Comparative Analysis of Machine Learning Models for Crime Prediction Based on Spatial and Temporal Features

Samuel Theodore Gunawan
Faculty of Engineering and Technology
Sampoerna University
Jakarta, Indonesia
samuel.gunawan@my.sampoernauniversity.ac.id

Calvin Willyanto
Faculty of Engineering and Technology
Sampoerna University
Jakarta, Indonesia
calvin.willyanto@my.sampoernauniversity.ac.id

Charles Agustin
Faculty of Engineering and Technology
Sampoerna University
Jakarta, Indonesia
charles.agustin@my.sampoernauniversity.ac.id

Nisrina Rahma Syaifullah
Faculty of Engineering and Technology
Sampoerna University
Jakarta, Indonesia
nisrina.syaifullah@my.sampoernauniversity.ac.ic

Michael Liem
Faculty of Engineering and Technology
Sampoerna University
Jakarta, Indonesia
michael.liem@my.sampoernauniversity.ac.id

***Abstract*—The high rates of crime pose severe challenges to economic development, social cohesion, and public security. In this paper, we discuss the potential impacts of Artificial Intelligence (AI) and Machine Learning (ML) on crime prediction and prevention. Through in-depth analysis of state-of-the-art prediction models, we demonstrate how AI-based techniques are revolutionizing strategies for crime prevention. With neural networks at 81% accuracy in historical crime data analysis, our methodical research demonstrates impressive advancements in predictive accuracy. For the prediction of crime incidents, Long Short-Term Memory (LSTM) networks demonstrate 75-90% accuracy. The findings show artificial intelligence's capabilities to improve public safety in metropolitan areas through complex spatial-temporal analysis. Though we find significant deficiencies in managing unlabeled real-world data, our results show a majority use of supervised learning methods. Emphasizing the need for stronger and flexible prediction systems, the study shows issues in data availability, model interpretability, and algorithmic bias. The report finds that criminologists must actively participate in moving from conventional statistical techniques to sophisticated AI-driven ones. This change guarantees an increase in the accuracy of predictions, the ability to handle ethical issues, and the strengthening of law enforcement capacity. Our results offer insightful analysis for creating more efficient crime prevention plans and point out encouraging avenues for future study in this fast-changing sector.**

Keywords*—*AI, Machine Learning, Crime Prediction, Researcher

I. Introduction

A crime is a form of violence or illegal act done by a perpetrator against another person that can cause harm or property damage and is punishable by the law of the governing state or authority in which the crime was carried out. Over the years, crimes have continued to increase within countries. Even in developed countries with abundant resources, for example, Crime Statistics & Trends in Los Angeles, CA (2025) report that Los Angeles, CA, currently has a crime rate of approximately 3,115 crimes per 100,000 residents based on 2024 data, which is 29.7% higher than the national average. Violent crime occurs at a rate of about 761 per 100,000 people, while property crime rates stand at roughly 2,354 per 100,000 residents.

It shows the difficulties in tackling crime through traditional means, with complex crime patterns challenging crime prevention efforts. In response, we collected the datasets and tried to compare them to multiple advanced machine learning models/algorithms, Which is used to enhance methodologies for predicting and preventing crimes. Of particular note, earlier studies in Vancouver have already effectively applied artificial intelligence techniques such as "K-nearest neighbors" to determine areas of high crime incidence. Globally, artificial intelligence is increasingly being used for the analysis of criminal data, the recognition of patterns, and the optimal deployment of law enforcement resources. By using spatiotemporal data to predict various forms of criminal activity, these technologies have shown excellent potential in cities such as Atlanta, Baltimore, Chicago, and Portland, thereby underlining their applicability across diverse urban and security contexts globally. However, the shift in law enforcement practices influenced by technological advancements gives rise to several challenges. Key issues include the precision of data and the broader ethical implications associated with increased surveillance and data utilization. The effective implementation of crime-prevention technologies relies on robust and forward-thinking training initiatives that encompass data management techniques and the integration of technology. Such initiatives ensure that law enforcement transitions from a reactive stance to a proactive approach, thereby enhancing the capacity to prevent criminal activities before they occur. Also, artificial intelligence in criminology is transforming the state of security, judicial rulings, and crime.

By analyzing crime data—police records and population data, for instance—AI's capacity to conduct tasks such as sorting data, detecting anomalies, and optimizing systems enables accurate forecasting of crime sites, thereby enabling effective resource deployment and focused preventive interventions. The use of communication and financial data analysis in combating organized crime has helped in decreasing the levels of crime, thus making the world a safer place. The study will conduct a literature review of the contribution of various artificial intelligence models in predicting crime, as well as the limits to their capability in predicting criminal behavior accurately.

II. Literature Review

The literature review purpose is to examine the present state of artificial intelligence use in crime forecasting, its improvement, constraints, and implications on lowering crime rates in the future. The review synthesizes studies, theoretical frameworks, and research methods to address gaps in research that exist and therefore establish a premise for future studies in this field.

The use of various deep learning models, which make use of sophisticated analyses of past criminal activity records, spatial information, and temporal trends, has been instrumental in the recent advancements in crime prediction. These models, including Neural Networks, RNN, LSTM, and Random Forest, have been critical in improving crime prevention along with detecting high-risk areas.

For instance, there has been research on the prediction of criminal behavior via neural networks based on various variables that translate to the particular context. in their paper, Hicham et al (2018), suggest a crime forecasting model based on prepared historical data and converted into space-time data by the type of crime, to be applied in machine learning algorithms and then forecast,, with the maximum precision, the risk of having crimes in a space-time point in the city.

The model illustrated in Figure 1, foresees various layers with two types of data: HISTORICAL CRIME DATA (HIST DATA) and SITE INFORMATION (LOC DATA).Machine learning algorithms such as Regression, Naive Bais, Support Vector Machine (SVM), Decision Tree, and Random Forest were utilized for the training and experiment process. In the same way, tests were conducted with algorithms like Neural Networks, Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) to identify the algorithm that yielded good results in terms of accuracy and response time.

It was found that certain algorithms are incompatible with the data format like Naive Bais and SVM. The Random Forest algorithm is time-consuming for one iteration and produces 59% accuracy. The Decision Tree produces a 38% accuracy in the second iteration and is steady. The Neural Network algorithm is more compatible with test data and has quicker response times producing 81% accuracy.

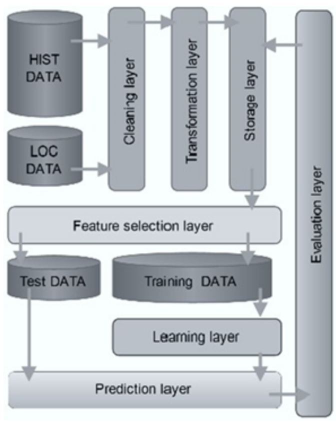

Figure 1. Predictive Model, Hicham et al (2018)

In Yuting and Li's (2019) study, the predictability of three types of theft is compared using LSTM (Long-Short-Space-Time), one type of Recurrent Neural Networks (RNN), to learn about the association of three types of theft with different characteristics so that its predictability is different at different spatial and temporal levels. Commercial, pedestrian, and house-to-room robberies are compared in Atlanta and Baltimore, USA. The results show that predictability in these differs between cities, for example, in Atlanta, commercial robbery is very predictable in relation to residential and pedestrian, where there is a correlation coefficient of approximately 0.75. In Baltimore, though, residential and commercial robbery has a predictability coefficient close to 0.90, much more than pedestrian robbery. On the other hand, the study by Stec (2018) aims to apply neural networks towards predicting occurrences of crime for the "next day" in specified areas of the cityscapes of Chicago and Portland.

As indicated in Table 1, the researchers experimented with four types of neural network models, such as the Feed-Forward Network, Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and Recurrent Convolutional Network (RCN), which function based on various spatial and temporal data sets to describe the interaction between these variables and criminal offense. They identified which network provides the highest levels of precision for each forecasting task, while validating the accuracy of the results provided by each type of network through alteration of the data sets under the same training processes. Lastly, an examination of the conditions that influence the model's performance is conducted.

	Chicago Total	Chicago Type 1	Chicago Type 2	Chicago Type 3	Portland Total
Feed Forward	71.3	64.3	61.0	56.5	62.2
CNN	72.7	65.1	62.7	56.9	62.9
RNN	74.1	65.5	63.6	57.6	63.8
RNN + CNN	**75.6**	**65.9**	**64.7**	**57.9**	**65.3**

Table 1. Accuracy of classification results byStec (2018)

Alparslan et al. (2020) explain that among the most utilized methods is the examination of the density of the critical point on a geographical map, with crime hotspots serving as pointers to possible conflict zones. The rationale is that criminal activity is influenced by numerous factors influencing multidimensional planes, a concept that has been largely embraced as an indicator of future criminal activity. The authors' strategy regarding their proposed crime forecasting models is not city-specific but instead formulates the concept of crime within a regression model. This kind of model demands the measurement of criminal activity across various sections of the geographic map and a summation of the figures over different time intervals in order to forecast anticipated crime occurrences within the respective areas, as indicated in Figure 2. The main issue with this kind of strategy is that researchers are required to devise a method for splitting the city into a grid of independent cells, something which can prove troublesome, particularly taking into consideration that not all big cities are square in shape or have shapes that can easily be treated as rectangles or squares.

Figure 2. Crime mapping points per year on a map of Philadelphia by Alparslan et al (2020)

The suggested approach by the authors includes the formation of clusters with the help of the data, which is used for counting crimes, as an alternative to the use of cell grids in mapping. They conducted the application of both supervised and unsupervised learning models.

The findings as presented in Figure 3 show some trends regarding the hours when crime rates are highest in the city. Incidentally, the hour with the lowest incidence of criminal activities is at 6 a.m., when criminals are understandably inactive due to sleep hours. The highest hours of criminal activities are between 8 a.m. and 1 a.m., in addition to the lunchtime hours. As indicated in Figure 4, upon altering the time period from hours to months, there is a remarkable decrease in crime activity during winter months, while spring and summer months indicate a rise in crimes such as robbery and prostitution.

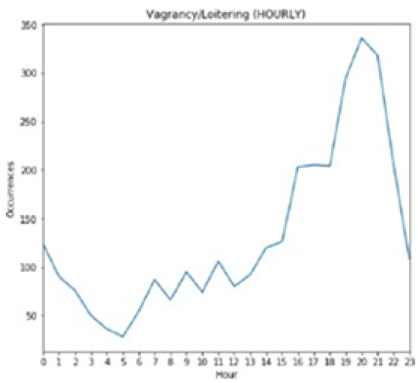

Figure 3. The hours of highest crime

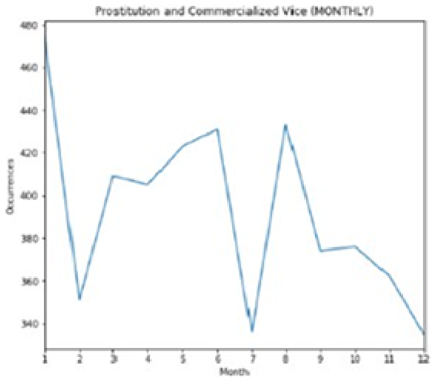

Figure 4. The months of highest crime

When the researchers ran the network using the time value of years, they had a more difficult time seeing the overall trends. They did notice, however, that certain crimes have dropped in recent years, such as vandalism, and others that have increased, such as theft. In short, this research made use of unsupervised learning techniques like the K-Means clustering algorithm to determine the ideal number of clusters, as well as supervised learning approaches from a datasets consisting of about 1.3 million records for training and testing.

A different approach, which also focused on crime prediction, was that of Bogomolov et al. (2014), in which a 70% rate of accuracy was achieved in crime hotspot prediction using human behavior data from mobile network traffic combined with demographics. Specifically, this approach aimed to determine whether a given geographic area in a large European city would experience more or less crime in the following month.

The work of Ying-Lung (2018), applies machine learning to grid-based crime prediction. The study incorporates the concept of a criminal environment into grid-based crime prediction modeling and proposes a set of spatial-temporal features by utilizing the Google Places API with 84 categories of geographic information on Taoyuan City theft data, Taiwan. A few of the other algorithms implemented in Kim (2019) for crime prediction, were K-Nearest-Neighbour at 39% and Boosted Decision Tree at 44% processing CrVancouver crime data from the last 15 years.

These developments are some of the broader uses of artificial intelligence in criminology, a field that has been extensively explored using comprehensive literature reviews spanning studies from 2000 to 2021. These reviews, which were carried out in diverse databases including the Criminal Justice Collection, Web of Science, and Google Scholar, comprehensively categorized and assessed the findings along with the ethical considerations of past research. The comprehensive documentation and expert consultation during the selection process yielded insightful information into the application of AI for crime prevention and prediction, substantiating areas for future research and putting emphasis on cautious application in relation to future biases and predictive model accuracy.

III. Methodology

The methodology of this crime forecasting study is centered on the supervised learning paradigm, where historical crime data was used to train models to predict future crime occurrences at a weekly and geographic area level. The dataset that contains crime incidents from various cities such as Chicago, Philadelphia, and Portland, was preprocessed to aggregate counts by week and places. Some features were engineered to include temporal attributes like week number, day of the week, spatial identifiers like area codes, and potentially some general variables such as weather, socioeconomic factors, or past crime trends. The target variable was the number of crimes reported in each area for each week. In addition, any missing values were handled through imputation or exclusion and the data should be normalized or scaled as needed for compatibility with distance-based and tree-based models.

Three machine learning algorithms were used for this project which are K-Nearest Neighbors (KNN), Random Forest, and XGBoost. The KNN model operated by identifying the 'k' most similar historical data points also called as neighbors based on feature space proximity and predicting crime count via averaging. While simple and easy to use, KNN required careful setting of the 'k' parameter and distance metrics, as it lacked internal mechanisms to manage irrelevant or redundant features. Random Forest on the other hand is a bagging-based ensemble method that was implemented to build multiple decision trees using bootstrapped data samples and random subsets of features, which probably helps to improve robustness and reduce overfitting. Lastly, XGBoost was used in this case as a gradient-boosted decision tree algorithm, which builds a kind of trees sequentially to correct previous errors, helpt on optimizing via gradient descent and do regularization to prevent overfitting.

Model evaluation was conducted using a test set gained from the dataset, and performance was measured using several indicators such as accuracy within ±20 crimes, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 (coefficient of determination). These metrics were carefully chosen to provide a comprehensive understanding of model performance from multiple perspectives. Mean

Absolute Error or MAE, calculates the average absolute difference between both the predicted and the actual values. It is quite straightforward to interpret and is particularly useful for basic understanding of prediction errors without being overly influenced by outliers. In contrast, RMSE or Root Mean Squared Error, also measures the difference between predicted and the actual values but does so by squaring the errors in advance before averaging them and then taking the square root. This method gives more weight to larger errors, making RMSE very useful when large deviations from the actual values are particularly unpleasant, such as in public safety scenarios where severe overestimation or underestimation of crime can have real-world consequences.

R^2, or the coefficient of determination, helps to complement these error metrics by evaluating how well the model captures all the variance in the target variable. It is ranged from 0 to 1, whereas the value closer to 1 would indicate that a large proportion of the variance in actual crime counts is explained by the model's predictions. Partially, R^2 quantifies the goodness of fit, showing how well the future outcomes are likely to be predicted by the model based on the previously observed data. Accuracy within a tolerance band (±20 crimes) was also included as a practical benchmark, showing a real-world acceptability where perfect predictions are rare and difficult to achieve due to the inherently random and complex nature of crime data. Every model was well tuned using grid search or empirical parameter heuristics to achieve the most optimal performance. Due to the large size of the dataset, all models were trained and evaluated locally, to ensure full use of computational resources for faster and more efficient processing. The results are showing clear performance differences like XGBoost that emerged as the most reliable model, achieving the highest R^2 and lowest MAE and RMSE, followed closely by Random Forest, and KNN that might lag significantly in predictive precision for some reason.

IV. Significance of the project

The integration of Artificial Intelligence in the crime prediction system represents an advancement in the field of criminology and public safety. With the fast growth of crime data and advancements in machine learning techniques, there will be an increasing need for these systems that can analyze complex data, multiple patterns of criminal activity. This project is significant in the capabilities of AI particularly in deep learning models such as Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and hybrid models that are used for predicting criminal activity based on time and place. By using the approaches from a wide body of research, this project aims to strengthen the precision, responsiveness, and practicality of predictive crime models in real-world urban contexts.

Studies such as those by Hicham et al. (2018) and Stec (2018) had demonstrated the effectiveness of using neural networks in spatial temporal crime prediction. Hicham et al.'s model highlights the value of preprocessing historical and locational data through multiple layer of machine learning pipelines, while Stec's work had clearly showed that using hybrid, both RNN and CNN models outperform traditional feed-forward (FNN) and standalone models, resulting up to 75.6% accuracy in Chicago-based datasets. These findings provide actual support for the development of multi-layered, high-performance prediction architectures adapted to crime forecasting.

The project also draws upon spatialized analysis techniques as demonstrated by Alparslan et al. (2020), who created crime density mapping to identify the point of high-risk zones without being restricted by artificial grid systems. Instead, using clustering techniques allows more clean interpretation of the city layouts, which improve crime count-based regression modeling. This spatial strategy is not only used to increase model accuracy but also aligns with real-world city dynamics, offering direct applicability for law enforcement and urban planners.

Temporal crime patterns, such as those shown in Figures 3 and 4, further support the essential of important time series modeling. Knowing that crime incidence occurs significantly by hour and season, the use of RNN and LSTMs becomes essential, as these architectures are well structured for capturing successive dependencies. For example, Alparslan et al. found critical hours of crime between 8 p.m. and 1 a.m., while seasonality was also seen to spikes in offenses such as prostitution and loitering. Such findings highlight the importance of integrating temporal awareness into AI models that moves beyond predictions to dynamic forecasting..

Moreover, the project is completely implemented by using deep advanced research. A sample project by Bogomolov et al. (2014) and Ying-Lung (2018) demonstrates the behavioral data and geospatial features and can directly create hotspot prediction accuracy when combined with machine learning. These perceptions validate the use of diverse data from the source of mobile activity to location-based APIs and could possibly support the project's goal of building a crime forecasting model.

V. Result Analysis

Models	Accuracy	MAE	RMSE	R^2
KNN	45.6%	29.5	40.9	0.578

Random Forest	69.5%	16.8	24.6	0.847
XGBoost	71.8%	16.3	24	0.854

Table 2. Models' statistical results

In this study, there are three machine learning models that we use, K-Nearest Neighbors (KNN), Random Forest, and XGBoost that were evaluated for their ability on predicting weekly crime counts within specified geographic regions based on the data. Each model's performance was accessed using a variety of statistical tools such as the accuracy within ±20 crimes, the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). The performance outcomes show a significant variation in their predicting capability, with XGBoost showing the most effectiveness, followed by Random Forest and lastly KNN.

The K-Nearest Neighbors (KNN) algorithm is used as a baseline model for crime prediction by estimating crime counts based on the average of the most similar historical instances for our case that are determined through feature-space proximity. While it is simple and intuitive, KNN might struggle with high-dimensional and noisy data, leading to reduced effectiveness in capturing complex spatiotemporal patterns. This was proved in its performance metrics, particularly the Mean Absolute Error (MAE), which has an average of 29.45 crimes per prediction. MAE itself measures the average magnitude of errors in predictions regardless of direction, and a high MAE would indicate poor precision in forecasting. Similarly, the Root Mean Squared Error (RMSE) for KNN was 40.85, which indicates larger errors more heavily due to the squaring process. The high RMSE reflects that KNN often made significantly inaccurate predictions, likely due to its inability to differentiate which one is important and irrelevant features. Furthermore, the coefficient of determination (R^2) was 0.578, meaning that KNN could only explain about 57.8% of the variance in the actual crime data. This relatively low R^2 value indicates that a substantial portion of the variation on a weekly crime counts remained unexplained by the model, reinforcing that KNN is not well-suited to run for the complex task of forecasting crime where interactions between time, location, and underlying factors are highly nonlinear and not easily captured through simple proximity-based methods.

Starting with the KNN model, it reached an accuracy of 45.60% within ±20 crimes, with an MAE of 29.45, an RMSE of 40.85, and an R^2 of 0.578. These values point shows a relatively weak fit to the underlying data. KNN is a non-parametric, instance based learning algorithm that operates using the assumption that has similar feature vectors (i.e., neighborhoods in the feature space) that would also produce similar outcomes. While intuitive and interpretable, KNN works less efficient from limitations in high dimensional or noisy environments. From the crime data, particularly at the weekly and regional level often shows up a high variance due to social, temporal, environmental and some other factors. These factors may not works efficiently in a straightforward Euclidean feature space, which limiting KNN's ability to generalize data. The relatively high MAE and RMSE indicate that the model frequently deviates substantially from the real actual crime counts. Moreover, KNN's has a sensitivity to irrelevant or redundant features that works without any internal mechanism for feature selection, contributing to its suboptimal performance.

In contrast, the Random Forest model demonstrated a significantly improved performance with 69.46% accuracy within ±20 crimes, an MAE of 16.82, an RMSE of 24.58, and an R^2 of 0.847. All of this method constructs multiple decision trees in the system using different subsets of the data and would aggregates their outputs, which tends to reduce an error such as overfitting and improves generalization. Random Forest basically handles feature interactions and non-linear relationships, where it is critical in modeling the complex dynamics of crime incident. It has lower MAE compared to KNN that shows on average, the predictions are much closer to the true values. The relatively lower RMSE are significantly less than KNN's would indicates better handling of large prediction errors or outliers. Importantly, the value of R^2 suggests that the model explains a substantial proportion of the variance in crime data, restoring its capacity to model real-world complexity.

The XGBoost model, which is considered as the best performance among the three, had achieved 71.79% accuracy within ±20 crimes, an MAE of 16.26, and an R^2 of 0.854. The RMSE is at 24.58, further strengthening XGBoost's superiority in this context by indicating consistently lower magnitude of large prediction errors compared to other models. XGBoost is commonly a highly optimized implementation of gradient boosting that includes regularization, shrinkage, and important features like weighting. These characteristics will help XGBoost to avoid overfitting, maintain generalizability, and learn the intricate relationships within the data. While the marginal improvement over Random Forest in MAE and R^2 has relatively small numerical data, it is significant in the use of practical forecasting applications. The MAE being slightly lower than Random Forest suggested more consistent predictions, and the higher R^2 confirms its strong explanatory power. This model has the ability to prioritize more relevant features and discount noise contributes to this performance.

The performance that had been just witnessed can be largely explained by each model's ability to manage the complexity of the data. Crime data could be inherently noisy, with underlying patterns that are influenced by countless variables including time of day, social, economic conditions, law enforcement, and special events. A healthy dataset for predictive modeling would ideally have low noise, balanced class distributions, limited outliers, and minimal multicollinearity characteristics that could be rare in real-world crime datasets. KNN's approach lacks internal mechanisms that could identify relevant patterns or weight features, which is the ability to generalize from such noisy data. Conversely, Random Forest and XGBoost are both tree-based ensemble learners that capture nonlinear relationships and interactions between inhibit features more effectively. XGBoost, in general, adds further refinements such as gradient boosting, regularization, and column sampling, which helps to outperform even Random Forest in difficult prediction tasks.

The R^2 differences are illustrative of each model's power to explain variance. The KNN's R^2 of 0.578 means it might leave for more than 42% of the variance unexplained, which could severely limit its value in reliable forecasting. Random Forest for instants, with R^2 of 0.847, and XGBoost, at 0.854, both exceed the generally accepted threshold of 0.8 for strong predictive models. These models did not only produce lower error rates but also indicated a deeper understanding of the complex relationships in the data. Additionally, for policy-making or crime prevention data allocation is crucial for predictive precision.

In conclusion, this result analysis demonstrates that the model used, particularly XGBoost, provides the best reliable crime forecasting results in this study. The performance benefits are measurable across all key metrics and its accuracy, MAE, RMSE, and R^2. The results emphasize the importance of implementing robust, flexible models capable of handling high variance data. Future work may involve using feature engineering, including spatial-temporal attention mechanisms, and extend the model to deep learning models such as Temporal Graph Neural Networks (TGNN) to improve further forecasting accuracy.

VI. Implementation

The implementation of this research centers around the development of an interactive web application built with Streamlit to showcase and compare the performance of different machine learning models in predicting crime patterns. Instead of focusing heavily on the internal mechanisms or training processes of the models themselves, the application serves as an interactive interface for exploration, visualization, and interpretation of the results generated by the Random Forest, K-Nearest Neighbors (KNN), and XGBoost regressors. The emphasis is placed on making the analysis accessible and actionable, particularly for stakeholders such as policy analysts, law enforcement strategists, or data science learners.

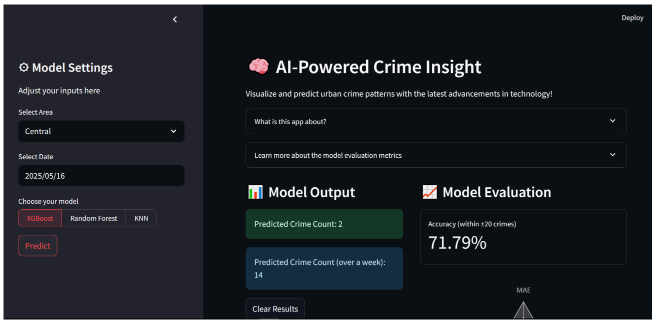

Figure 5. Streamlit dashboard

The Streamlit dashboard was designed to be user-friendly and intuitive. It allows users to dynamically adjust key parameters such as the model selection, the train-test split percentage, and filters for specific years within the dataset. In addition, users can choose a specific date and area to generate predictive outputs. Once a model is selected and parameters are configured, the app fetches the saved model results from disk, including performance metrics such as MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), and R^2 (coefficient of determination). These metrics are then displayed visually through custom charts including line charts and radar plots for single-model analysis.

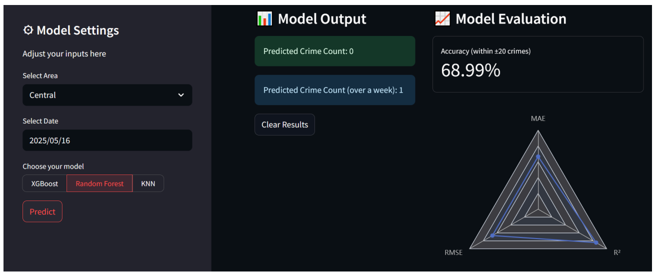

Figure 6. Model analysis on radar plot

Each model's prediction accuracy is also presented using progress bars or gauge charts to give users a quick visual sense of model performance. Furthermore, the dashboard includes a spatial heatmap that visualizes total crime density across different geographic regions based on historical data, helping to contextualize the prediction outputs geographically. For users interested in deeper understanding, an expandable markdown section explains how each metric is calculated and what it represents in the context of predictive modeling.

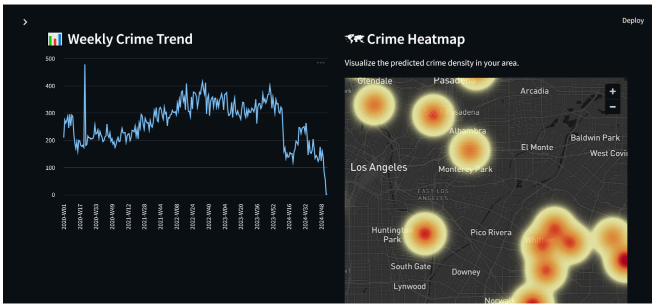

Figure 7. Crime trend display

While the core machine learning models were implemented and evaluated offline, the Streamlit app was structured to load precomputed results using Joblib, ensuring fast and responsive interaction. This design also enables modular programming and scalability, where future models or evaluation metrics can easily be added to the interface without restructuring the entire pipeline. Through this implementation, the application transforms complex analytical results into interactive insights, serving as both a demonstrative tool and an exploratory platform for comparative crime prediction.

VII. Conclusion

In Conclusion, the comparative evaluation of KNN, Random Forest, and XGBoost models for weekly crime forecasting reveals significant differences in their suitability on handling complex, real-world data. Although KNN looks simple and easy to use, it underperformed with only 45.60% accuracy and a high MAE of 29.45, highlighting its limitations in modeling nonlinear relationships and dealing with noisy or high-dimensional data. Its limited ability to differentiate between informative and irrelevant features shows a result in less reliable predictions, emphasizing the need of dimensionality reduction or advanced preprocessing when using such models.

On the other hand, ensemble methods like Random Forest and XGBoost do deliver much better results, due to their robust handling of feature interactions and noise. Random Forest, with an R^2 of 0.847 and a 42.9% lower MAE than KNN, showed strong generalization by leveraging the power of multiple decision trees. XGBoost itself further produces predictive performance by incorporating gradient boosting and regularization, reaching the highest accuracy of 71.79%, lowest MAE of 16.26, and RMSE of 24.58. These metrics are showing XGBoost's ability to minimize both average and large-scale errors, while maintaining 85.4% of the variance in the target variable meaning a significant improvement over simpler approaches.

Overall, the study fully confirms that model selection is very important in crime forecasting, where spatiotemporal dynamics and data variability are used in a major role. MAE and RMSE provide direct insight into prediction reliability, while R^2 reflects the model's explanatory power. The findings suggest that most advanced ensemble learning techniques, particularly XGBoost, are better equipped for real-world deployment in predictive policing systems. This conclusion is strengthened by the practicality focused evaluation metric which has an accuracy within ±20 crimes which further highlighted XGBoost's super performance. In addition, future work may be built on these findings by further exploring deep learning models such as temporal Graph Neural Networks (GNNs) to create even richer temporal spatial relationships that enhance predictive accuracy in urban crime analytics.

VIII. References

[1] Alparslan, Y., et al (2020). Perfecting the Crime Machine. Documento disponible en: arXiv:2001.09764v1 [cs.CY] 14 Jan 2020

[2] Bogomolov, A., et al (2014). Once upon a crime: towards crime prediction from demographics and mobile data. https://dl.acm.org/doi/10.1145/2663204.2663254

[3] Crime Statistics & Trends in Los Angeles, CA (2025). 2025. [Online]. Available: https://getsafeandsound.com/blog/los-angeles-crime-statistics/#:~:text=Los%20Angeles%20currently%20has%20a,rates%20below%201%2C500%20per%20100%2C000.

[4] Ensign, D., et al (2018). Runaway Feedback Loops in Predictive Policing. Proceedings of Machine Learning Research 81:1-12. Conference on Fairness, Accountability, and Transparency.

[5] Gallar, A., De Lara, A., (2020). "Conceptos y Contextos", UMH Sapiens 26 | Inteligencia Artificial.

[6] Hicham, A., et al (2018). A crime prediction model based on spatial and temporal data. Periodical of Engineering and Natural Sciences. Vol. 6, No.2, pp.360-364. Disponible en: http://pen.ius.edu.ba Machine Learning and Applications: An International Journal (MLAIJ) Vol.8, No.1, March 2021

[7] IALAB (2019). Laboratorio de Innovación e Inteligencia Artificial de la Universidad de Buenos Aires – Argentina. Disponible en: https://ialab.com.ar/prometea/

[8] Kim S., Joshi P., Kalsi P.S. and Taheri P. (2019). Crime Analysis Through Machine Learning, doi: 10.1109/IEMCON.2018.8614828

[9] Stec, A., Klabjan, D. (2018). Forecasting Crime with Deep Learning. Documento disponible en: https://arxiv.org/pdf/1806.01486.pdf

[10] YingLung. L., et al. (2017). Using machine learning to assist crime prevention, IEEE 6th Intl. Congr. on Advanced Appl. Inform. (IIAIAAI), Hamamatsu, Japan.
https://ieeexplore.ieee.org/document/8113405

[11] Yuting, M., Li, F., (2019). Predictability Comparison of Three Kinds of Robbery Crime Events Using LSTM. Association for Computing Machinery, ACM, ISBN 978+1-4503-7216-9. https://doi.org/10.1145/3354153.3354162

[12] Ying-Lung L., et al(2018). Grid-Based Crime Prediction Using Geographical Features. International Journal of Geo-Information.https://www.mdpi.com/2220-9964/7/8/298

[13] Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324

[14] Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). https://doi.org/10.1145/2939672.2939785

[15] Cover, T. M., & Hart, P. E. (1967). Nearest neighbor pattern classification. *IEEE Transactions on Information Theory*, 13(1), 21–27. https://doi.org/10.1109/TIT.1967.1053964

[16] Mohler, G. O., Short, M. B., Brantingham, P. J., Schoenberg, F. P., & Tita, G. E. (2015). Randomized controlled field trials of predictive policing. *Journal of the American Statistical Association*, 110(512), 1399–1411. https://doi.org/10.1080/01621459.2015.1077710

[17] Ratcliffe, J. H. (2010). Crime mapping: Spatial and temporal challenges. In A. R. Piquero & D. Weisburd (Eds.), *Handbook of Quantitative Criminology* (pp. 5–24). Springer. https://doi.org/10.1007/978-0-387-77650-7_2

[18] Bogomolov, A., Lepri, B., Staiano, J., Letouzé, E., Oliver, N., Pianesi, F., & Pentland, A. (2014). *Once upon a crime: Towards crime prediction from demographics and mobile data*. Proceedings of the 16th International Conference on Multimodal Interaction, 427–434. https://doi.org/10.1145/2663204.2663254

[19] Hicham, L., Toumi, H., & Ennaji, A. (2018). *Crime forecasting using recurrent neural networks*. International Conference on Advanced Intelligent Systems for Sustainable Development (AI2SD), 1–6. https://doi.org/10.1109/AI2SD.2018.8478535

[20] Kim, Y. H. (2019). *Crime prediction model using machine learning techniques: A case study of Vancouver city*. Journal of Information and Communication Convergence Engineering, 17(3), 169–174. https://doi.org/10.6109/jicce.2019.17.3.169

[21] Stec, A. (2018). *Deep learning for crime prediction*. arXiv preprint arXiv:1801.03073. https://arxiv.org/abs/1801.03073

[22] Ying-Lung, L. (2018). *Grid-based crime prediction incorporating criminal environment features*. IEEE Access, 6, 41301–41310. https://doi.org/10.1109/ACCESS.2018.2858526