INTELLIGENT POLICING SYSTEM: HARNESSING LLMs for SMARTER LAW ENFORCEMENT

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ABSTRACT

The increasing complexity and frequency of crimes in modern society demand intelligent, efficient, and proactive solutions to support law enforcement. This project presents the *Intelligent Policing System*, an AI-powered web application designed to analyse and interpret crime scenarios to assist police personnel, legal professionals, and the public. The system accepts both textual descriptions and images related to crime incidents as input and generates actionable insights as output. By integrating traditional machine learning models such as Support Vector Machine (SVM) and K-Nearest Neighbours (KNN) with cutting-edge large language models (LLMs) like Gemini-2.0-Flash, the application predicts the crime category, recommends appropriate response actions, identifies applicable sections from the Bharatiya Nyaya Sanhita (BNS) , forecasts future related crimes, and visualizes crime hotspots on an interactive map. The image-based crime prediction feature enhances usability, particularly in cases where victims or witnesses are unable to articulate the situation in words. Overall, the system bridges the gap between AI capabilities and law enforcement needs, offering a robust, multimodal platform for smarter, faster, and legally aligned crime analysis.

Keywords— SVM, KNN, LLM, Gemini 2.0 flash, BNS, Intelligent Policing System

I. INTRODUCTION

Increased crime rates and evolving challenges in law enforcement have necessitated a shift toward smart policing approaches. AI, particularly large language models like GPT-3 and GPT-4, has shown significant promise in crime classification and forecasting due to its adaptability and contextual understanding [1].Smart policing leverages AI tools such as machine learning and natural language processing to process vast crime data, supporting efforts like crime prediction, surveillance, and digital documentation. These tools enhance police efficiency but also require ethical scrutiny due to potential biases in data [2].Technologies like surveillance robots (Robocops), GPS, drones, and smart sensors are transforming the concept of public safety by enabling ethical and efficient enforcement. They also present an opportunity to reimagine policing in ways that reduce bias and improve community relations [3]. Smart policing strategies emphasize the use of data analytics, collaboration, and digital tools for decision-making. These approaches can convert raw crime data into actionable insights, strengthening both resource allocation and operational efficiency in police departments [4].Few-shot learning models like GPT-3 have demonstrated strong potential in adapting to new tasks without needing large labeled datasets. This characteristic is highly beneficial for dynamic and diverse crime prediction tasks where labeled data may be scarce [5].In metropolitan areas, predictive policing models based on historical and real-time data, combined with ML techniques, enable better forecasting of crime location, timing, and type, which leads to more targeted and effective interventions by authorities [6].The use of predictive policing in the U.S. highlights the role of criminological theories like rational choice and broken windows theory, which support the idea that criminal behavior follows predictable patterns—essential for model training and validation [7].Algorithms are now central to decision-making in criminal justice, from surveillance to sentencing. However, their lack of transparency raises significant legal and ethical concerns, demanding oversight in how they are applied in policing contexts [8].

II. LITERATURE REVIEW

The emergence of Large Language Models (LLMs) has significantly influenced the domain of smart policing. A study conducted by Sarzaeim et al. investigates the capabilities of BART, GPT-3, and GPT-4 in the context of crime classification and prediction. Using crime datasets from San Francisco and Los Angeles, the study evaluates these LLMs under zero-shot, few-shot, and fine-tuning scenarios. It concludes that GPT models outperform traditional ML techniques in most experimental settings. The research highlights how LLMs can revolutionize conventional crime analysis practices and enhance predictive policing by recognizing patterns from historical and real-time data [1].

A systematic review by the same authors presents a broader exploration of how machine learning and natural language processing are employed in smart policing. This work delves into applications like surveillance, crime prediction, and documentation. The study not only emphasizes the promise of AI in improving police operations but also warns about biases inherited from training data. It outlines various tools used in predictive policing, ranging from facial recognition to crime heatmaps, and systematically reviews over 150 relevant studies, shedding light on both the potential and challenges in this evolving field [2].

In contrast to the technical optimism, Maliphol and Hamilton emphasize the ethical considerations and management of robotic policing systems. Triggered by high-profile cases of police brutality, the paper examines the introduction of robocops and other smart technologies as tools for reducing human bias and violent encounters. The authors critique the limited scope of current smart policing research, advocating for a broader approach that includes ethical performance metrics and reallocation of policing funds towards socially responsive technologies [3].

Afzal and Panagiotopoulos provide a comprehensive review of smart policing from a public management perspective. Analyzing 112 articles, they categorize smart policing applications based on four primary data sources and explore innovations such as network analysis and interagency collaboration. Their critical framework underlines the strategic integration of big data tools in transforming traditional police methods into more analytical and efficient processes [4].

Brown et al.'s influential paper introduces GPT-3, a 175 billion parameter autoregressive language model capable of few-shot, one-shot, and zero-shot learning. Although not focused on policing specifically, the paper's relevance lies in demonstrating how few-shot learning models can perform tasks like classification, translation, and reasoning with minimal task-specific training. These capabilities underpin many modern smart policing systems that use LLMs to automate classification of crime types and suspect profiling [5].

Khan et al. propose a predictive policing framework tailored to metropolitan cities. Using crime datasets and applying supervised machine learning models (e.g., decision trees and SVMs), the study predicts crime categories and hotspots. The authors emphasize the importance of integrating real-time spatial data and deploying mobile applications for field operatives. Their approach aims to assist law enforcement agencies in resource optimization and proactive crime prevention [6].

Yang's work presents a historical and critical perspective on predictive policing practices in the U.S. It catalogs widely adopted systems such as CompStat, PredPol, and Patternizr, outlining their functionalities and ethical dilemmas. The study underscores how these tools rely on historical data and criminological theories like broken windows and routine activity theory. However, it also raises concerns over civil rights, biased surveillance, and the militarization of police forces [7].

Almanie et al. explore the use of data mining for crime prediction based on crime type and temporal-spatial hotspots. Focusing on datasets from Denver and Los Angeles, the study applies Apriori algorithms and classifiers like Naïve Bayes and Decision Trees. The researchers combine crime patterns with demographic data to understand neighborhood-level risk factors. This integration aids both citizens in awareness and police in crime prevention and resource deployment [8].

III . PROPOSED WORK

The *Intelligent Policing System* follows a well-structured pipeline, visually represented in the flowchart, to process user inputs and deliver comprehensive crime analysis. The system begins with the user providing an input, which can be either a textual description of the crime or an image related to the incident. This dual-input design ensures that the system is accessible even in situations where the user cannot articulate the crime in words, making it suitable for real-world emergency use cases.

Once the input is received, it undergoes preprocessing based on its type. For textual inputs, the system performs cleaning and applies TF-IDF vectorization to convert the crime description into a format that can be understood by machine learning models. For image inputs, the image is encoded and included in a prompt sent to the Gemini-2.0-Flash model, which supports multimodal inputs. This preprocessing stage ensures that the raw input—whether text or image—is transformed into a meaningful format for further analysis.

The next stage involves crime classification using traditional machine learning models: Support Vector Machine (SVM) and K-Nearest Neighbours (KNN). These models, trained on historical police data, help in predicting the crime category based on the user input. SVM is particularly effective in handling high-dimensional and sparse data, offering high accuracy across various crime types. KNN, on the other hand, classifies based on the proximity of feature vectors and provides robustness to the classification process by identifying similar past crime descriptions.

The outputs from these models are then combined with the user's original input and relevant sections of the Bharatiya Nyaya Sanhita (BNS) to form a structured prompt. This prompt is sent to the Gemini-2.0-Flash API, a large multimodal language model capable of interpreting both visual and textual data. Gemini analyses the prompt to refine the crime category, provide a brief legal analysis, recommend police actions, identify applicable BNS sections, and forecast related future crimes. This stage adds a layer of legal intelligence and semantic reasoning to the predictions made by the machine learning models.

Following the analysis, the system filters historical crime data based on the predicted category and generates an interactive crime hotspot map. This map is created using geolocation data and displays the most frequent regions of crime, helping authorities and users visualize spatial crime patterns. The markers on the map are color-coded to represent the severity or nature of the crime, adding visual clarity.

Finally, the system presents all results to the user. The output includes the predicted crime category, recommended law enforcement actions, a list of applicable BNS sections with brief descriptions, a forecast of related crimes that may occur in the future, and an interactive hotspot map. This multi-layered output makes the system a powerful tool for real-time crime assessment, legal referencing, and strategic planning for law enforcement. The flow from user input to AI-enhanced legal guidance showcases a seamless integration of machine learning, natural language processing, and geospatial visualization within a single application.

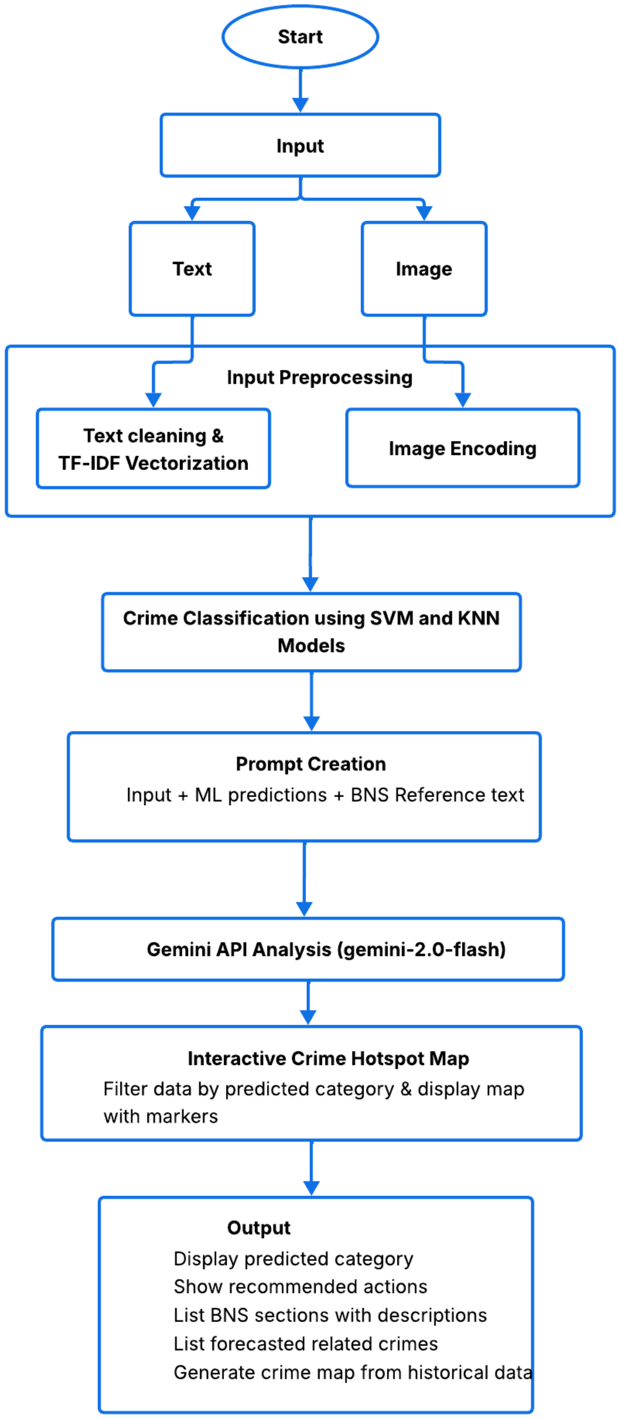

Figure 1: Flow Chart

IV. RESULTS and DISCUSSION

Crime	Precision	Recall	F1-score	Support
ASSAULT	0.94	0.94	0.94	16
BURGLARY	1.00	1.00	1.00	8
DISORDERLY CONDUCT	1.00	0.75	0.86	4
DRUG/NARCOTIC	1.00	0.86	0.92	7
FRAUD	1.00	1.00	1.00	3
LARCENY/THEFT	1.00	1.00	1.00	44
LIQUOR LAWS	0.00	0.00	0.00	3
MISSING PERSON	1.00	1.00	1.00	7
NON-CRIMINAL	1.00	0.97	0.98	29
OTHER OFFENCES	0.74	1.00	0.85	25
PROSTITUTION	1.00	1.00	1.00	1
RECOVERED VEHICLE	1.00	1.00	1.00	1
ROBBERY	1.00	1.00	1.00	2
SECONDARY CODE	1.00	0.50	0.67	2
SEX OFFENCES , FORCIBLE	0.00	0.00	0.00	1
STOLEN PROPERTY	1.00	1.00	1.00	1
SUSPICIOUS OCC	1.00	0.91	0.95	11
TRESPASS	1.00	1.00	1.00	3
VANDALISM	1.00	1.00	1.00	8
VEHICLE THEFT	1.00	1.00	1.00	10
WARRANTS	1.00	1.00	1.00	13
WEAPON LAWS	1.00	1.00	1.00	1
Accuracy			0.95	200
Macro average	0.89	0.86	0.87	200
Weighted average	0.94	0.95	0.94	200

Figure 2 . SVM Classification Report

The SVM model has demonstrated high effectiveness in crime classification. Based on the classification report, it achieved an overall accuracy of 95%, with a weighted average precision and F1-score of 0.94. The model showed consistent performance across various categories, including perfect classification for crimes such as burglary, fraud, larceny/theft, and vehicle theft. Even with limited support data for categories like prostitution, recovered vehicle, robbery, and suspicious occurrences, the model managed to deliver perfect scores, which indicates that SVM is well-suited for high-variance, sparse-input crime classification tasks. However, some classes with low support, like disorderly conduct and secondary codes, showed slightly lower recall and F1-scores, reflecting potential underrepresentation in the training data.

Crime	Precision	Recall	F1-score	Support
ASSAULT	0.73	0.80	0.76	20
BURGLARY	0.67	1.00	0.80	4
DISORDERLY CONDUCT	1.00	1.00	1.00	1
DRUG/NARCOTIC	0.83	1.00	0.91	5
DRUNKNNESS	0.00	0.00	0.00	1
FORGERY/COUNTERFETTING	0.00	0.00	0.00	1
FRAUD	1.00	0.75	0.86	4
LARCENY/THEFT	1.00	0.98	0.99	60
LOQUOR LAWS	0.00	1.00	0.86	3
MISSING PERSON	0.91	0.95	0.93	21
NON-CRIMINAL	0.88	0.82	0.85	28
OTHER OFFENCES	1.00	1.00	1.00	1
PROSTITUTION	0.80	1.00	0.89	4
RECOVERED VEHICLE	1.00	1.00	1.00	2
ROBBERY	0.00	0.00	0.00	1
RUNAWAY	0.00	0.00	0.00	1
SEX OFFENCES, FORCIBLE	0.00	0.00	0.00	1
SEX OFFENCES, NON FORCIBLE	1.00	1.00	1.00	5
SUSPICIOUS OCC	1.00	1.00	1.00	3
TRESPASS	1.00	1.00	1.00	12
VANDALISM	1.00	1.00	1.00	7
VEHICLE THEFT	1.00	0.86	0.92	7
Accuracy			0.90	200
Macro average	0.67	0.69	0.67	200
Weighted average	0.89	0.90	0.89	200

Figure 3. KNN Classification Report

In contrast, the KNN model exhibited a slightly lower performance with an overall accuracy of 90% and a weighted F1-score of 0.89. While it performed well in major categories such as larceny/theft, non-criminal activity, and vandalism, it struggled in underrepresented or zero-support categories like drunkenness, forgery, sex offenses, and runaway crimes, where both precision and recall were zero. This suggests that KNN, although useful for pattern matching, may not generalize well for sparse or less frequent crimes compared to SVM. Nevertheless, KNN contributes by reinforcing predictions in well-supported classes and adds an additional perspective for cross-verifying classification outcomes.

Once the crime category is predicted, the Gemini-2.0-Flash API takes over to perform advanced reasoning and contextual decision-making. Gemini receives structured input, including the user's crime description or image along with the SVM and KNN model outputs. In the case of text input, Gemini analyzes the semantic content in combination with machine learning predictions and references from the Bharatiya Nyaya Sanhita (BNS), to determine the most appropriate crime category, offer recommended actions for authorities, list applicable legal sections, and even predict future crimes that might occur based on the current situation. For image-based inputs, Gemini uses its multimodal capabilities to analyze visual elements and infer the possible criminal activity depicted in the image. This image understanding is then processed similarly to text descriptions—producing legal, actionable, and interpretable insights for the user.

V. CONCLUSION

The *Intelligent Policing System* is a comprehensive AI-driven platform designed to assist in crime analysis, legal referencing, and decision-making for law enforcement and public safety stakeholders. The system intelligently processes both textual descriptions and images of crime incidents, making it versatile and accessible for a wide range of users. Whether a user provides a detailed narrative or an image depicting the scenario, the application is capable of interpreting the input and delivering meaningful, structured output. The system uses machine learning models—Support Vector Machine (SVM) and K-Nearest Neighbors (KNN)—trained on real-world crime datasets to predict crime categories with high accuracy. These models analyze the input data, extract key patterns, and classify the crime into appropriate categories. The predictions are then enhanced by Gemini-2.0-Flash, a powerful large language model that interprets the scenario in a legal and contextual framework. Gemini takes into account the ML predictions, the input content, and relevant excerpts from the Bharatiya Nyaya Sanhita (BNS) to generate detailed outputs. These include the predicted crime category, legal analysis, recommended actions for authorities, applicable BNS sections with descriptions, and a forecast of related crimes that may follow.

To aid spatial understanding and strategic planning, the system also generates an interactive crime hotspot map using historical data filtered by the predicted category. This map visually highlights areas with a high concentration of related crimes, supporting proactive policing and situational awareness.This project demonstrates the effective application of AI in public safety and lays the groundwork for smarter, faster, and more informed policing.

VI. REFERENCES

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