-code for crime link prediction across geographical locations

Evaluation Metrics

This section presents the evaluation metric used in this research for implementation of the proposed objectives. These metrics include hold-out cross-validation technique, the receiver operating characteristics (ROC) curve, and the confusion matrix as explained in [19].

D. Result and Discussion

The implementation software used in this research is Python. The crime dataset is obtained from the Africa-based crime and Canada-based crime database repositories [22].

Africa-Based Dataset

The South Africa (SA) crime dataset used in this implementation starts from April 2015 to June 2019 [22]. For the scope of this research, only seven crime types were used, and these include murder, sexual assault, burglary, kidnapping, robbery, theft, and vandalism. To avoid biases in the implementation, the statistics of the crime types used are as follows; robbery has 10,066, sexual assaults have 10,076, vandalism contains 10,066 crime types, murder has 10,089, burglary has 10,109, theft has 10,090 and kidnap consists of 10,110 crime types. As part of the contribution of this research, data engineering was done to derive temporal attributes such as the month, time, weather, seasonality, and Modus operandi (how the crime was committed) from the crime dataset to improve the crime link prediction performance of the proposed method as shown in Table 2.

Table 2. Samples of the Africa-based crime dataset after feature engineering

Month	Days	Period	Time	Weather	Seasonality	Modus Operandi	Crime City	Crime Province	Crime Type
May	Friday	Weekend	13.10	Mild	No	Contact-related crime	Soweto	Gauteng	Murder
June	Monday	Weekday	15.05	Sunny	No	Sexual-offense crime	Johannesburg	Gauteng	Sexual Assault
June	Monday	Weekday	14.45	Sunny	No	Property-related crime	Pretoria	Gauteng	Theft
June	Saturday	Weekend	20.08	Sunny	No	Sexual offence crime	Vereeniging	Gauteng	Assault

Legend: Modus Operandi tells how crime is committed

Canada-Based Dataset

The publicly available crime dataset acquired from the Canada crime data repository was obtained in 2003 [23]. Although there are many crime types in the crime dataset, this research focused on only seven crime types which are murder, sexual assault, burglary, kidnapping, robbery, theft, and vandalism. To avoid biases in the implementation, the statistics of the crime types used are as follows; robbery has 10,115, sexual assaults have 10,115, vandalism contains 10,115 crime types, murder has 10,110, burglary has 10,297, theft has 10187, and kidnap consists of 10,205 crime types. In this research, the extracted features used to train and test the performance of the classifiers are the month, time, weather, seasonality, modus operandi, crime province, and crime type as shown in Table 3.

Table 3. Samples of the publicly available Canada-based crime dataset after feature engineering

Month	Day	Period	Time	Weather	Seasonality	Modus Operandi	Crime City	Crime Province	Crime Type
January	Thursday	Weekday	10.21	Cloudy	Yes	Property-related crime	Strathcona	British Columbia	Theft
March	Sunday	Weekend	18.00	Cloudy	No	Property-related crime	Central Business District	British Columbia	Vandalism
April	Sunday	Weekend	17.30	Cloudy	Yes	Property-related crime	Dunbar Southlands	British Columbia	Burglary
June	Friday	Weekend	14.15	Cloudy	No	Sexual-offense crime	West End	British Columbia	Theft
June	Wednesday	Weekday	07.45	Cloudy	Yes	Property-related crime	Grandview Woodland	British Columbia	Theft

Legend: Modus Operandi tells how crime is committed

EXPERIMENT 1.1: Predicting Crime Occurrence in a Province

The objective of this experiment is to determine whether the proposed method can accurately predict the crime types in a province with temporal features added to the original dataset features. A cross-validation technique was used in the evaluation, where 90% of the dataset was used for training and 10% was used for testing. This experiment was repeatedly done on an SVM, GBM, RF, k-NN, and DT. The results of the validation of the different classifiers used in the implementation are presented as confusion matrices in Figure 5.

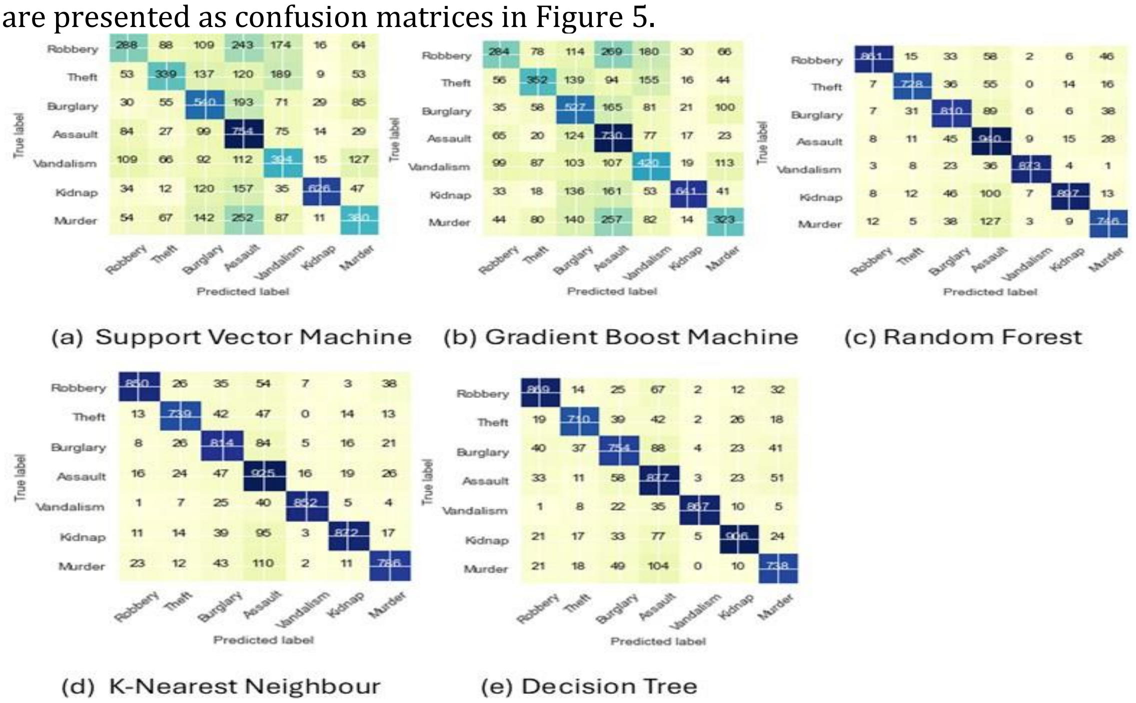


Figure 5. Confusion matrices capturing the performances of the implemented methods

Figure 5 represents the confusion matrices generated from the evaluation of the selected machine learning methods for the prediction of crime type in Table 5. The diagonal blue box in the confusion matrices depicts the instances that are correctly predicted by the methods while others are those that are wrongly predicted. The performance results are further evaluated with the Receiver Operating Characteristics (ROC) curve as shown in Figure 6.

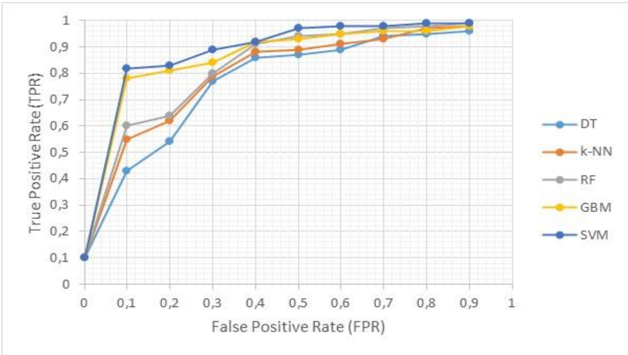


Figure 6. ROC-curve of five classifiers used in the experiment

From Figure 6, the correctly predicted links are computed as TPRs, while the incorrectly predicted crime links or false alarms are the FPRs. One can see that the TPRs of the DT are higher while their FPRs are lower in comparison to other classifiers used in the experiment. Other metrics such as precision, recall, F1-score, and accuracy of all the five methods used are further evaluated and the summary of the overall implementation performance is shown in Table 4.

Table 4. Performance evaluations of ML methods

Method	Recall	Precision	F1-Score	Accuracy (%)
SVM	0.81	0.79	0.80	80
GBM	0.83	0.80	0.80	80.06
RF	0.84	0.82	0.82	82.50
k-NN	0.89	0.87	0.87	88.12
DT	0.94	0.93	0.93	93.51

Our findings indicate that higher accuracy of 98.5% is not associated with poor performance in F1-score, recall, and precision. The proposed method mat benefit from a classifier chain temporal feature-data frame joins and statistical properties of data engineering used for features extraction to reveal the hidden information of criminals without negatively affecting crime link prediction accuracy. The best classifier is chosen from Table 4, since one of the objectives of this study is to add some temporal features derived from the research findings to improve the performance of the link prediction systems, hence, the best classifier with strong predictive results to form the proposed method is chosen as shown in in the 10th column of Table 5.

Table 5. Crime prediction on test set results

								Target	Predicted
Month	Weekday	Period	Time	Weather	Seasonality	Modus Operandi	Crime City	Gauteng Crime	Proposed DT
February	Thursday	Weekday	9.13	Mild	No	Aggravated Robbery	Johannesburg	Robbery	Theft
March	Wednesday	Weekend	14.13	Hot	Yes	Aggravated Robbery	Pretoria	Burglary	Burglary
August	Saturday	Weekend	9.06	Cold	Yes	Aggravated Robbery	Pretoria	Robbery	Robbery
August	Sunday	Weekend	21.09	Cold	Yes	Property-Related Crime	Krugersdorp	Carjacking	Carjacking
December	Friday	Weekend	15.41	Hot	No	Aggravated Robbery	Soweto	Robbery	Robbery
December	Friday	Weekend	14.55	Hot	Yes	Property-Related	Pretoria	Arson	Theft
December	Saturday	Weekend	20.56	Hot	Yes	Property-Related Crime	Johannesburg	Burglary	Burglary

Table 5 presents the evaluation results of the different classifiers used in the experiments with their capability to predict the crime type across Gauteng province using the historical Africa-based crime datasets.

4.2.2 EXPERIMENT 1.2: Predicting Crime Links between Two Provinces Using Classifier Chains Principle

Our intention here is to determine whether the proposed method can accurately predict the link between crime types that occur in two provinces using the principle of multi-label classifier chains that preserve correlations as described in Section 3.4. If the decision must be made between the crime types that occur in the two provinces, then we make a query on the resulting model as follows:

Query: What is the likelihood of a crime type in Province 2 that is linked to an occurrence of a crime type in Province 1, given the observed and temporal features?

For instance, forensic investigators or investigative police doing investigation research may want to find the link between the crime types that happened across the two provinces, such as KwaZulu-Natal and Gauteng on a specific month, time, seasonality, period, and weather, as illustrated in equation (8).

Pr {(Crime_Type = ?, KwaZulu-Natal) : (Crime_Type = Burglary, Gauteng) | Month = March, Time = 14.13, Seasonality = Public holiday, Period=Weekend, Weather = Hot) } = ? (8)

In the first scenario of equation (8), the security operative wants to know whether the Burglary crime type that occurred in Gauteng is linked to a crime type that occurred in KwaZulu Natal in March, during public holidays when the weather is hot. Using the proposed methodology in Section 3.3, the month column data frame is used in this experiment to join the two provinces' data together. The predicted results in Experiment 1.1 are also used as part of feature attributes used in the prediction of the link between the crime types that occurred in Gauteng and KwaZulu-Natal. The revealed states of knowledge of all scenarios in equation (8) are therefore shown by using the cross-validation technique, where 90% of the dataset was used for training and 10% was used for evaluation. The results are further expressed as confusion matrices in Figure 7.

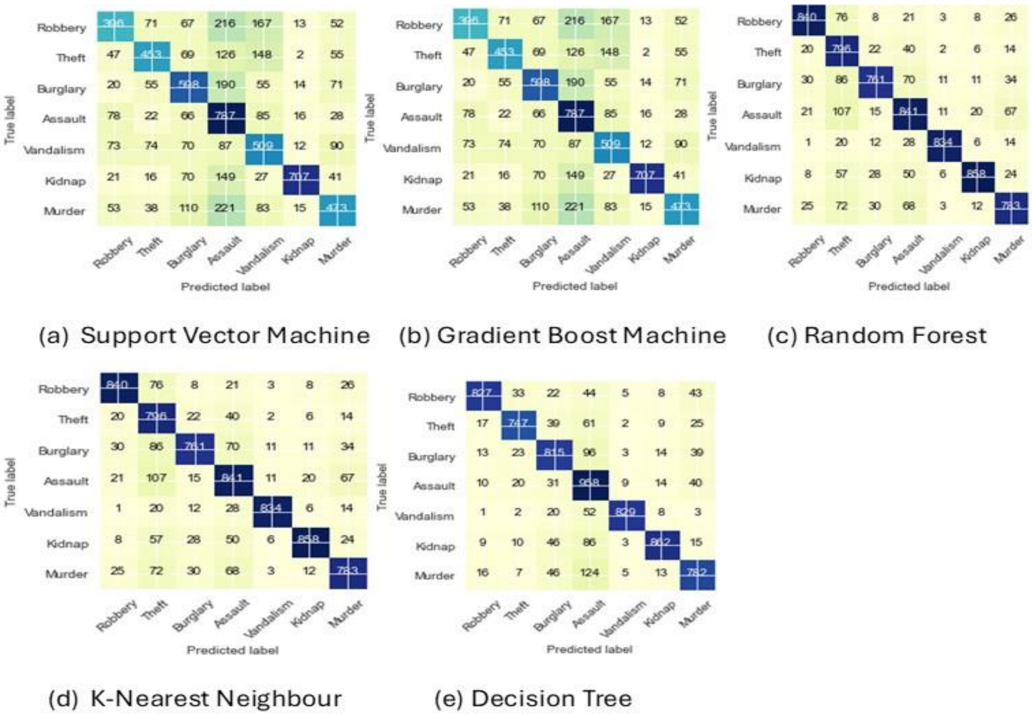


Figure 7. Confusion matrices capturing the performances of the implemented methods

From Figure 7, the diagonal elements represent the number of crime types that the classifiers predicted as the same as actual, while the non-diagonal elements are the crime types that were misclassified by the classifiers. To further evaluate the robustness of the methods, the ROC is utilized as shown in Figure 8.

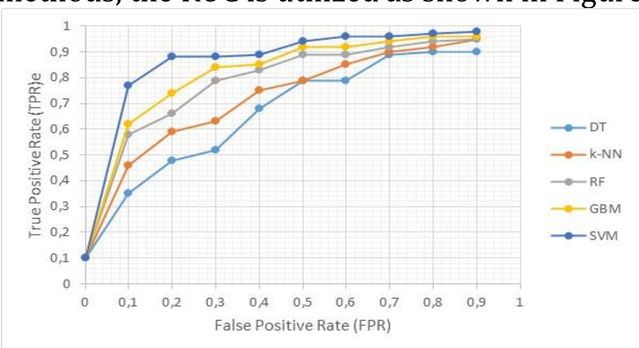


Figure 8. ROC-curve of five classifiers used in the experiment on a crime with temporal features on an Africa-based crime dataset

In comparison, one can see from the ROC curve that some algorithms have higher TPRs than others for the predictive methods when used for predicting the crime types in a province. We found that integration of the temporal features such as time, weather and seasonality have influence on crime link prediction across geographical locations which correlates with inference made in [24]. The proposed method in this study tended to have an inordinately higher proportion of overall implementation performance in terms of precision, recall, F1-score, and accuracy are shown in Table 6.

Table 6. Performance evaluations of ML methods

Method	Recall	Precision	F1-Score	Accuracy (%)
SVM	0.92	0.91	0.91	91.25
GBM	0.93	0.95	0.94	93.55
RF	0.98	0.97	0.97	97.50
k-NN	0.99	0.98	0.98	98.13
DT	0.99	0.98	0.99	98.99

Our findings indicate that higher accuracy of 98.99% is not associated with poor performance in F1-score, recall, and precision. The proposed method mat benefit from a classifier chain temporal feature-data frame joins and statistical properties of data engineering used for features extraction to reveal the hidden information of criminals without negatively affecting crime link prediction accuracy. The best classifier is chosen from Table 6, since one of the objectives of this study is to add some temporal features derived from the research findings to improve the performance of the link prediction systems, hence, the best classifier with strong predictive results to form the proposed method is chosen as shown in in the 11th column of Table 7.

Table 7. Results of the link between crime types prediction across provinces with temporal features

Mon th	Week day	Period	Time	Weat her	Seas on- ality	Modus Operandi	Crime City	Gauteng Crime	Target KwaZulu -Natal	Predicted Proposed DT
Feb ruary	Thurs day	Week day	9.13	Mild	No	Aggravated Robbery	Johannes burg	Rob bery	Kidnap	Murder
March	Wed nesday	Week end	14.13	Hot	Yes	Aggravated Robbery	Pretoria	Burg lary	Theft	Theft
August	Satur day	Week end	9.06	Cold	Yes	Aggravated Robbery	Pretoria	Rob bery	Kidnap	Kidnap
August	Sun day	Week end	21.09	Cold	Yes	Property-Related Crime	Krugers dorp	Car jacking	Rape	Rape
Dece mber	Fri day	Week end	15.41	Hot	No	Aggravated Robbery	Soweto	Rob bery	Kidnap	Murder
Dece mber	Fri day	Week end	14.55	Hot	Yes	Property-Related	Pretoria	Arson	Theft	Theft
Dece mber	Satur day	Week end	20.56	Hot	Yes	Property-Related Crime	Johannes burg	Burg lary	Kidnap	Kidnap

From this result, it is observed that the proposed DT produced results like the target column and achieved better performances compared to other methods used in the implementation. This improved performance makes the proposed method suitable for assisting forensic experts or security investigators in accurately finding the connection between crime types that occurred in a particular province with their neighboring provinces.

Temporal Reasoning on Specific Scenarios

Forensic investigators or investigative police doing investigation research may now use the proposed method to answer the below queries from the implementation results as shown in equation (9).

Pr {(Crime_Type = Theft, KwaZulu-Natal) : (Crime_Type = Burglary, Gauteng) | Month = March, Time = 14.13, Seasonality = Public holiday, Period=Weekend, Weather = Hot) } = Theft (9)

Having seen the crime types of situations across provinces over time, season and weather conditions, the decision can be made easily after knowing what was not known by answering the four questions on the multi-label classifier chain integrating DT theory about the crime type link prediction across the provinces.

Q1: What is happening?
A1: The Burglary crime that happened in Gauteng is linked with the Theft crime type in KwaZulu-Natal during a public holiday at 14.13 in the afternoon when the weather was hot, and people were far away from their homes to enjoy the holiday.

Q2: Why is this happening?
A2: The crime type between Gauteng and KwaZulu-Natal is a true reflection of the presence in the link connection between the criminals across the two provinces, perhaps due to the seasonality, period, and weather conditions.

Q3: What will happen next?
A3: Similar crimes are likely to reoccur at the same months, time, and seasonality in KwaZulu-Natal and Gauteng provinces since there are linked networks between the crime types committed in these two provinces unless appropriate security measures are established in these two provinces at these months, time, and seasonality.

Q4: What can be done about it?
A4: It is a clear indication that these criminals have a linked network across these provinces, the security operatives must ensure that the security resources are allocated to these provinces, especially during public holidays.

Experiment 2: Benchmarking the Proposed Methodology on Publicly Available Canada-based Data.

To generalize this research, the temporal features are used to evaluate the performance of the classifier chain on the publicly available crime dataset acquired from the Canada crime data repository obtained in 2003 [23].

Experiment 2.1: Predicting Crime Types in a Province with Temporal Features

Here, the aim is to determine the consistency and predictive performance of the proposed method on the publicly available Canadian crime dataset in predicting the crime types in a province when adding temporal features to the original crime dataset. A cross-validation technique like Experiment 1.1 was therefore used in the evaluation of the SVM, GBM, RF, k-NN, and DT. The confusion matrices for each classifier are obtained as shown in Figure 9.

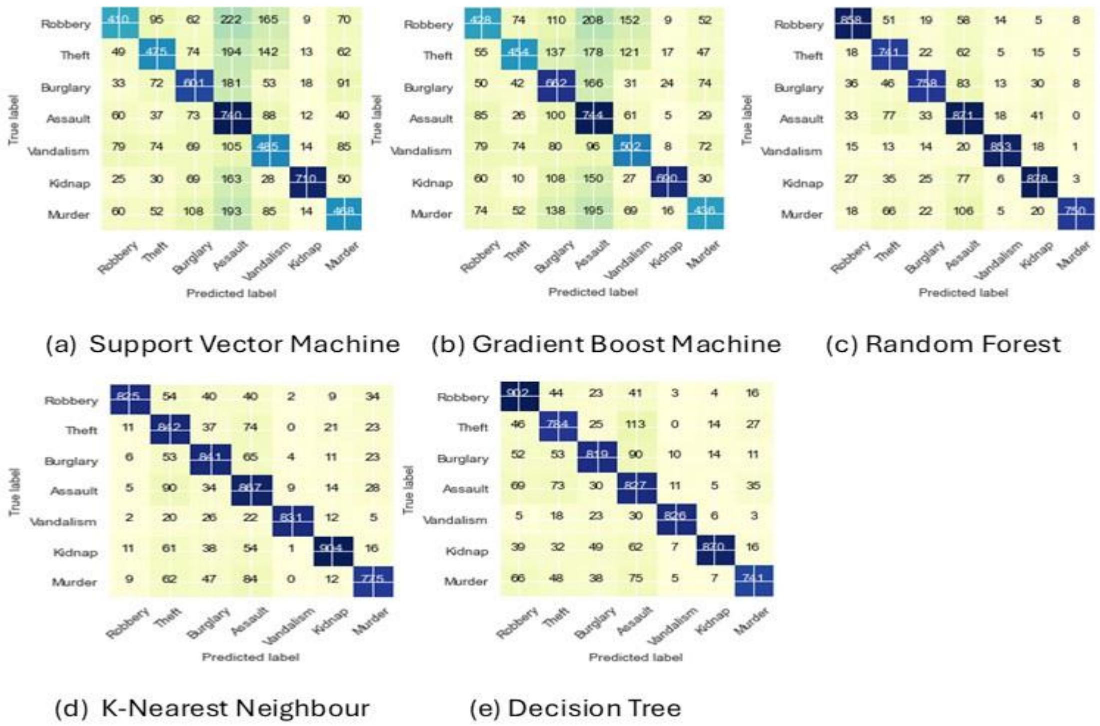


Figure 9. Confusion matrices capturing the performances of the implemented methods

From Figure 9, the diagonal of the confusion matrices represents the number of correct predictions in each crime type category with performance metrics shown in Table 8. To obtain a more complimentary view of the results of the classifiers, the ROC curves are established as shown in Figure 10.

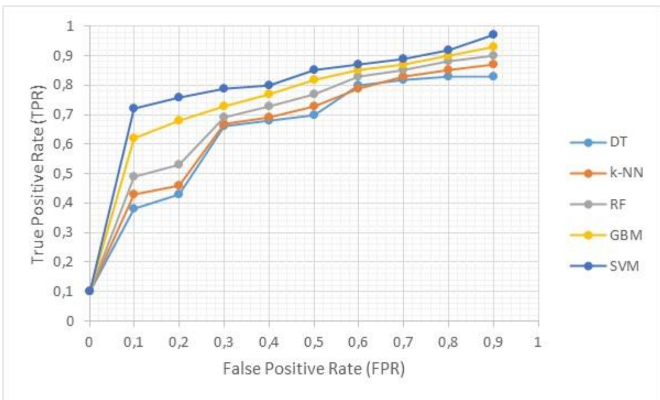


Figure 10. ROC-curve of five classifiers used in the experiment on a crime with temporal features on a Canada-based crime dataset

From Figure 10, the correctly predicted links are computed as TPRs, while the incorrectly predicted crime links or false alarms are the FPRs. One can see that the TPRs of the DT are higher while their FPRs are lower in comparison to other classifiers used in the experiment. Other metrics such as precision, recall, F1-score, and accuracy of all the five methods used are further evaluated and the summary of the overall implementation performance is shown in Table 8.

Table 8. Performance evaluations of ML methods

Method	Recall	Precision	F1-Score	Accuracy (%)
SVM	0.83	0.82	0.83	83.35
GBM	0.83	0.84	0.83	83.86
RF	0.86	0.89	0.87	89.41
k-NN	0.88	0.88	0.88	89.70
DT	0.95	0.95	0.95	95.40

Table 8 provides a summary of all the overall results achieved by the classifier for the link prediction of crime types between provinces. The DT method produced the best prediction performance results with 0.95 recall, precision is 0.95, the F1-score of 0.95, and accuracy is 95.40%. Since DT emerges with the best performance, it is proposed as the appropriate method for deployment in the 10th column of Table 9.

Table 9. Crime prediction on test set results

								Target	Predicted
Month	Weekday	Period	Time	Weather	Seasonality	Modus Operandi	Crime City	Saskatchewan Crime	Proposed DT
February	Monday	Weekday	23.30	Cold	No	Property-Related Crimes	Richard	Assault	Assault
June	Wednesday	Weekday	13.00	Hot	Yes	Property-Related Crimes	Melville	Riot	Vandalism
July	Tuesday	Weekday	14.50	Hot	Yes	Property-Related Crimes	Melville	Theft	Theft
August	Monday	Weekday	13.30	Hot	No	Property-Related Crimes	Richard	Theft	Theft
August	Monday	Weekday	16.17	Hot	Yes	Property-Related Crimes	Biggar	Burglary	Theft
November	Thursday	Weekday	16.01	Hot	Yes	Property-Related Crimes	North Battleford	Theft	Theft
December	Friday	Weekend	21.10	Cold	Yes	Property-Related Crimes	Richard	Burglary	Robbery

Table 9 presents the evaluation result of the proposed DT with its capability to understand the link between crime types across two provinces that occur on a specific month, time, seasonality, and weather of the year using a Canada-based crime dataset.

EXPERIMENT 2.2: Predicting Crime Types Links between Two Provinces with Temporal Features

This experiment aims to determine the consistency of the proposed method in terms of predicting the link between crime types that occur in two provinces using the principle of multi-label classifier chains that preserve correlations as described in section 3.4. If the decision must be made between the crime types that occur in the two provinces, then we make a query on the resulting model as follows:

Query: What is the likelihood of a crime type in Province 2 that is linked to an occurrence of a crime type in Province 1, given the observed and temporal features?

For instance, forensic investigators or investigative police doing investigation research may want to find the link between the crime types that happened across the two provinces, such as Saskatchewan and British Columbia, on a specific month, time, seasonality, period, and weather, as illustrated in equation (10).

Pr {(Crime_Type = ?, British Columbia) : (Crime_Type = Vandalism, Saskatchewan) | Month = July, Time = 14.50, Seasonality = Public holiday, Period=Weekday, Weather = Hot) } = ? (10)

From the scenario of equation (10), the forensic investigators or investigative police doing investigation research may want to know whether the Theft crime type that happened in British Columbia is linked to the Vandalism crime type that happened in Saskatchewan at 14.50 in the afternoon in July when there is a public holiday and when the weather is hot. This is similarly repeated for the rest of the scenarios in equation (10). To reveal the states of knowledge of all scenarios in equation (10), a cross-validation technique is employed where 90% of the dataset was used for training and 10% was used for evaluation. This experiment was repeatedly done on SVM, GBM, RF, k-NN, and DT. The confusion matrices are utilized for each classifier as shown in Figure 11.

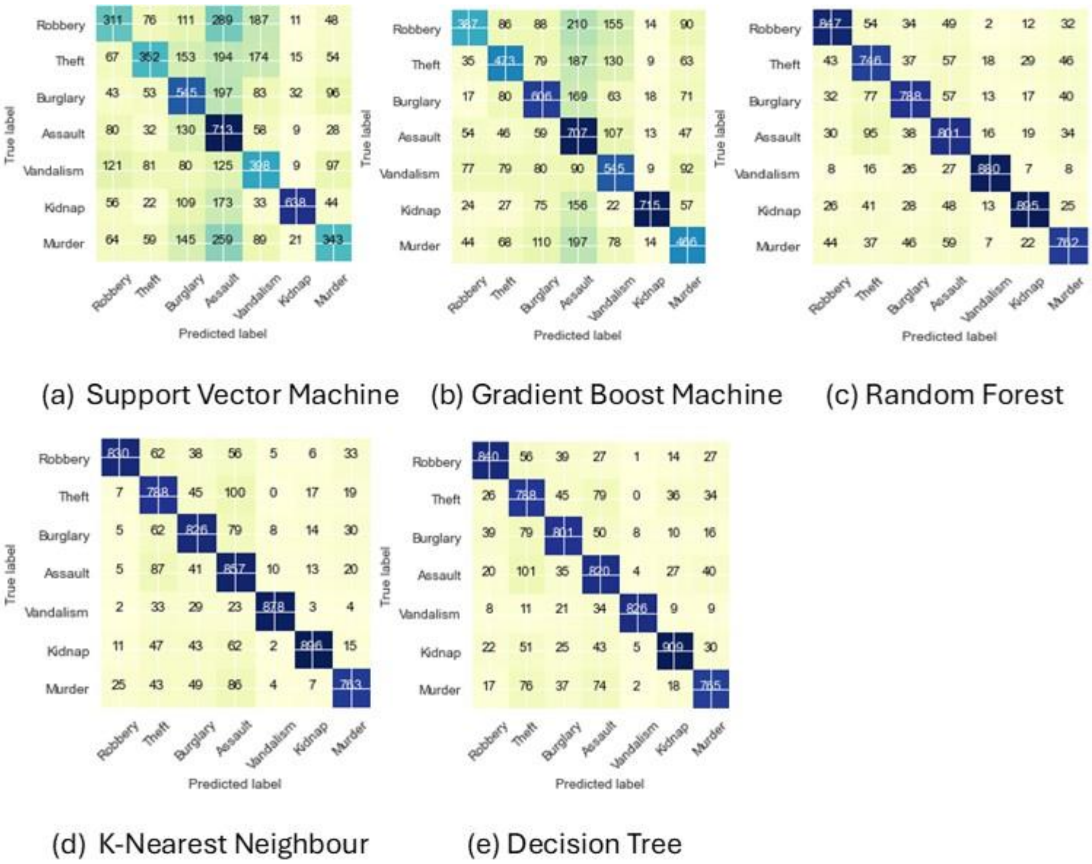


Figure 11. Confusion matrices capturing the performances of the implemented methods

The diagonal blue box in the confusion matrices depicts the instances that are correctly predicted by the methods while others are those that are wrongly predicted as shown in Figure 11. To further validate the performance of the classifiers used in the experiment based on the Canada-based crime dataset, the ROC curves for each classifier are established as shown in Figure 12.

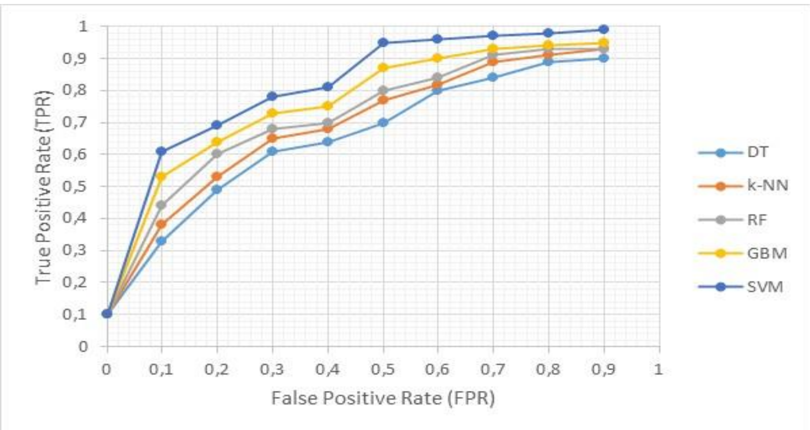


Figure 12. ROC-curve of six classifiers used in the experiment on temporal crime features of a Canada-based crime dataset

In comparison, one can see from the ROC curve that some algorithms have higher TPRs than others for the predictive methods when used for predicting the crime types in a province. We found that integration of the temporal features such as time, weather and seasonality have influence on crime link prediction across geographical locations which correlates with inference made in [24]. The proposed method in this study tended to have an inordinately higher proportion of overall implementation performance in terms of precision, recall, F1-score, and accuracy are shown in Table 10.

Table 10. Performance evaluations of ML methods

Method	Recall	Precision	F1-Score	Accuracy (%)
SVM	0.85	0.86	0.85	85.28
GBM	0.89	0.89	0.90	89.41
RF	0.92	0.94	0.91	91.50
k-NN	0.94	0.96	0.95	95.50
DT	0.97	0.98	0.97	97.88

Our findings indicate that higher accuracy of 97.88% is not associated with poor performance in F1-score, recall, and precision. The proposed method mat benefit from a classifier chain temporal feature-data frame joins and statistical properties of data engineering used for features extraction to reveal the hidden information of criminals without negatively affecting crime link prediction accuracy. The best classifier is chosen from Table 4, since one of the objectives of this study is to add some temporal features derived from the research findings to improve the performance of the link prediction systems, hence, the best classifier with strong predictive results to form the proposed method is chosen as shown in in the 11th column of Table 11.

Table 11. Results of the link between crime types prediction across provinces with temporal features

Month	Weekday	Period	Time	Wether	Seasonality	Modus Operandi	Crime City	Saskatchewan Crime	Target	Predicted
									British Columbia	Proposed DT
February	Monday	Weekday	23.30	Cold	No	Property-Related Crimes	Richard	Assault	Theft	Theft
July	Tuesday	Weekday	14.50	Hot	Yes	Property-Related Crimes	Melville	Theft	Vandalism	Vandalism
August	Monday	Weekday	13.30	Hot	No	Property-Related Crimes	Richard	Theft	Robbery	Robbery
November	Thursday	Weekday	16.01	Hot	Yes	Property-Related Crimes	North Battleford	Theft	Theft	Theft
December	Friday	Weekend	21.10	Cold	Yes	Property-Related Crimes	Richard	Burglary	Robbery	Kidnap

From the implementation, the proposed DT method achieved predictive performance almost like the target column as shown in Table 11. The improved performance of the proposed method is an indication that the method can successfully be used as an application to help forensic experts and police investigators doing investigative research in the prediction of a link between the crime types across provinces in a specific month, time, weather, and seasonality of the year.

Temporal Reasoning on Specific Scenarios

By reasoning, a set of random scenarios in equation (11) was obtained based on the forensic investigators or investigative police doing investigation research using the proposed method. The reasoning results are presented in Table 11. The scenario of the equation (11) is interpreted as follows:

Pr {(Crime_Type = Theft, British Columbia) : (Crime_Type = Vandalism, Saskatchewan) |Month = July, Time=14.50, Seasonality=Public holiday, Period=Weekday, Weather = Hot) }=Vandalism (11)

With the result obtained from the scenarios in equation (11) using the proposed method, the security operators can decide after knowing what was not known by answering the four questions on security about crime link type across various crime provinces.

Q1: What happens?
A1: The Theft crime types that occurred in British Columbia and the Theft crime types that happened in Saskatchewan in January at 14.50 when there was a public holiday, during the weekdays, and when the weather was Hot in British Columbia are linked.

Q2: Why is this happening?
A2: There is a link between the Theft and Vandalism crime types that happened in British Columbia and Saskatchewan in July at 14.50 in the afternoon on the weekdays during the holiday period when people would have been far away from their homes. This is a true reflection that seasonality periods (such as New Year, Thanksgiving Day, Christmas Day, etc.) influence the link crime types across the two provinces. This shows that the crime linked between British Columbia and Saskatchewan has a sharp response to public holidays and weather conditions.

Q3: What will happen next?
A3: For instance, to avoid the reoccurrence of this crime and prevent the crime syndicates from perpetuating this same crime type across these two provinces, security operatives should be deployed to these provinces for the next holiday periods.

Q4: What can be done about it?
A4: Concerning the predictive results, from the crime dataset it is an astute decision to routinely deploy security operatives and resources to these provinces during holidays in the afternoon period when the weather is hot. This might minimize the crime rates between the two provinces.

Performance Comparison of Proposed Method with Other Existing Methods

This section compares the performance of the proposed methods with other state-of-the-art prediction methods that are currently in use on the Canada crime dataset regarding the following: problem addressed, method used, precision, recall, F1-score, and accuracy as shown in Table 12.

Table 12. Performance comparison of the proposed method with existing link prediction methods.

Ref	Method	Precision	Recall	F1-Score	Accuracy (%)
[25]	Crime Graph Net	0.82	0.80	0.81	85
[26]	Random Forest	-	-	0.89	91
[27]	Rule-based	0.891	0.74	0.809	90
[4]	Time Evolve Deep Reinforcement Learning Criminal Network Analysis (TDRL-CAN)	0.73	0.72	0.72	74
Proposed model	classifier chain and data frame join on temporal features	0.98	0.97	0.97	97.88

Table 12 indicates that, when compared to other methods used in this study, the proposed method performs significantly better on the Canadian crime dataset, with an accuracy of 97.88%. The method is appropriate for real-time applications because of its accuracy.

Discussion

This study investigated a novel approach to advance the prediction of crime links between geographical locations which integrates multiple inputs and outputs, employing a classifier chain transformation for enhanced predictive accuracy, while prior studies have focused on using historical data directly on machine learning, they have not explicitly addressed the intricacies of crime link prediction hampered by multifaceted criminal information on crime link prediction systems.

From the experiment conducted, we found that integrates multiple inputs and outputs, employing a classifier chain transformation enhances predictive accuracy for crime link prediction which correlates with inference made in [2]. The proposed method in this study tended to have an inordinately higher proportion of accuracy of 97.88%.

Compared with other crime link prediction methods used in literature as shown in Table 12, Our findings indicate that higher accuracy is not associated with poor performance in terms of recall, precision, and F1-socre. The proposed method mat benefit from a classifier chain temporal feature-data frame joins and statistical properties of data engineering used for features extraction to reveal the hidden information of criminals without negatively affecting crime link prediction accuracy.

Limitations, this study investigated a comprehensive and advanced approaches to deal with the intricacies of integrating multiple inputs and outputs, facilitated by a classifier chain transformation and data frame joins on temporal features to enhance the predictive accuracy of crime linkages between two geographical locations. However, additional and in-depth research may be required to confirm its prediction performance using two or more feature extraction methods to improve the crime link prediction accuracy, particularly on historical crime dataset.

Implication of future research, our research shows that the proposed method is more resilient than the conventional link prediction methods used in this study. Future research may look into the use of a combination of texture and statistical-based feature extraction methods with feasible ways of producing robust crime link prediction accuracy and practical methods for developing an intelligent criminal link prediction prototype.

E. Conclusion

This study investigated the detection of crime link prediction between two provincials using multiple inputs and outputs, facilitated by a classifier chain transformation and data frame joins on temporal features while earlier studies have explored different methods such as crime graph net, kartz score, Rule-based, Random Forest (RF), Deep Reinforcement Learning (DRL) to predict crime linkage, they have not explicitly addressed the intricacies of accurately predicting crime link between two provincials.

From the experiment conducted, findings show that the temporal feature such as weather, seasonality, time, modulus operandi, etc., was extracted from the original crime datasets used in the implementation. The temporal features extracted method showed the revealed variations of hidden criminal information embedded in the crime dataset and the extracted features are trained with classifier chains as shown in Tables 7 and 11. The best classifier that gives optimal link prediction results is the Decision Tree which is then used as the proposed classifier method in this research. Furthermore, the proposed method used in this study tended to have an inordinately higher proportion of predictive precision of 0.98, recall of 0.99, F1-score of 0.99, and accuracy of 98.99% on real-life crime datasets. While tested on the publicly available Canadian crime datasets, a precision of 0.98, recall of 0.97, F1-score of 0.97, and accuracy of 97.88% were achieved. In comparison of the proposed method with other crime link prediction methods used in literature as shown in Table 12, the study suggests that higher accuracy is associated with data frame join on the temporal features of the crime data.

This study explored comprehensive and advanced approaches to deal with the intricacies of crime link prediction between two geographical locations in addition to improvement in predictive accuracy. However, further, and in-depth studies may be needed to confirm its crime link prediction performance using two or more feature extraction methods to improve the crime link prediction accuracy. This study demonstrates that utilizing the proposed method is more resilient than the other state-of-the-art methods used in this study. Future studies may explore the use of more temporal features with feasible ways of establishing a relationship between crime-independent and dependent variables to resolve the misalignment problems of crime link prediction.

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G. References

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