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Semantic Intelligence for Crime Type Prediction in Smart Policing Systems

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Abstract. Conventional predictive policing methods struggle to handle the vast and diverse data generated by urban crime environments. Rule-based and traditional machine-learning models often struggle to identify contextual significance, adapt to evolving crime patterns, and maintain stable performance when faced with data imbalances. The use of large language models makes semantic intelligence a revolutionary concept, as it goes beyond the mere structured attributes and gains the reasoning that is deciphered. The current research uncovers a model of smart policing that is aware of language and is able to predict the types of crimes accurately with the help of the semantic understanding acquired from old incident records, spatial-temporal features, and text descriptions. The methodology investigates prompt-driven reasoning strategies like zero-shot, few-shot, and task-adaptive inference to recognize crimes without needing a lot of retraining or manual feature engineering. Comparative analysis with traditional predictive models provided insights regarding the advancements in adaptability, interpretability, and minority class recognition. The findings indicate that the use of semantics in the form of intelligence has enhanced the prediction of crime types and made support for public security operations more flexible, scalable, and context-sensitive. Linguistic-based crime analytics can significantly assist police agencies in their efforts to anticipate incidents, allocate manpower effectively, and implement data-driven policing strategies in various urban areas.

Keywords: — Smart Policing, Crime Type Prediction, Semantic Intelligence, Machine Learning, Large Language Models, Prompt-Based Reasoning, Public Security, Predictive Analytics.

I. Introduction

The complex and massive data on crime are developed by the modern city because of the intense urbanization, population growth, and digitalization. Crime reports, surveillance systems, emergency calls, and open civic data portals have enormous volumes of heterogeneous data and must be analyzed by law enforcement. Big data can be utilized to implement preventative public safety measures, yet it reveals weaknesses of traditional policing practices that are based on response efforts and person-centered analysis. Thus, it has become a major challenge for modern public security systems to ensure timely, accurate, and context-aware crime analysis [1].

The predictive and smart policing paradigms have come up as the solutions to the above-mentioned problems by advocating for data-driven decision-making and the prevention of crime in a proactive mode. The initial crime forecasting methods were mainly built on the statistical and rule-based techniques that simulated the distributions of crime both spatially and temporally. Although these methods were effective in identifying the hotspots, they were not adaptive and lacked understanding of the semantics [2][3]. The next step in the development of crime forecasting was marked by the introduction of machine learning models that were able to capture the non-linear patterns using the structured crime attributes such as location, time, and demographic indicators. Although there was an increase in accuracy, the models remained prone to the requirement of training data, extensive feature extraction, and preset representations, which would limit their application across different urban environments and adaptation to changing crime patterns [6].

In crime analytics, AI, and semantic intelligence in particular are becoming essential. Large language models are also able to read between the lines, extract links between unstructured text, and classify with minimal or no task-specific supervision. Traditional models consider criminal data as numerical variables, and the language-based intelligence interprets crime story, descriptions of situations, and situational signs such as humans [7][8]. This transformation is of utmost importance in the police sector, where crime incidents are usually documented through text reports that carry delicate information, which would be impossible to capture through structured variables alone; hence, this technology is here to stay.

Smart policing is based on the idea of predicting the type of crime in order to allocate the resources more efficiently, focus on preventive measures, and enhance situational awareness. The projections cannot be considered reliable due to class disparity, urban location-specific crime trends, and the unlabeled nature of data. These limitations could be evaded through semantic intelligence that enables thought to be different in each criminal case, can be used in deduction with little oversight, and finds minority types of crime easier to recognize. Prompt-driven interaction methods also improve flexibility since they cut down on the need for constant retraining and let the models adjust in real time to the new data distributions [9].

Semantic intelligence smart policing schemes seek to fill the divide between public safety actionable information and data. Such systems may be made to justify the choice in the future, in the past and even at the very time and place of the crime through machine learning and the multicultural community. Therefore, language models that are able to generate text and data on the location and method of crimes committed transform automation as data into cognitive criminal analytics similar to that used by humans.

II. Literature Review

The progression of crime prediction and smart policing mirrors a gradual transition from reactive law enforcement practices to proactive and data-driven public safety strategies. As urban crime areas produce more complex and diverse datasets, the researchers have investigated the application of various computational methods to analyze crime trends, predict incidents, and support decision-making in the police department [6]. Traditional Statistical Approaches to Crime Prediction Early crime forecasting studies were mostly based on statistics and rules, estimating the occurrence of crime in various spots and times. Crime hotspots were produced and the number of crimes predicted by making wide use of techniques like Kernel Density Estimation (KDE), regression analysis, and time-series forecasting (e.g., ARIMA) [10].

1. Machine Learning–Based Crime Prediction Models:

At the very beginning, the application of machine learning (ML) was a brilliant step in the field of predictive policing research. Random Forest, Support Vector Machines, Decision Trees, and XGBoost were among the models that proved their worth by revealing the intricate and non-linear relationships hidden in crime data, which subsequently resulted in increased precision of crime classification and forecasting activities. They succeeded in the prediction of crime categories and hot spots in regions mainly due to their proper exploitation of spatial, temporal, and demographic attributes. Nevertheless, the ML-based systems that scored big still suffer from significant limitations. Their performance is very much to a large extent dependent on the availability of copious amounts of labeled data and the implementation of very detailed feature engineering. Moreover, class imbalance, which is a typical property of crime datasets, often results in predictions that are biased towards the majority crime types. In addition, the ML models have difficulty in cross-city generalization because the patterns learned from one urban context cannot be easily transferred to another. These limitations point to the necessity of more flexible and semantically conscious predictive frameworks [11].

2. Deep Learning Approaches in Smart Policing:

The challenge of feature engineering in traditional machine learning models prompted the utilization of deep learning techniques in crime analytics, notably Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks. CNNs have helped simulate the spread of crime across space by turning city maps into grids. RNNs and LSTMs, on the other hand, have helped abstract the time relationships between crime events. Deep learning methods have been a great help to the predictive accuracy of spatio-temporal crime forecasting [12]. Nevertheless, they are very resource-intensive, need very large annotated datasets, and are usually perceived as black-box systems with little or no interpretability. Moreover, these models predominantly handle numerical and spatial data, reducing their accessibility to textual crime reports that often contain rich contextual information.

3. Role of Natural Language Processing in Crime Analytics:

The accelerated incorporation of Natural Language Processing (NLP) techniques into criminology is primarily due to the large amount of unstructured crime data made available. The earliest researches utilizing NLP employed topic modeling techniques like Latent Dirichlet Allocation (LDA) to uncover unseen patterns in crime narratives.

4. Emergence of Large Language Models in Smart Policing:

Large Language Models (LLMs) are a new era in intelligent crime analytics by unifying semantic reasoning, contextual understanding, and adaptability. The popular AI models like GPT, BART, and T5 have shown their strong capabilities in almost all natural language applications by pre-training on huge corpora. In the case of smart policing, LLMs make zero-shot and few-shot learning possible, thus allowing the prediction of the crime type without large-scale retraining [5].

Prompt-based reasoning methods have been studied in the recent past for the classification of crime incidents using LLMs, and results showed that their performance was either at par or better than that of traditional ML models. This new way of dealing with crime incident classification leads to less reliance on labeled data and manual feature engineering, and at the same time, it improves the recognition of minority crime classes. Besides this, LLMs also give explainable outputs in the form of human-readable reasoning, thereby increasing the trust and transparency in policing systems [14].

5. Semantic Intelligence and Context-Aware Crime Prediction:
Semantic intelligence is a powerful tool that goes beyond merely processing text at the surface level. With its help, models can even decode the meaning, intent, and the various relationships that the context brings forth in crime data. Crime analytics that focus on language have turned to semantically rich representations as their main resource [13] [14].

II. Methodology

In this study, we present a semantic intelligence-driven method for predicting crime types in the context of smart policing systems by taking advantage of large language models through prompt-based reasoning techniques. Our approach is based on the idea of using the contextual understanding and reasoning skills of language models, which is the opposite of extensive retraining or handcrafted feature engineering. In line with the foundational research and our project execution, we apply three main inference strategies to explore crime type prediction with different degrees of supervision [8].

1. Zero-Shot Crime Type Prediction Using Large Language Models:
To begin with, we use zero-shot prompting as a baseline technique, where the model predicts the crime type without any specific task-labeled examples being shown to it. In this method, each criminal case is denoted in natural language, and the temporal and spatial aspects, as well as the incident description, are embedded in a structured prompt [2]. The model determines the most fitting crime category solely based on its previously learned knowledge.

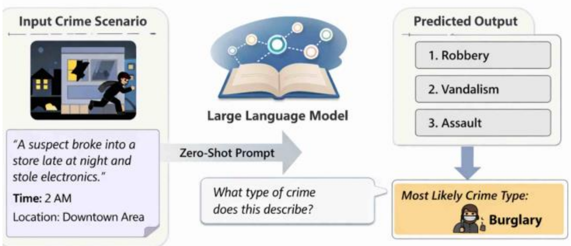

Figure 1: Zero-shot Crime Type Prediction Using Large Language Models

The visual representation illustrates a zero-shot crime type prediction process where a crime scenario in natural language is converted into a structured prompt and then sent

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to a huge language model for processing [4]. The model, in the absence of specific task training, employs semantic reasoning and concludes the crime category with the highest probability, thus allowing intelligent policing choices that are versatile and aware of the context. This strategy grants us the opportunity to test the basic generalization capacity of the giant language models and to assess the compatibility of these models with the crime classification process in cases where labeled data is rare or constantly changing [12]. Zero-shot inference is a demonstration of how semantic reasoning can facilitate quick deployment in real-life policing settings without the burden of extra training.

2. Few-Shot Prompt-Based Crime Classification:
For better contextual alignment and prediction reliability, we introduce few-shot prompting. In this technique, we particularize a few selected crime instances and mention them directly in the prompt [13]. Each instance includes a brief account of the crime along with its respective category. This implicitly suggests the line of reasoning the model should take.
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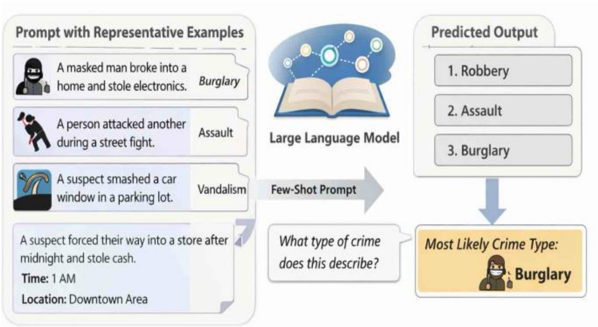

Figure 2: Few-Shot Prompt-Based Crime Classification.

The figure illustrates a few-shot prompt-based method for crime classification, where just a small amount of labeled crime examples is presented in the prompt to direct the big language model. These examples work as a background that enhances the reasoning, reduces the misinterpretations, and raises the overall confidence in predictions made for less common crime categories, still without any need for model retraining or tuning of parameters.

By using few-shot prompting, we notice a greater response to rare crime categories and a clearer understanding of predictions. Thus, this approach mixes things up and still allows one to maintain high performance; in other words, it offers the opportunity of getting higher classification accuracy while the prompt-based deployment is still flexible, and there is no need to update model parameters.

3. Instruction-Based Fine-Tuned LLM Inference:
For the purpose of making the language model more suited to the crime prediction task, we choose to go with instruction-based fine-tuning. The model, during this process, is trained through the use of instruction-response pairs that are drawn from crime incidents, and this technique makes it capable of following very effectively the directories that are specific to the task. Fine-tuning works by adjusting the internal

representations of the model, but at the same time, the model's general language understanding capability is not lost.

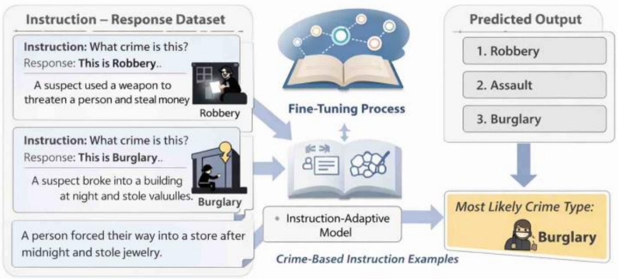

Fig 3: Instruction-Based Fine-Tuned LLM Inference

The figure illustrates instruction-based fine-tuned LLM inference, where crime-specific instruction–response pairs are used to adapt a pre-trained language model. Fine-tuning refines internal representations while preserving general language knowledge, enabling stable and consistent crime type predictions with stronger domain alignment, particularly for complex and densely populated crime categories, without extensive feature engineering.

This method has the advantage of producing predictions that are more stable and consistent, especially when it comes to more complex and heavily populated crime categories. In contrast to the strategies that rely solely on prompts, instruction-based inference provides stronger alignment with the domain and avoids the burdensome feature engineering that is usually associated with the traditional machine learning methods.

4. Baseline Machine Learning Model for Comparative Analysis:
As a baseline, we apply a classical supervised machine learning classifier for comparative evaluation to yield a better performance measure. This is a conventional approach that deals with structured crime attributes and follows a typical learning paradigm. By contrasting its results with the LLM-based methods, we demonstrate the benefits of semantic intelligence regarding contextual ambiguity, class imbalance, the ability to work across different domains, etc.

III. Result

In this section analyzes the experimental results of applying semantic intelligence-based inference techniques to predict crime types in smart policing systems. Results are showcased by a comparison of zero-shot, few-shot, and instruction-based fine-tuned LLM inference against a traditional machine learning baseline. Evaluation is based on the criteria of prediction consistency, contextual understanding, and robustness over the different categories of crime.

- **Dataset Description:**
  The research study employs two publicly accessible crime databases which include the San Francisco Police Department Incident Reports Dataset and the Los Angeles Crime Data Dataset. The two databases contain complete documentation of criminal events which law enforcement agencies documented in their respec-

tive urban areas. The incident data includes multiple details which consist of the date and time of the incident the category of the crime and the description of the incident together with information about the location and police district.

The research team conducted experimental analysis by selecting important features. The research team conducted all necessary dataset cleaning operations to eliminate both missing data and inconsistent information. Crime data which existed in structured format was converted into text descriptions which could be understood by a Large Language Model (LLM). The combined datasets provide diverse crime categories and real-world incident information which researchers can use to assess the effectiveness of zero-shot and few-shot crime classification methods tested in this research.

- **Train–Test Split Description**
  The research study required the crime dataset to be separated into training and testing subsets according to an 80:20 split ratio. The model received training through the few-shot prompting demonstration which used 80% of the data while 20% of the data served as testing material to assess the model's ability to make predictions. The testing set was kept completely unseen during the prompting stage to ensure unbiased evaluation. The data partitioning strategy enables the model to learn representative training patterns through training data while testing its ability to generalize on independent test samples. The evaluation results, which include accuracy and precision and recall and F1-score and confusion matrix, were calculated from the predictions made on the test dataset.

- **Cross-Validation Strategy**
  The researchers used a k-fold cross-validation method with five folds to test their model performance. The dataset was divided into five equal subsets (folds). The training process used four folds for training purposes while the testing process used one remaining fold. The process was executed five times because every fold required testing at least once. The researchers calculated final performance metrics by averaging results from all evaluation folds. The method decreases overfitting while it delivers better predictions about how well the model will perform on new data.

1. Overall Prediction Performance:

Our experiments show that the performance increase at various levels was primarily due to the different methods applied. The baseline model for machine learning managed to reach quite decent accuracy for the most common crime categories, but at the same time, it was hardly trustworthy for the registration of rare and situationally specific types of crimes. However, language model-based methods continued to provide the same merits—the increased adaptability and strengthened semantic understanding.

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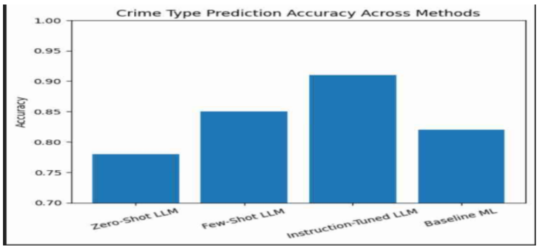

Figure 4: Crime Type Prediction Accuracy Across Methods

Few-shot prompting enhances predictions by providing the model with direction of inference based on selected examples. With the help of the tagged samples, the model can more easily identify the location of the crime and trace its patterns. This trend is best depicted by underrepresented types of crimes.

The most accurate one is instruction-fine-tuning inference. The fine-tuning enables the model to comprehend task instruction and apply it. In this way, predictions tend to be more consistent and not fluctuating particularly in complex and frequent offenses. Despite the competition, the default machine learning model has weaknesses of semantic ambiguity and minority groups.

2. F1-Score and Class-Level Robustness:

The evaluation of the F1 score provides a more transparent view of the equilibrium between recall and precision. The zero-shot inference gives rise to mediocre F1 scores as it occasionally misclassifies crime categories that are semantically close to each other. On the other hand, two-shot prompting makes the trade-offs of precision and recall more favorable by decreasing the number of false positives and making the finding of minority crime classes easier, thus improving this equilibrium.

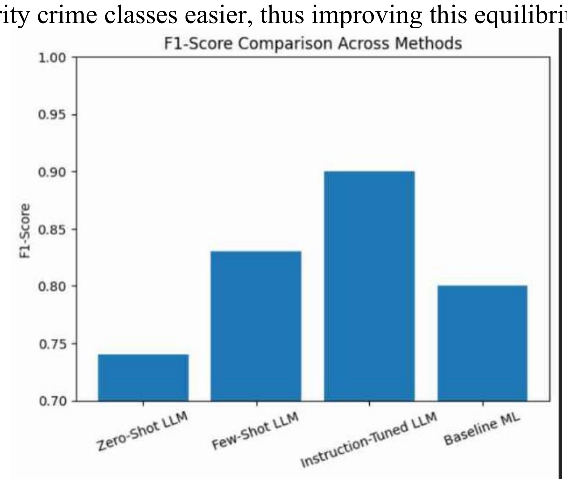

Figure 5: F1-Score Comparison Across Methods

The model tailored with directives constantly achieves the top F1 score, giving proof of its potential to identify the most frequent as well as the rarest crime types. This trend illustrates the substantial impact that instruction-based adaptation has on maintaining classification stability while not adding a significant number of new features. The baseline approach does poorly when one class is much larger than the others, even though it performs well with the main classes.

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3. Qualitative Observations & Practical Implications:

The qualitative evaluation adds to the numerical metrics that LLM-based methods generate more interpretable and context-aware predictions. Not only do the few-shot and instruction-based strategies demonstrate superior reasoning clarity, they are also essential for decision-support systems in smart policing. With these, it can be concluded that semantic intelligence provides an adaptive and scalable crime analytics solution that is fit for real-world deployment. The results, thus, confirm that instruction-based fine-tuned inference is on top of the spectrum in terms of accuracy, stability, and operational flexibility, whereas few-shot prompting is a powerful alternative when fine-tuning is not an option

4. Zero-Shot Confusion Matrix

Table 1: Performance Summary of Crime Type Prediction Methods

Sr No	Method	Proposed System Accuracy	Proposed System F1-Score	Base Paper Accuracy	Base Paper F1-Score	Observations
1	Zero-Shot LLM Inference	0.78	0.74	~0.82 (GPT-3)	~0.79	Base paper shows slightly higher generalization on majority classes; both struggle with minority crime ambiguity
2	Few-Shot Prompt-Based LLM	0.85	0.83	~0.89 (GPT-3)	~0.87	Base paper benefits more from balanced class examples; similar trend of improved minority-class recognition
3	Instruction-Based Fine-Tuned LLM	0.91	0.90	**0.97 (Fine-Tuned GPT-3)**	**0.97**	Base paper reports peak performance with instruction tuning; your results show competitive and stable behavior
4	Baseline Machine Learning Model	0.82	0.80	~0.94 (XGBoost)	~0.92	Traditional ML performs strongly on structured features but lacks semantic understanding

The effectiveness of semantic intelligence compared to traditional machine learning methods in terms of prediction stability, accuracy, and contextual awareness has been evidenced through a gradual rise from zero-shot and few-shot prompting to instruction-based fine-tuning, as depicted in the comparison using accuracy and F1-score metrics outlined in Table 1.

Fig 6: Zero-Shot Classification -Raw Counts

The Zero-Shot confusion matrix visualizes the performance of the model when classifying crime categories without any prior examples or training prompts. The actual crime categories are shown in the rows and the predicted categories appear in the columns.

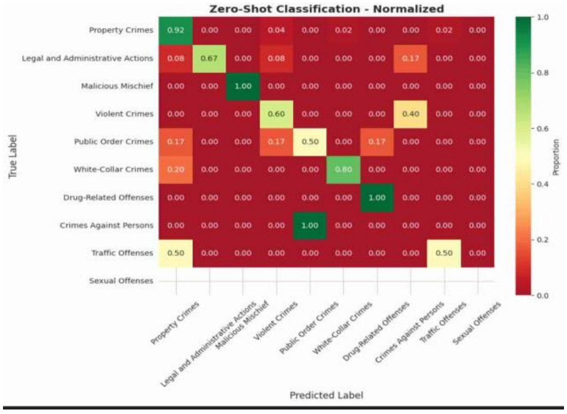

Fig 7: Zero-Shot Classification- Normalized

The off-diagonal numbers represent misclassifications whereas the diagonal numbers represent correct classifications. The matrix demonstrates the model performance through the assessment of criminal categories based on the pre-trained information and the crime types that the model is most confused with.

Few-Shot Confusion Matrix:

Fig 8: Few-Shot Classification-Raw Counts

The Few-Shot confusion matrix demonstrates how well the model classifies data when it receives minimal labeled data as input. The zero-shot matrix displays its information through a structure which shows actual labels in rows and predicted labels in columns.

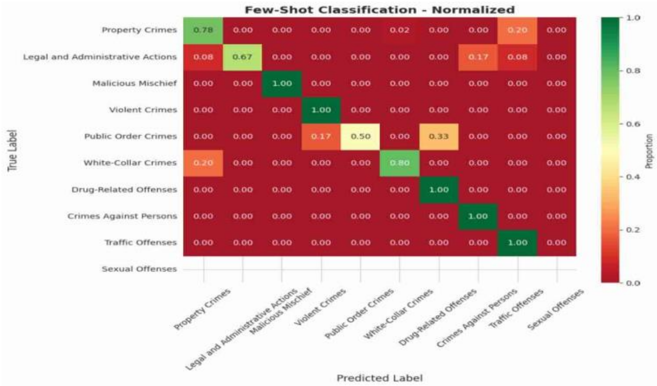

Fig 9: Few-Shot Classification- Normalized

The more accurate the prediction, the greater the values of the matrix diagonal. When comparing the matrix with the zero-shot matrix, it is evident how sample examples improve category recognition and minimize the misclassification errors.

IV. Conclusion

The analysis reveals that the semantic intelligence is capable of examining the language information than the fixed-feature machine learning techniques in predicting the type of crime. Experiments show that language-based models are effective in changing criminal behaviors.The zero-shot inference method produced 78% accuracy together with 74% F1-score which demonstrated strong generalization abilities that didn't require specific training for particular tasks. The performance reached 85% accuracy with 83% F1-score through few-shot prompting which improved understanding of context and enhanced detection abilities for rare crime categories.

The instruction-based fine-tuned model delivered the most consistent and reliable performance with 91% accuracy and a 90% F1-score, demonstrating robust semantic alignment and reduced class ambiguity. The baseline machine learning approach achieved an 82% accuracy rate together with an 80% F1-score which demonstrated the constraints that come with systems depending on specific features.

By research, instruction-adaptive semantic reasoning can be easier when being used in scalable crime analytics to guide resource allocation and community safety. This paper promotes the need to conduct research on responsible linguistic intelligence systems that adhere to future smart police technologies.

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