# An Improved Support Vector Model with Recursive Feature Elimination for Crime Prediction

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Abstract: The Support Vector Machine (SVM) model has proven relevant in several applications, including crime analysis and prediction. This work utilized the SVM model and developed a predictive model for crime occurrence types. The SVM model was then enhanced using feature selection mechanism, and the enhanced model was compared to the classical SVM. To evaluate the classical and enhanced models, two distinct datasets, one from Chicago and the other from Los Angeles, were used for experiment. In an attempt to enhance the performance of the SVM model and reduce complexity, this work utilised relevant feature selection techniques. We used the Recursive Feature Elimination (RFE) model to enhance SVM's performance and reduce its complexity, and observed performance increase of an average of 15% from the City of Chicago dataset and 20% from the Los Angeles dataset. Thus, incorporation of appropriate feature selection techniques enhances predictive power of classification algorithms.

## 1 INTRODUCTION

Recent statistics have shown that crime rates have been on the increase annually, with an exponential increase in the last few decades (Ceccato and Loukaitou-Sideris, 2022). This increase in crime rate poses a serious threat to the stability of societies, including financial and psycho-physiological (such as Post Traumatic Stress Disorder) effect on citizenry (Kushner et al., 1993). This continuous increase in crime rates can be an indicative parameter to examine the capabilities and/or limitations of current crime preventative strategies. Fortunately, the last few years have witnessed an increase in crime scene monitoring systems, specifically for reporting and investigative purposes. Crime records can then be analysed and used to develop preventative strategies for crime prediction. However, due to the large number of crimes, associated crime records are voluminous and gathered at a fast rate, making manual processing and analysis ineffective. Thus, intelligent means of analysis such as the use of machine learning is inevitable.

Machine learning has been extensively used in crime prediction and able to successfully anticipate the occurrence of crime, the possible location, as well as the type of crime that might occur (Kim et al., 2018),(Lin et al., 2018), (Alves et al., 2018), (Bogomolov et al., 2014), and (Chun et al., 2019). With this ability, law enforcement personnel and agencies can strategise and effectively allocate scarce resource to improve service delivery. There are a variety of machine learning algorithms that are used in crime, such as the Decision Tree, Random Forests, Extra Trees (May et al., 2021b), Deep learning, Support Vector Machines (SVM)(Cao and Chong, 2002). In this study, SVM is used to predict potential crime type. This work also attempts to improve the performance of the classic SVM algorithm for crime prediction by combining it with Recursive Feature Elimination (RFE) approach, similar to what was done in (May et al., 2021a). To the best of the researchers' knowledge, there is no research that has considered enhancing the SVM model for crime analysis using this approach.

## 2 LITERATURE REVIEW

There are various research on crime analysis and prediction, with numerous methodologies and theories used to attain the common objective of predicting crime and implementing preventive actions (Lin et al., 2018), (Sivaranjani et al., 2016), (Islam and Raza, 2020),(Isafiade and Bagula, 2020), (Kiran and Kaishveen, 2018). A variety of machine learning algorithms, which can be broadly classed as regression,



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clustering, and classification, have been applied to crime analysis.

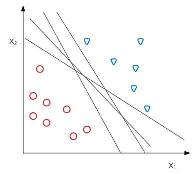
Clustering models, in addition to the ARIMA model, have been effectively used in the construction of robust predictive models, as shown in (Sivaranjani et al., 2016), (Kiran and Kaishveen, 2018), (Rodriguez et al., 2017), and (Hajela et al., 2020). The authors in (Hajela et al., 2020) used k-means to improve the predictive power of different classification algorithms, such as Nave Bayes, Decision Trees, and ensemble learning approaches. Obtained results showed that the incorporation of k-means clustering method improved the classification accuracies of the base algorithms.

While clustering enhanced models have been shown to improve classification accuracies, most researchers still rely on manual feature selection methods. It has also been reported that feature selection can increase a model's accuracy and in some cases decrease the complexity (Chu et al., 2012). However, despite this, the vast majority of scholars that investigated crime prediction via the lens of classification, such as (Hajela et al., 2020), (Ivan et al., 2017a), (Zaidi et al., 2019), (Iqbal et al., 2013), and (Ivan et al., 2017b), did not adopt feature selection approaches. There are several feature selection strategies, including intrinsic (or embedded), regularization, filter, and wrapper strategies. The intrinsic techniques allude to the algorithm's capacity to execute feature selection on its own. Tree-based algorithms, such as Decision Trees, Random Forests, and Extremely Randomized Trees are all capable of performing feature selection on their own; hence, can be considered intrinsic (May et al., 2021b), (Sylvester et al., 2018).

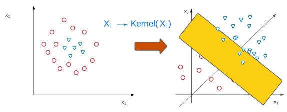
Other than the tree-based algorithms, there are also regularization methods which utilize a form of intrinsic penalization function to reduce over-fitting. Examples of these techniques are the Least Absolute Shrinkage and Selection Operator (LASSO) that performs L1 regularization (Baraniuk, 2007) and Ridge Regression that performs L2 regularization (Hilt and Seegrist, 1977). In (Nitta et al., 2019), the LASSO feature selection strategy was used to choose the optimal subset of features for building a Naive Bayes and SVM classifier for crime prediction and categorization. Filtering strategies are based on statistics and the relevance of features. Linear Discriminant Analysis (LDA), Analysis of Variance (ANOVA), and Chi-Square are common examples of statistical approaches. For example, in (Mohd et al., 2017), the correlation feature evaluator, correlation-based feature subset evaluator, and information gain were investigated as three different forms of filter selection techniques. These three strategies were used to determine the optimal collection of features required to build a crime prediction classifier. The authors concluded that the combination of correlation feature evaluator and correlation-based feature subset evaluator was the best feature selection approach, after evaluating their methods on a community crime dataset.

Wrapper feature selection methods search for the best performing subset of features. These wrapper strategies initially pick a subset of features to be used in training given models, then iteratively adds or removes features from the subset based on the inferences returned. The wrapper category includes several techniques, with the most noteworthy being the Forward Selection, Backward Selection, and Recursive Feature Elimination (RFE). Forward feature selection is an iterative procedure that begins with no features and incrementally adds them until the model's performance is no longer improved. Backward feature selection, in contrast to forward feature selection, starts with all features and repeatedly removes features until the model's performance does not improve. The authors in (Aldossari et al., 2020) obtained the optimal subset of features to train a Decision Tree and a Nave Bayes classifier for crime prediction using the backward feature selection technique. RFE is a form of backward feature selection method, that scores each feature based on its contribution to the model's overall performance (Guyon et al., 2002). The most widely utilized scoring factor is the feature importance. RFE thus recursively eliminates least scoring features based on computed priority or importance. In (Zhu et al., 2018), RFE was used to choose the best features, which were then fed into both the Linear Regression and Random Forest algorithms. RFE was also used in (Kadar et al., 2016) to create a model for estimating crime counts using the New York foursquare dataset. In another work, RFE was combined with Naive Bayes in (May et al., 2021a) to choose the optimal number of features for crime prediction. The developed model, which was tested using the Chicago Citizen Law Enforcement Analysis and Reporting (CLEAR) dataset, showed a 30% improvement over the pure Naive Bayes model.

In this work, we propose the enhancement of SVM by combining it with a feature selection model. This is similar to the work done in (Cao and Chong, 2002) where three component analysis models, Principal Component Analysis (PCA), kernel principal component analysis (KPCA) and independent component analysis (ICA) were used with SVM. Unlike in that work, we apply RFE to perform feature selection for SVM, then compare this improved SVM to the pure SVM.



(a) Two class linearly separable data



(b) Non-linearly separable data

Figure 1: Data separation by Hyperplanes.

## 3 MODELS AND EXPERIMENTAL DESIGN

### 3.1 Support Vector Machine (SVM) Model

SVM is a non-liner solver for classification and regression problems developed by Vapnik (Vapnik, 1999). SVM is a widely used ML model because it can perform both regression and classification, works well with small datasets and robustness against outliers (Martínez-Ramón and Christodoulou, 2005),(Wang, 2005). SVM seeks to draw a line (hyperplane) to separate data into respective classes, as illustrated in Fig 1a and 1b.

Formally, the hyperplane in a n-dimensional space is an n-1 dimensional subspace. For instance, in a two dimensional space, the hyperplane is a one dimensional straight line. For a set of n training samples, $x_i, (i = 1, 2, \ldots, n)$, the optimal hyperplane is defined as shown in Equation (1):

$$w^T x + b \begin{cases} \leq 1 \; for \; y_i \; = 1 \\ \leq -1 \; for \; y_i \; = -1 \end{cases} \tag{1}$$

Where $w^T$ is the transpose of the n-dimensional normal vector and $b$ a bias term. Data that lies closest to the optimal hyperplane either from the right or from the left are referred to as the support vectors.

This hyperplane must maximise the distance from support vectors of each class, and must have the smallest possible data separation error (Steinwart and Christmann, 2008). Hence, data falls on either of two sides of the optimal hyper-plane, the left $(y = 1)$ or right $(y = -1)$. There are instances where the data sample are not linearly separable, thus not possible to draw a straight hyperplane. In such instances, a soft margin is used instead, which can be obtained using Equation (2):

Table 1: Various Kernel functions frequently used for non-linear data classifications.

| **Type of Classifier** | **Kernel Function** |
|---|---|
| Sigmoid | $K(x_i, x_j) = (\alpha(x_i \cdot x_i) + \vartheta)$ |
| Multilayer perceptron | $K(x_i, x_j) = tanh(yx_i^T x_j + \mu)$ |
| Linear | $K(x_i, x_j) = (x_i^T x_j)^\rho$ |
| Guassian RBF | $K(x_i, x_j) = \exp(\frac{-[\lVert x_i - x_j \rVert^2]}{2\upsilon^2})$ |
| Dirichlet | $\frac{sin(\frac{n+1}{2})(x_i - x_j)}{2sin((x_i - x_j)/2)}$ |

$$d(x) = \sum_{i=1}^{N} \alpha_i y_i K(x, x_i) + b \tag{2}$$

where $\alpha_i$ is the Lagrange multiplier, $b$ is the bias, and K is the Kernel function.

The Kernel function ($K$) is used to separate non-linearly separable data, by changing into a higher dimensional space, where they become linearly separable. There are several types of kernel functions and these are summarized in Table 1

### 3.2 Recursive Feature Elimination (RFE) Method

As discussed in the literature review section, the RFE method is a backward approach of selecting features. It uses models to fill all the features and recursively eliminates features which either decreases or have no influence on the overall performance of the selected model. In this work, the baseline models considered for the RFE were Linear Regression (LR), Extremely Randomized Trees (ERT) and Random Forest (RF), from which the one with the highest accuracy was selected. Fig.2 is a flowchart depicting our process of integrating RFE into SVM for optimal feature selection and improved classification.

### 3.3 Experimental Setup

We conducted our experiment on a Dell Desktop PC with Intel Core i5 $10^{th}$ Gen processor, with a 1.19 GHz base clock, and 8 GB of RAM. Data processing and exploration, coding and evaluation of the predictive models were all done using Python and Jupyter Notebook. Furthermore, we used 10 fold cross-validation to evaluate the models.

### 3.4 Data Description and Pre-processing

Two datasets were used to test the models, which are: i) the Chicago Police Department's Citizen Law Enforcement Analysis and Reporting (CLEAR) dataset

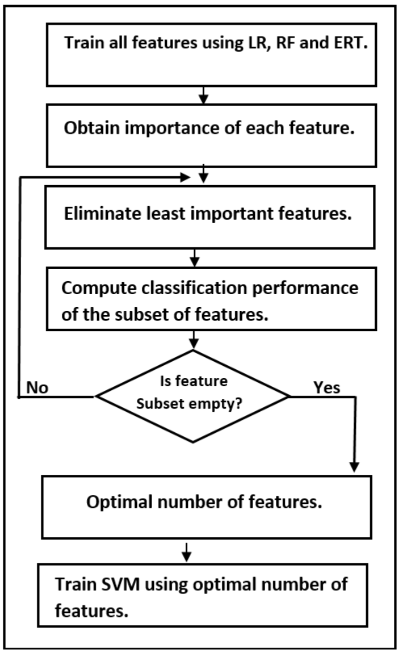



Figure 2: Process of integrating RFE with SVM.

which contains about 7.26 million records of crime data with 21 features collected between year 2001-2020 (Cit, 2001a); ii) Los Angeles Dataset, with 2.12 million crime records, and 24 features collected between year 2010 and 2019 (Cit, 2001b). The CLEAR dataset initially had 32 unique crimes, from which we selected the 5 frequently (about 70%) occurring crimes (about 70% of the entire dataset. These were Theft, Battery, Criminal Damage, Narcotics, and Assault. Similarly, the Los Angeles dataset was filtered from 110 unique crimes to the top 5 common crimes, namely Robbery, Battery (Simple Assault), Assault With Deadly Weapon, Aggravated Assault, Intimate Partner - Simple Assault. All five were numerically encoded as 0 to 4. Furthermore, certain features that we identified as not having high predictive power such as ID and X, Y coordinates were removed. To this end, the features left in the CLEAR dataset were: Description, IUCR, FBI Code, Arrest, Longitude, Community Area, Block, Beat, District, Location Description, Ward, Year, Case Number, Domestic, Updated On, Latitude, Day, Month, Hour, DayOfWeek, and WeekOfYear features, for a total of 21 features as summarized in Table 2. Similar processes were carried out on the Los Angeles dataset, with the final feature set summarized in Table 3.

## 3.5 Evaluation Metrics

Accuracy, Precision (P), Recall (R), and $F1_{Score}$ were used to assess the performance of the models. Accuracy is a measure of how often the model correctly classified instances. Precision is the fraction of relevant instances among the successfully retrieved instances, while recall is the fraction of relevant instances that were successfully retrieved. $F1_{Score}$ is obtained from precision and recall by computing their harmonic mean.

Table 2: Features considered in the Chicago Dataset.

| Feature | Description |
|---|---|
| Description | The secondary description of the IUCR code, a subcategory of the primary description |
| IUCR | The Illinois Unifrom Crime Reporting code |
| FBI Code | Indicates the crime classification as outlined in the FBI's FBI National Incident-Based Reporting System (NIBRS). |
| Arrest | Indicates if an arrest was made |
| Longitude | The longitude of the location where the incident occurred |
| Latitude | The latitude of the location where the incident occurred |
| Community Area | Indicates the community area where the incident occurred |
| Block | Partially redacted address where the incident occurred but within the same block as the actual address |
| Beat | Indicates the beat where the incident occurred. A beat is the smallest police geographic area |
| District | Indicates the police district where the incident occurred |
| Location Description | Description of the location where the incident occurred |
| Ward | The ward (City Council district) where the incident occurred |
| Year | Year the incident occurred |
| Case Number | The Chicago Police Department RD Number (Records Division Number), which is unique to the incident |
| Domestic | Indicates whether the incident was domestic-related as defined by the Illinois Domestic Violence Act |
| Updated On | Date and time the record was last updated |
| Month | The month the incident occurred |
| Day | The day the incident occurred |
| DayOfWeek | The day of the week the incident occurred |
| WeekOfYear | The week of year the incident occurred |
| Hour | The hour of the day the incident occurred |

Table 3: Features considered in the Los Angeles Dataset.

| Feature | Description |
|---|---|
| Weapon Used | The type of weapon used in the crime |
| Weapon Desc | Defines the Weapon Used Code provided. |
| Vict Sex | Victim Sex, F - Female, M - Male, X - Unknown |
| Vict Age | Two character numeric. |
| Mocodes | Modus Operandi: Activities associated with the suspect in commission of the crime. |
| LON | The longitude of the location where the incident occurred |
| LAT | The latitude of the location where the incident occurred |
| Vict Descent | Descent Code: A - Other Asian, B - Black, C - Chinese D- Cambodian, F - Filipino, G - Guamanian ,H - Hispanic/Latin/Mexican I - American Indian/Alaskan Native, J - Japanese, K - Korean, L - Laotian O - Other P - Pacific Islander S - Samoan U - Hawaiian V - Vietnamese W - White X - Unknown Z - Asian Indian |
| LOCATION | Street address of crime incident rounded to the nearest hundred block to maintain anonymity. |
| Date Rptd | Date Reported, MM/DD/YYYY |
| AREA NAME | The 21 Geographic Areas or Patrol Divisions are also given a name designation that references a landmark or the surrounding community that it is responsible for. For example 77th Street Division is located at the intersection of South Broadway and 77th Street, serving neighborhoods in South Los Angeles. |
| Premis Cd | The type of structure, vehicle, or location where the crime took place. |
| Premis Desc | Defines the Premise Code provided |
| Status Desc | Defines the Status Code provided |
| Status | Status of the case. (IC is the default) |
| Cross Street | Cross Street of rounded Address |
| Month | The month the incident occurred |
| Day | The day the incident occurred |
| DayOfWeek | The day of the week the incident occurred |
| WeekOfYear | The week of year the incident occurred |
| Hour | The hour of the day the incident occurred |
| TIME OCC | The hour of the day the incident occurred |
| Rpt Dist No | A four-digit code that represents a sub-area within a Geographic Area. All crime records reference the "RD" that it occurred in for statistical comparisons |

# 4 RESULTS AND DISCUSSION

As stated earlier, two distinct datasets were used - the Chicago and Los Angeles dataset. In both datasets we followed the same procedure of experimentation, we first varied the C and Gamma values and then

Table 4: Comparison of Kernel functions on the Chicago dataset.

| Evaluation Metric (%) | Gamma=0.01, C=0.01 | Gamma=1, C=1 | Gamma=10, C=10 |
|---|---|---|---|
| Linear Kernel | | | |
| Accuracy | 35.80 | 40.34 | 55.78 |
| Precision | 28.82 | 47.9 | 53.79 |
| Recall | 35.80 | 48.01 | 55.57 |
| F1_Score | 27.88 | 46.8 | 54.51 |
| Polynomial Kernel | | | |
| Accuracy | 49.34 | 56.1 | 65.73 |
| Precision | 47.57 | 54.54 | 62.56 |
| Recall | 46.86 | 55.36 | 63.2 |
| F1_Score | 45.61 | 54.54 | 64.78 |
| Gaussian RBF kernel | | | |
| Accuracy | 59.27 | 65.9 | 74.73 |
| Precision | 57.45 | 64.9 | 71.56 |
| Recall | 55.60 | 66.6 | 74.2 |
| F1_Score | 56.71 | 63.57 | 73.78 |

Table 5: Comparison of Kernel functions on the Los Angeles dataset.

| Evaluation Metric (%) | Gamma=0.01, C=0.01 | Gamma=1, C=1 | Gamma=10, C=10 |
|---|---|---|---|
| Linear Kernel | | | |
| Accuracy | 36.61 | 42.19 | 56.91 |
| Precision | 29.19 | 48.17 | 55.78 |
| Recall | 36.89 | 41.19 | 57.20 |
| F1_Score | 28.11 | 48.1 | 56.15 |
| Polynomial Kernel | | | |
| Accuracy | 41.52 | 56.17 | 6.71 |
| Precision | 48.59 | 56.71 | 63.19 |
| Recall | 44.17 | 57.61 | 65.18 |
| F1_Score | 45.71 | 54.81 | 64.51 |
| Gaussian RBF kernel | | | |
| Accuracy | 59.34 | 66.1 | 75.73 |
| Precision | 56.51 | 65.16 | 73.16 |
| Recall | 57.81 | 64.16 | 74.58 |
| F1_Score | 56.51 | 65.34 | 75.51 |

used three distinct kernels. Gamma value dictates the radius of influence for single samples, while C is the trade off between maximization of the decision function's margin and correct classification of samples. Grid Search was used for hyper-parameter tuning (Bergstra and Bengio, 2012). For brevity, we only show the results for values of 0.01, 1 and 10. Due to the dataset being non-linearly separable, we used Kernel functions for feature space transformation. We considered the Linear, Polynomial, and RBF kernel functions, in order to determine which of these will yield a better result (Wang, 2005).

### 4.1 Performance Comparison of the Kernel Functions

Table 4 summarizes results obtained from the Chicago dataset, while Table 5 presents those of the Los Angeles dataset, based on the different parameters considered.

For the Chicago dataset, it was observed that generally, the model improved as the parameter values increased, with the Gaussian RBF kernel having the best result, followed by Polynomial and Linear kernels.

The results obtained for the Los Angeles dataset were consistent with those of the Chicago dataset with similar findings. Observing the different values from 0.01 to 10 for C and Gamma, a gradual performance increase was noted and the best performance was obtained at 10 as seen on Tables 4 and 5.

### 4.2 Process of Enhancing SVM with RFE (RFE-SVM)

This section presents the results obtained by enhancing the SVM algorithm with RFE as earlier discussed and presented in Fig 2.

Table 6: RFE with three (3) models.

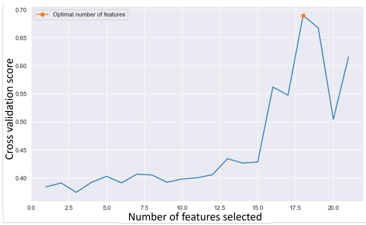
| | Chicago Dataset | Los Angeles Dataset |
|---|---|---|
| Models | Accuracy (%) | Accuracy (%) |
| LR | 40.39 | 39.55 |
| ERT | 83.71 | 82.23 |
| RF | 96.33 | 92.51 |

A. Selecting the RFE Wrapper Model

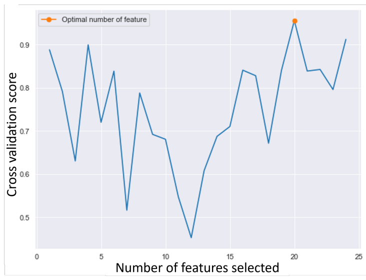
As discussed earlier, RFE requires a base model to execute the feature selection process. We considered three models for this task, which are LR, ERT, and RF. Table 6 shows a comparison of the three selected models on the Chicago dataset.

It can be observed that RF outperforms the two other models, hence it was selected as the wrapper method to obtain the optimal features as shown in Fig. 3. The orange dot depicts the peak of the curve and represent the optimal number of features considered. For the Chicago (see Fig. 4a ) and Los Angeles datasets (see Fig. 4b), 21 and 23 features were considered respectively. Fig. 4 presents the list of selected features for both datasets and ranked by feature importance in a descending order.

Fig.5 (best viewed in colour mode) presents a line graph of all feature versus feature significance. For the Chicago dataset, 18 features were eventually selected by the RFE model, thus eliminating features after the 18 cut-off mark, i.e., the red vertical line in Fig.5a. For the Chicago dataset, Latitude, Case Number, and District were deemed least influential by the wrapper method. A similar process was carried out for the Los Angeles dataset, with Part 1-2, Status Desc, and Hour being the least influential features that were eliminated (see Fig.5b). Thus, 20 features were even-




(a) Chicago Dataset




(b) Los Angeles Dataset

Figure 3: Optimal number of features selected by RFE for both Chicago and Los Angeles datasets.

tually selected by the feature selection model.

B. Enhanced SVM (RFE-SVM)

Having identified the most significant features, we ran two simulations with SVM, the first with all features (tagged "Pure SVM") and the second with the RFE selected features (tagged "RFE-SVM"). Table 7 shows a comparison of both models, and reveals that for all the metrics, the enhanced version had a 20% performance boost on the average for Chicago dataset and 15% for the Los Angeles dataset. Fig. 6 gives a graphical depiction of the comparisons.

Table 7: Comparison of Enhanced SVM with Pure SVM.

| | Chicago Dataset | | Los Angeles Dataset | |
|---|---|---|---|---|
| Evaluation Metrics(%) | Pure SVM | RFE-SVM | Pure SVM | RFE-SVM |
| Accuracy | 74.73 | 89.91 | 75.73 | 88.7 |
| Precision | 71.56 | 87.57 | 73.16 | 86.96 |
| Recall | 74.20 | 83.41 | 74.58 | 84.37 |
| F1_Score | 73.78 | 84.59 | 75.51 | 85.33 |

## 5 CONCLUSION

There are numerous machine learning (ML) algorithms in use in a wide variety of disciplines including finance, medical, crime, to mention a few. Common among these ML models is the Support Vector Machine (SVM). This study considered the efficacy of SVM for crime prediction, and adopted feature

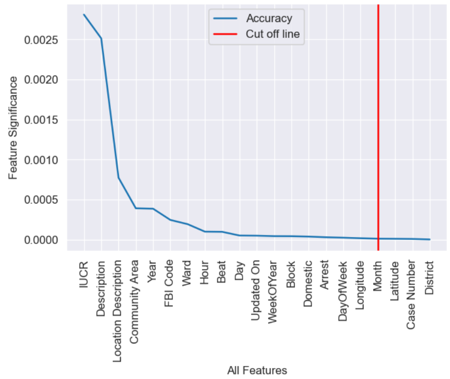
| | Feature_Significance | Ranking |
|---|---|---|
| IUCR | 2.809165e-03 | 1.0 |
| Description | 2.512726e-03 | 2.0 |
| Location Description | 7.726601e-04 | 3.0 |
| Community Area | 3.900114e-04 | 4.0 |
| Year | 3.845280e-04 | 5.0 |
| FBI Code | 2.441376e-04 | 6.0 |
| Ward | 1.913825e-04 | 7.0 |
| Hour | 9.776843e-05 | 8.0 |
| Beat | 9.570508e-05 | 9.0 |
| Day | 4.929147e-05 | 10.0 |
| Updated On | 4.747279e-05 | 11.0 |
| WeekOfYear | 4.198704e-05 | 12.0 |
| Block | 4.117547e-05 | 13.0 |
| Domestic | 3.635535e-05 | 14.0 |
| Arrest | 2.765897e-05 | 15.0 |
| DayOfWeek | 2.242749e-05 | 16.0 |
| Longitude | 1.589027e-05 | 17.0 |
| Month | 9.980777e-06 | 18.0 |
| Latitude | 8.662990e-06 | 19.0 |
| Case Number | 6.593437e-06 | 20.0 |
| District | 5.747992e-07 | 21.0 |

(a) Chicago Dataset

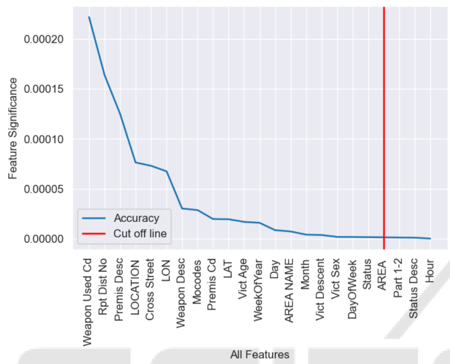
| | Feature_Significance | Ranking |
|---|---|---|
| Weapon Used Cd | 2.220127e-04 | 1.0 |
| Rpt Dist No | 1.639503e-04 | 2.0 |
| Premis Desc | 1.251377e-04 | 3.0 |
| LOCATION | 7.627412e-05 | 4.0 |
| Cross Street | 7.295818e-05 | 5.0 |
| LON | 6.743473e-05 | 6.0 |
| Weapon Desc | 3.016061e-05 | 7.0 |
| Mocodes | 2.858172e-05 | 8.0 |
| Premis Cd | 1.959274e-05 | 9.0 |
| LAT | 1.941254e-05 | 10.0 |
| Vict Age | 1.676251e-05 | 11.0 |
| WeekOfYear | 1.581765e-05 | 12.0 |
| Day | 8.454832e-06 | 13.0 |
| AREA NAME | 7.143385e-06 | 14.0 |
| Month | 3.962796e-06 | 15.0 |
| Vict Descent | 3.597203e-06 | 16.0 |
| Vict Sex | 1.719905e-06 | 17.0 |
| DayOfWeek | 1.623106e-06 | 18.0 |
| Status | 1.470043e-06 | 19.0 |
| AREA | 1.290805e-06 | 20.0 |
| Part 1-2 | 1.106825e-06 | 21.0 |
| Status Desc | 9.391981e-07 | 22.0 |
| Hour | 0.000000e+00 | 23.0 |

(b) Los Angeles Dataset

Figure 4: Selected features ranked by significance.

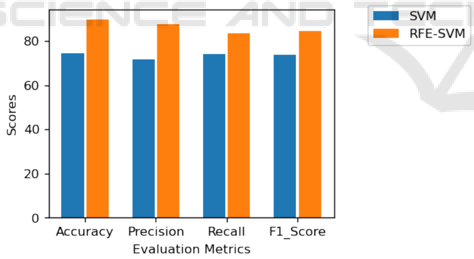



(a) Chicago Dataset

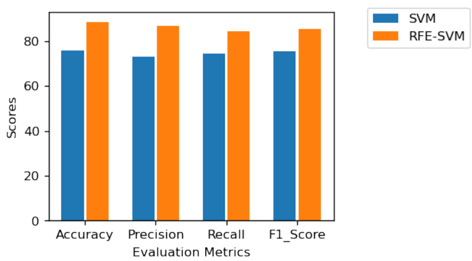



(b) Los Angeles Dataset

Figure 5: Feature significance and cut-off feature.




(a) Chicago Dataset




(b) Los Angeles Dataset

Figure 6: Comparative evaluation of RFE-SVM and SVM.

selection mechanism to enhance the performance of SVM. Two crime datasets were used, the Chicago Police department's Citizen Law Enforcement Analysis and Reporting system (CLEAR) dataset, and the Los Angeles crime dataset. In applying SVM, three kernels were compared, Linear, Polynomial and Guassian RBF, with the Guassian RBF proving to be the best of these kernels based on results obtained. To enhance the performance of SVM, this work introduced the use of feature selection through Recursive Feature Elimination (RFE). RFE was used to select the optimal number of features from the datasets before applying SVM (RFE-SVM). We then compared the performance of the classic SVM with the enhanced SVM (i.e., RFE-SVM model). This enhancement improved the prediction accuracy of SVM by up to 15% in the Los Angeles dataset and 20% for the Chicago dataset. It can therefore be concluded that the incorporation of feature selection algorithms enhanced SVM's performance.

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