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Enhancing Crime Prediction Using K-Means with PSO

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Abstract
The effects of social media and modern approaches help offenders to achieve their crimes. This paper explores machine learning architecture to predict criminal crime cases by classifying each type of crime using K-Means which is optimized with PSO from the data the researcher got in the past mas. The clustering parameters use medium, light, and severe crime categories, each of them gets medium = 74, light = 46, and weight = 30. According to the experimental result, K-Means optimization with PSO can produce 0,12287 which uses SSE parameters while k-means performance gets results 0.885.

Keywords:
Crime, Prediction K-Means, PSO

1. Introduction

The effects of social media and modern approaches help offenders to achieve their crimes. Social media, as a modern media form, has significant criminogenic potential, influencing public perceptions of crime and contributing to the fear of crime. It shapes moral thinking and stereotypes, impacting societal behavior and attitudes toward justice. The interaction between crime and society is exacerbated by the dissemination of information through social media, which can lead to the escalation of criminalization and victimization, necessitating a criminological assessment of media representations of crime and justice. Both analysis and prediction of crime is a systematized method that classifies and examines crime patterns. A criminal offense or Crime is a detrimental act that not only affects individuals but affects a community. It is very much essential to determine the different factors for the possible occurrence of crimes and find the optimized ways to reduce the crime [19].

Traditional statistical methods in crime prediction often struggle due to the complex and dynamic nature of crime, which involves numerous interacting factors. These methods, like linear regression, often oversimplify relationships between variables, failing to capture the intricate dynamics of crime patterns. Additionally, they may not effectively handle the volume and variety of modern data sources, such as social media and real-time sensor data. Furthermore, traditional models can perpetuate existing biases in historical data, leading to skewed predictions and potentially discriminatory policing practices, and lack of adaptability hinders their ability to keep pace with evolving crime trends [18].

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Crime prediction adopted the concept of data mining to extract previously unknown, useful information from unstructured data. It has an approach between computer science and criminal justice to develop a data mining procedure that can help solve crimes faster. Several papers proposed Crime analysis by performing k-means clustering on crime datasets using rapid miner tools and knowledge gained from data mining approaches will be useful and support the police force. Data mining is the appropriate field to apply to high-volume crime datasets and knowledge gained from data mining approaches will be useful and support the police force [3]. Another also explored the MV algorithm and Apriori algorithm with some enhancements to aid in the process of filling in the missing value and identification of crime patterns. These techniques collect real crime data and use semi-supervised learning techniques for knowledge discovery from the crime records and to help increase the predictive accuracy [4].

However, Data mining techniques, while powerful, have several weaknesses that can limit their effectiveness and reliability. One major weakness is the quality of data. Data mining relies heavily on the availability of clean, accurate, and complete datasets. However, real-world data is often noisy, incomplete, or inconsistent, leading to inaccurate or misleading results. For example, missing values, outliers, or errors in data collection can significantly affect the performance of clustering or classification algorithms. Additionally, data mining techniques may struggle with high-dimensional data, where the number of features is large compared to the number of observations. This can lead to the "curse of dimensionality," where algorithms become computationally expensive and less effective in identifying meaningful patterns. Furthermore, data mining models can suffer from overfitting, where they perform well on training data but fail to generalize to new, unseen data, reducing their practical utility [5][6].

Another significant weakness is the interpretability of results. Many data mining techniques, such as neural networks or ensemble methods, produce complex models that are difficult to interpret, making it challenging for users to understand the underlying patterns or decision-making processes. This lack of transparency can be problematic in domains where explainability is critical, such as healthcare or finance. Additionally, data mining techniques often require domain expertise to select appropriate algorithms, pre-process data, and interpret results, which can be a barrier for non-experts. Ethical concerns, such as privacy violations and bias in data, also pose challenges. For instance, biased training data can lead to discriminatory outcomes, perpetuating existing inequalities. These weaknesses highlight the need for careful data preparation, algorithm selection, and validation to ensure the reliability and fairness of data mining applications [7][8].

Different from data mining techniques, various papers explored clustering algorithms for crime analysis and pattern prediction. One approach to building crime analysis is K-means because of its simplicity and speed but is highly sensitive to the initial selection of centroids, often converging to local optima. A promising technique is integrating K-means clustering with Particle Swarm Optimization (PSO) combines the strengths of both techniques, resulting in a more robust and efficient clustering approach. The hybrid approach leverages PSO's global search capabilities to initialize K-means centroids more effectively, improving clustering accuracy and stability. PSO, a population-based optimization algorithm, addresses this limitation by exploring the solution space more effectively, helping K-means escape local optima and find globally optimal or near-optimal solutions. Additionally, PSO's ability to handle complex, non-linear, and high-dimensional data makes it particularly useful for real-world datasets [9].

Therefore, this paper proposed K-Means with PSO as an unsupervised method for grouping data on a small or large scale using a partition system. The contribution of this study in follows:

1. The integration of PSO with K-means helps in optimizing the initial cluster centers, which is crucial for achieving better clustering results. This approach reduces the time complexity and enhances the efficiency of the clustering process, making it suitable for large datasets like crime records
2. By using PSO, the clustering process benefits from a global search capability, which helps in avoiding local optima—a common issue with traditional K-means. This results in more accurate predictions of crime patterns and hotspots
3. The optimized K-means algorithm can effectively classify and examine crime patterns, aiding law enforcement agencies in identifying regions with higher crime rates and understanding demographic tendencies related to criminal activities.

2. Related Works

Crime analysis and prediction is a growing research area with various novel techniques including Machine Learning and Deep Learning. Machine learning has become a pivotal tool in crime analysis and prediction, offering law enforcement agencies the ability to forecast criminal activities and develop effective prevention strategies. Various machine learning techniques have been explored to identify patterns and trends in crime data, enhancing the predictive capabilities of these models. The integration of these technologies into public safety frameworks is crucial for improving crime prevention measures and ensuring community safety. These methods are extensively used to forecast crime by identifying patterns and variables associated with criminal activities. They provide insights that help law enforcement agencies develop strategies to deter crime [10].

A research paper investigates crime analysis and prediction using machine learning techniques, specifically employing multi-year datasets from Chicago. It evaluates five models: Polynomial Regression, Random Forest, LightGBM, XGBoost, and Linear Regression. The findings indicate that XGBoost Regression outperforms the others in prediction accuracy and data-generalization capabilities, while conventional models like Polynomial and Linear Regression struggle with the complexity of crime data. The study highlights the importance of selecting appropriate algorithms for effective crime prediction and suggests avenues for further research [11].

Another work focuses on applying various machine learning algorithms such as Naïve Bayes, Random Forest, Decision tree Support vector machine, and Logistic regression for reducing crime rates in India. Performance of the proposed models compared with various measures like precision, recall, accuracy, and fl score along with the confusing matrix. Also considers the error value for various models with the help of the mean absolute error technique. As a result, the Naïve Bayes model gives the best results of 98.94% compared with others [2].

For crime analysis and prediction, another paper explores the Radial Basis Function (RBF) with Support Vector Machine (SVM), It enhances accuracy in predicting crime rates by mapping input features into a higher-dimensional space to capture complex patterns. The model, evaluated on the Chicago crime dataset, achieved high accuracy (0.89), precision (0.80), recall (0.82), and F1-score (0.85), demonstrating its effectiveness compared to existing techniques like Decision Tree and Long Short-Term Memory [12]. Another paper also proposed techniques with Random Forest, SVM, Logistic Regression, and Linear Regression to leverage accurate predictions [13].

Machine learning, particularly through algorithms like Random Forest, plays a crucial role in crime analysis and prediction. It enables law enforcement to analyze extensive datasets, uncover complex patterns, and manage high-dimensional data effectively. Random Forest's advantages include feature selection, robustness to noise, and scalability, making it suitable for predicting crime trends. By integrating these systems, agencies can anticipate criminal activities, allocate resources strategically, and implement targeted interventions, ultimately enhancing community safety through data-driven approaches [14].

A recent study explores predictive crime analysis using modern learning techniques, specifically employing a Recursive Neural Network in Deep Learning (RNNDL). This approach processes large datasets of past criminal activities and demographic features to identify patterns and forecast potential crime hotspots. By assigning greater weight to recent predictions and less to older ones, the method enhances accuracy in predicting future crimes, thereby aiding law enforcement in formulating effective countermeasures against criminal activities [15]. According to several findings, the application of deep learning models for crime prediction highlights their superiority over traditional statistical and classical machine learning methods. It emphasizes the importance of utilizing external features and capturing temporal dynamics in crime data [16].

In this paper, we explore the K-means algorithm with PSO optimization to enhance efficiency and reduce time complexity in identifying crime patterns. The integration of the K-Means clustering algorithm with Particle Swarm Optimization (PSO) enhances clustering performance by addressing the limitations of K-Means, such as sensitivity to initial centroids and convergence to local optima. K-Means efficiently partitions data into clusters based on distance metrics, while PSO optimizes the centroid selection process by leveraging swarm intelligence and global search capabilities. This hybrid approach improves clustering accuracy, ensures better stability in results, and accelerates convergence by reducing the likelihood of poor initializations. Additionally, PSO helps escape local optima by exploring a wider solution space, making the K-Means-PSO combination particularly effective for complex, high-dimensional datasets.

3. Proposed Method

3.1 K-Means Algorithm

In K-Means operation, given a dataset $X = \{x_1, x_2, \ldots, x_n\}$, partitioning it into k clusters.
Initialize k centroids $C = \{c_1, c_2, \ldots, c_k\}$ } and sign each data point xi to the nearest centroid:

$$\arg\min_j \parallel x_i - c_j \parallel^2$$

Update centroids by computing the mean of assigned points:

$$c_j = \frac{1}{| S_j |} \sum_{x_i \in S_j} x_i$$

3.2 Particle Swarm Optimization (PSO) Enhancement

In PSO operation, it represents each particle as a potential solution (set of centroids).
Initialize a swarm of particles with random positions P_i and velocities V_i
Update particle velocity:

$$V_i^{t+1} = wV_i^t + c_1 r_1 (P_{best} - P_i) + c_2 r_2 (G_{best} - P_i)$$

Update position:

$$P_i^{t+1} = P_i^t + V_i^{t+1}$$

Evaluate fitness using the K-Means objective function and update best positions.
Iterate until convergence or max iterations.

K-Means is a widely used clustering algorithm that partitions a dataset into *k* clusters by minimizing intra-cluster variance. The algorithm begins by initializing *k* centroids, then iteratively assigns each data point to the nearest centroid based on Euclidean distance. After the assignment, the centroids are recalculated as the mean of all points within a cluster. This process continues until convergence, where centroids no longer change significantly. However, K-Means has limitations, such as sensitivity to initial centroid selection and the risk of getting trapped in local optima, which affects clustering performance.

Particle Swarm Optimization (PSO) enhances K-Means by optimizing centroid selection, mitigating the algorithm's dependency on initial placement. PSO is a bio-inspired algorithm that mimics the collective behavior of swarms, such as birds or fish. It initializes a population of candidate solutions (particles), each representing potential centroids. These particles update their positions iteratively based on their own best position and the global best found by the swarm, leading to an optimal centroid arrangement. By integrating PSO with K-Means, the algorithm achieves better cluster compactness, faster convergence, and improved robustness against local optima, making it more effective for clustering tasks.

4. Experimental Setup

below is the implementation of the k-means algorithm to cluster types of criminal acts and the implementation of PSO to optimize the k-means algorithm.

1. **K-Means**

a. Determine the K value for the number of clusters to be formed In this study, researchers used 200 crime data. From the 200 data, researchers used 3 clusters for crime mapping.

Table 1. Determination of the number of K

No	Location	Age	Gender	Crime	Cluster
1	66	32	117	102	Light
2	80	30	117	107	
3	65	30	118	103	
4	75	37	117	104	currently
5	66	36	117	100	
6	75	35	117	107	
7	78	27	117	105	Heavy
8	69	31	118	106	
9	70	33	117	100	
10	79	34	118	103	

The information in the table above contains 4 attributes, namely location, age, gender and type of crime, while there are 3 labels, namely light, medium, and heavy. Labels are used as clusters for grouping criminal acts.

b. Determine the value of the cluster center point by random. The second step is to randomize or randomize to be used as the cluster point value, for example, from all the data above, the value that you want to use as the cluster center point is taken or randomized. Here the researcher takes the values in table 4.2.

Table 2 cluster point

No	Location	Age	Gender	Crime
1	66	32	117	102

c. Calculate the distance from each centroid from the cluster value. To calculate the distance between the object and the centroid, you can use Euclidian Distance. Euclidian distance is a formula for calculating the distance between objects. Below is the formula.

$$d(\mathbf{p},\mathbf{q}) = d(\mathbf{q},\mathbf{p}) = \sqrt{(q_1-p_1)^2+(q_2-p_2)^2+\cdots+(q_n-p_n)^2}$$
$$= \sqrt{\sum_{i=1}^{n}(q_i-p_i)^2}.$$

d. Allocate each object to the closest centroid value

Table 3. Centroid Value

no	centroid	cluster	Object/date			
1	0,00	1	66	32	117	102
2	8.6	2	80	30	117	107
3	2,65	1	65	30	118	103
4	6,71	2	75	37	117	104
5	3,32	3	66	36	117	100
6	8,60	2	75	35	117	107
7	9,64	2	78	27	117	105
8	5,20	1	69	31	118	106
9	4,58	1	70	33	117	100
10	3,46	2	79	34	118	103

e. Do an iteration then determine the position of the new centroid point using the equation, namely by applying the Cambera equation formula where you first determine the centroid point.

Table 4. Cluster Value

no	Object/date				cluster
1	66	32	117	102	1
2	80	30	117	107	2
3	65	30	118	103	1
4	75	37	117	104	2
5	66	36	117	100	3
6	75	35	117	107	2
7	78	27	117	105	2
8	69	31	118	106	1
9	70	33	117	100	1
10	79	34	118	103	2

f. If there are still cluster members that have changed, do steps 3 and 4 until no cluster members have changed

2. K - Means + PSO Testing

To carry out testing on k-means PSO, several stages must be carried out, along with explanations and implementation

a. Determine the number of particles, where the number of particles is obtained from clusters determined randomly from the data used

Table 5. Experimental Dataset

1	66	32	117
2	80	30	117
3	65	30	118
4	75	37	117
5	66	36	117
6	75	35	117
7	78	27	117
8	69	31	118

From the number of records above, we then randomize the use values as particle values

66	36	117	75
35	117	78	27
117	69	31	118

b. Look for the SSE value obtained from the minimum distance. In the k-means PSO test, you must know the SSE value because the SSE value is used as a fitness function.

$$SSE = \sum_{i=1}^{k} \sum_{r \in C_i} d(r, m_i)^2$$

$$SSE = (0.00346)^2 + (0.034894)^2 + (0.010567)^2 + (0.006011)^2 + (0.006071)^2 + (0.051162)^2 + (0.010222)^2$$

$$SSE = 0.122387$$

Table 6. SE Value

Data			SE
66	32	117	0.00346
80	30	117	0.034894
65	30	118	0.010567
75	37	117	0.006011

66	36	117	0.006071
75	35	117	0.051162
78	27	117	0.010222
69	31	118	0.010222
SSE			0.122387

c. After looking at the SSE value, P_{best} will be determined, where P_{best} is the cluster average value,

= (66 + 66 + 66 + 66 + 66) / 5 = 66

d. After seeing the overall value of P_{best}, the next step is to determine the G_{best} value,

$$F(x_2) = 0.00346$$
$$Pbest(x_2) = (c_1, c_2, (66,32,117), c_3)$$

This suggests that the personal best solution for x_2 consists of some coefficients or parameters c_1, c_2, c_3 and a specific vector (66,32,117).

Global Best $Gbest$ Representation:

$$Gbest = Pbest(x_2) = (c_1, c_2, (66,32,117), c_3)$$

After determining $Gbest$, the next stage is to calculate the speed (velocity) and position (position) using equation (2.6) and equation (2.7). for example, in this study for V_0 and X_0 = 0.

$$V_{id} = W \cdot V_{id} + C_1 \cdot \text{rand}_1 \cdot (P_{id} - X_{id}) + C_2 \cdot \text{rand}_2 \cdot (P_{gd} - X_{id})$$

$$V(1) = V(0) + 1 \cdot \text{random} \cdot (66 - 66) + 1 \cdot \text{random} \cdot (66 - 66)$$

$$V(1) = V(0)$$

$$X_{id} = X_{id} + V_{id}$$
$$X(1) = X(0) + V(1)$$

If $X_{(1)}$ has been obtained, then repeat the second step in the same way, starting from determining the particles randomly.

5. Result and Analysis

The research results in classifying criminal acts which contain 4 attributes with 3 labels can be displayed in Table 7.

Table 7. Crime Level Clustering using K-Means with PSO

Label	Cluster	Crime Level	Value
Label 1	Cluster 1	Serious Crime	109
Label 2	Cluster 2	Moderate Crime	41
Label 3	Cluster 3	Minor Crime	50

a. Label 1 is cluster 1 which has a value of 109, where label 1 is a cluster of serious crimes

In this context, Label 1 represents Cluster 1, which contains data points categorized under serious crimes. The value of 109 indicates the number of data points or cases that fall under this classification. This means that within the dataset, 109 instances have been grouped due to their similarities in crime-related attributes, such as type, severity, frequency, or location. The clustering process likely performed using K-Means, has identified this group as distinct from others based on patterns within the data.

The classification of Label 1 as serious crimes suggests that this cluster includes offenses that have a significant impact on public safety, such as homicide, aggravated assault, armed robbery, or violent crimes. The clustering algorithm groups these crimes based on shared characteristics, enabling law enforcement and analysts to better understand crime distribution and develop effective strategies for crime prevention. If Particle Swarm Optimization (PSO) was used to enhance the clustering process, it means that the model aimed to optimize centroid selection and minimize intra-cluster variance, leading to more accurate crime pattern detection.

b. Label 2 is cluster 2 which has a value of 41, where label 2 is a cluster of moderate crime

Label 2 represents Cluster 2, which consists of 41 instances categorized as moderate crimes. This clustering implies that the dataset has identified 41 cases that share common characteristics, distinguishing them from both serious and minor crimes. The classification of moderate crimes typically includes offenses that are less severe than violent crimes but still have legal consequences, such as property crimes, vandalism, fraud, or minor assaults.

The clustering process, possibly using K-Means, groups these moderate crime incidents based on factors like crime type, location, or frequency. By identifying Cluster 2, analysts can better understand crime patterns in this category, helping law enforcement allocate resources effectively. If Particle Swarm Optimization (PSO) was applied, it would have refined the centroid positions, improving the accuracy of cluster formation and ensuring that moderate crimes are distinctly separated from both serious and minor offenses.

c. Label 3 is cluster 3 which has a value of 50, where label 3 is a cluster of minor crimes

Label 3 represents Cluster 3, which consists of 50 instances categorized as minor crimes. This clustering indicates that these 50 cases share similarities in terms of offense severity, distinguishing them from both moderate and serious crimes. Minor crimes typically include petty theft, disorderly conduct, trespassing, or public nuisance offenses, which are less severe and often result in fines or minimal legal consequences rather than imprisonment

By forming Cluster 3, the dataset helps in understanding the distribution of minor crimes, allowing law enforcement or policymakers to focus on prevention strategies such as community policing or awareness campaigns. If clustering was performed using K-Means with Particle Swarm Optimization (PSO), the optimization process would enhance the precision of centroid selection, ensuring that minor crimes are accurately grouped based on key attributes like location, frequency, or crime type. This classification aids in crime trend analysis and efficient resource allocation.

The results showed that K-Means clustering using Particle Swarm Optimization (PSO) demonstrates that PSO successfully enhances the accuracy of standard K-Means clustering. The accuracy value achieved through PSO optimization is 0.122387, which indicates an improvement over the conventional K-Means approach. This enhancement occurs because PSO refines the centroid initialization process, reducing the sensitivity of K-Means to initial conditions and minimizing the risk of converging to local optima.

By integrating PSO with K-Means, the algorithm benefits from PSO's ability to explore a broader solution space efficiently. The swarm intelligence mechanism of PSO enables better centroid positioning, leading to improved cluster compactness and separation. This optimization reduces intra-cluster variance and enhances the model's performance in classifying data accurately. As a result, the combination of PSO with K-Means proves to be a more robust and reliable clustering technique, particularly in datasets where standard K-Means struggles with local minima or unevenly distributed data points.

6. Conclusion

The integration of K-means with Particle Swarm Optimization (PSO) for crime prediction is a promising approach that enhances clustering efficiency and accuracy. This method leverages the strengths of both algorithms to address the limitations of traditional clustering techniques in crime analysis. K-means is known for its simplicity and effectiveness in clustering, while PSO optimizes the clustering process by improving convergence speed and accuracy. This combination is particularly useful in identifying crime patterns and predicting potential crime hotspots.

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