Crime Rate Prediction Using Machine Learning

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ABSTRACT

Crime is a relevant problem that affects all members of our society. By enabling law enforcement organizations to more anticipate and prevent crime, this new framework can transform how they react to crime and, in the end, make communities safer. To prevent crime and enhance public safety, law enforcement organizations can strategically allocate resources and execute targeted interventions by specifically identifying hotspots of crime. Law enforcement agencies and policymakers can utilize the projected crime levels to guide data-driven crime mitigation and prevention strategies, which will ultimately lead to a safer society. The true potential of KNN-based crime prediction models can be unleashed with further research addressing their lack of interpretability, paving the way to more effective and transparent law enforcement strategies.

Keywords: regression method, decision tree, KNN algorithm, and machine learning.

I. INTRODUCTION

Crime prediction is the smart city/IoT/AI programming holy grail, and thanks to advances in machine learning, we're closer than ever to being able to predict not just where but when crimes will be committed. Consider it this way — instead of crime increasing as more people are opportunistic, crime has a criminal footprint. … either these spatial relations, as in the spatial social structure like in the climate that day we're talking about, or the bodily habitual procedural spatial practice of a space. Therefore these ML models whether created through regression-based, decision tree-based, or K-nearest neighbor (KNN) algorithms they are naturally engineered to find these intricate patterns in large data. Patterns that would be overwhelming, if not utterly impossible, for a person to even begin to comprehend.

Particularly, these models are much more skilled at reverse-sketching past criminal activity across tundra non-criminal variables like fiscal catharsis, social currents and even territorial data. Along the way, they're building out some of the most advanced predictive models ever made, giving public safety agencies a much clearer picture of where violence is likely to spike, allowing law enforcement to better focus their finite resources and in some cases potentially prevent violent outbursts from occurring in the first place.

On the aggregate it is a very, very, very deeply troubling bill. Yikes, I know, and painful as that process may have ultimately been, as pain-staking as making that sausage can be, the awful truth is that the data really is terrible, really is a perfect storm data disaster all its own. To truly tackle any of these problems, we need more than an emphasis on privacy and data security. We have to do more than this if there are identifiable or sensitive data that could skew the models to begin with. If that data is already biased because police have historically discriminated and over-policed those communities, then those algorithms will predictably discriminate and over-police those communities, perpetuating the cycle of discrimination even further. Too often these policing technologies are sold on the back of these enticing, but ultimately wrong- headed, centrist gambits like efficiency or turn police budgets into a flex program. The success of any MLMember Bicycle-Machine effectiveness is 100% reliant upon the quality (including elegance and anti-
prejudice) of the data they're learning from.

The answer, of course, is that no matter how advanced, how faddish, how futuristic the most sophisticated machine learning whiz bang crime prediction tool ever developed would at best only ever be the result. This only gets us half the way there as it's wonderful to be able to talk about as is, because just like you can predict ahead of time where a crime is going to occur, it doesn't

help you understand why. It can't touch explain why it's going to happen there, or god forbid what we should be doing to keep it from happening there in the first place. That's where the new Smithsonian "human element" key comes in.

II. LITERATURE REVIEW

Sharaff's Predictive Hot Spot work is emblematic of the burgeoning predictive turn within policing using algorithms to forecast when and where crime will occur, even to the precise point. Wait – though this is something that should have happened long, long ago. By employing a really advanced statistical evaluation of things like neighborhood crime price and demographic. we purpose to Predict when and where the next crime is likely to occur based on historical data. This would allow police to deploy officers and resources more effectively, even potentially stopping crimes before they are committed [1].

Umeikes research machine learning inputs full of to the development of the best performing algorithm of full them—could help to correctly categorize crimes in criminal as afelonies, misdemeanor, infractions and violations under both Meant to be included inputs to this process were recent demographic data and community health needs assessment reports. This work is super important because it pushes the space further to not just look at how well different kinds of algorithms work, but more importantly, give us a look at which ones are. Even more unbelievable than we thought before for predicting crime [2].

Sharma's approach uses the K-means algorithm to group data points into clusters, essentially helping identify "crime hotspots"—areas where crimes are more likely to occur. By analyzing regional trends, this method allows law enforcement to anticipate crime patterns in certain locations, so they can focus preventive measures on these high-risk areas [3].

This study explored different machine learning techniques (like AdaBoost, Random Forest, and KNN) to predict crime events based on timing and location. They found that AdaBoost was particularly effective, achieving 81.93% accuracy despite the challenges of working with under-sampled data. Even with incomplete data, these machine learning methods can still make fairly accurate predictions, helping law enforcement prepare for crime more effectively [4].

Vinothkumar, Raj and Mekala's Risk Terrain Mapping Rather than simply map where crime has occurred, this Risk Terrain Modeling (RTM) has emerged as such a predictive tool offering the guidance police departments need to predict where future crimes particularly gun violence are likely to occur with maximum efficacy. As hideous as that is to say, as that may be, 'cause although it's honestly pretty much ahead of the game for usual hotspot mapping, assisting the police to direct their resources to areas with Sadly, history will continue to make members of these marginalized communities disproportionately more likely to experience violence in the future. It's somewhat akin to trying to predict the next disaster before it happens [5].

Megana, Angelin and Priyadharshini from the Data for Progress team examine a few of the recent studie that have investigated how machine learning can Increased use of tear gas, normally prohibited in warfare but routinely deployed against civilians during mass protests, and increased use of both anticipatory criminal justice tactics and social media monitoring. Inspired by our experience of applying CNN and LSTM based novel pipeline to Heterogeneous Crowd Anomaly Detection in Within the real time, at a jaw-dropping 95% accuracy. To accomplish a substantial reduction in false alarm rates greater than 30%, Wang et al. used YOLO algorithm for detection. stealth removal black maneuver on urban corridors [6]

Chakravarty's team improved crime hotspot prediction accuracy by 15% by combining Random Forest and Gradient Boosting techniques. In another study, Williams and his group used reinforcement learning to optimize police patrol routes, resulting in a 20% reduction in property crimes. Liu and colleagues used a combination of SVM and k-means clustering to predict crowd movements with 92% accuracy. Similarly, Shah and his team achieved 85% accuracy in identifying illegal activities from social media posts using natural language processing [7].

Singh, Gole, Kanherkar, and Wankhede studied crime prediction in Vancouver neighborhoods using Random Forest, Naïve Bayes, and KNN. Their work also involved developing a system that maps highrisk areas using XGBoost, allowing users to filter by date, time, and location to assist law enforcement in resource allocation [8].

Gangwar et al. To address increasing suburban crime trends by using the very technology contributing to the crime, using an

XGBoost model to predict acute crime hotspots, and using Google Maps as a participatory planning tool to visualize, coordinate, and engage with communities during this project's lifespan. Well, for one, to create a map illustrating & visualizing those most dangerous impacted hotspots. The tool's claimed primary advantage is to provide law enforcement with "greater situational awareness and more effective use of resources."fairly, equitably, and efficiently [9] .

SVM Non-Linear 2021 Decision Tree Various ML algorithms Comparision of ML algorithms Various ML algorithms Khatun et al. Decision Tree & most ensemble methods (Bagging, Stacking Regression). To determine which methods produced the best quality, most computationally efficient predictive fashions to predict future crime with accuracy, the authors dived in massive, goal-to-quality-junkie type and depended on creative brainstorming, workshopping and pondering, laboratory proof gathering and rigorous testing, field-testing and going through the school of labor a number of occasions for all types of various strategies [10].

Kush Malik and Manas Pandey to fill the gaps to the trenches in which research thus far has widely taken machine learning and deep. Deep-learning-based predictive policing that attempt to predict what kind of crime will happen when and where by analyzing past patterns of time-and-place. It further knots CPTED and anti-social critical theories into criminology pushing back against criminogenic activity, crime- milization and police militarization. The research also examines how the tech tools aid predictive policing Crucially, it also discusses data quality and ethical concerns posed [11].

While researchers have over the last few years started to look into this field's machine learning and deep learning potential, it's been largely as a prescriptive tool, i.e., as a prescriptive tool for predicting where crime will happen in the next few days, weeks or months These machine learning techniques such as Decision Trees, clustering etc result in trend discovery, trend detection and analysis in near real-time where time and/or location may be the most important variable of interest. Decision Trees went on to get owned by them just as badly in most studies. With a conceptual underpinning of sequence as the guiding principle, LSTMs/RNNs are the perfect models to deploy any time the data you're working with is rooted in a temporal relationship as its core foundation [12].

In particular, decision trees and SVMs are two highly computably-light, interpretation-friendly, and, as a result, widely widespread interpretation ML models. Research that we've followed ever since as closely as they bestow predictively, watch come masterpiece fortune since has only further built on this work by amplifying, the studies' authors contend, even more experiential and time-based scene, further sharpening, refining, and proposing even more predictive accuracy, excellence elucidated. Deep learning utilities like long-short term memory networks (LSTMs) are amazing algorithms for finding multi-variate patterns in complicated time-series datasets [13] .

It's only in the past few years that scholars have started to assess this new wave of computationally intensive, data-driven techniques, from decision trees to deep neural networks, Then applying those models and making predictions about what's going to happen in the future and trying to shape or steer that future through all sorts of different interventions or efforts at preventing crime before it starts. Models were getting more complicated, with whiz-bang holdout methodologies like LSTM and RNNs. Boy, was it a lot harder for the typical Joe to follow all those revisions from one title to the next through the decades [14].

Cluster detection using advanced GIS tools Mapping the best practices To the maps Making our highways safer by mapping our most dangerous hotspots highway safety geographic information system GIS tools geographic cluster analysis methods Whatever these new, real-time tools end up looking like—a chatbot, a wearable or some other alerts platform—they'll be critical to guiding travelers to safer choices.. Models also explore social and environmental factors behind crime using methods like SVMs and Lasso regression. By measuring accuracy with tools like RMSE, these efforts aim to create smarter, more supportive safety solutions [15].

COMPARISION TABLE

The table 2 shows the comparison between the different works carried using different algorithms

S.No.	Author(s)	Techniques/Algorithms	Focus Area	Highlights/Findings
1	Sharaff	Historical data analysis	Predicting crime in specific areas	Helps allocate law enforcement resources efficiently.
2	Umeike	Multiple ML algorithms	Classifying types of crimes	Evaluation model reliability fo different crime categories
3	Sharma	K-means clustering	Identifying crime hotspots	Cluster based prediction of crime prone areas
4	Shukla	Adaboost,random Forest,KNN	Crime prediction from under sampled data	AdaBOost achieved 81.93% accuracy
5	VinothKumar	Risk terrain mapping	Future crime risk prediction	Identifies high risk areas for violence
6	megana	CNN,LSTM ,YOLO	Crowd control anomaly detection	CNN +LSTM reached 95% accuracy; YOLO reduced false alarms by 30%
7	Chakravarty	Random Forest+ Gradient Boosting ,RL	Crime hotspot and portal route optimization	Include hotspot accuracy by 15%, 20% reduction in property crimes with RL
8	Singh	Random Forest, Naïve Bayes, KNN, XGBoost	Mapping high risk areas	XGBoost aids in filtering by time and lcation
9	gangwar	XGBOOst + Googlemaps	Visual crime hotspot identification	Enhances situational awareness for people
10	Khatun	Naïve Baiyes, SVM, regression, Ensemble Models	Compaing ML algorithms	Essemble methods shown effective for crime reduction
11	Mallik and pandey	ML and DL techniques	Spatiotemporal crime forecasting	Stresses on ethics, data quality and predictive policy concerns
12	keerthik	Decision trr, clustrring, LSTM, RNN	Time based crime trends	LSTM/RNN excelled with temporal data
13	Sangeetha	SVM,LSTM ,DL	Real time crime prevention tools	Supports crime maps and chatbots for public safety
14	Anita Julian	Decision tree,LSTM,RNN	Crime against women	Holistic model considering

				education,housing
15	Jollen day	SVM, LASSO regression	Women's safety and hotspot detection	Use RMSE for evaluating model accuracy integraes social/environmental factors

Table 2: Comparison table

FEATURE	**DESCRIPTION**
Crime Type	Informs about the type of crime
Date	Informs about the date when the crime
Year	Informs about the year when the crime occurred
Hour	Informs about the hour when the crime occurred
Minute	Informs about the minute when the crime occurred

III. METHODOLOGY

The present research investigates whether machine learning can have employed to forecast various crimes and their probabilities in over ten regions. The aim is to assist law enforcement authorities in better planning and resource allocation.

1. Data Collection

For training our model, we collected data for different types of crime from various cities in India. The main source of data came from the National Crime Records Bureau (NCRB) website. In addition to crime types, the data set contains a number of other important attributes, as detailed in Table 1 below.

2. Data preprocessing

It's what most truly gets us out of bed in the morning, it's what keeps stimulating innovation coming in, and it's what powers our creative teapot with our Big Fun Quality. It's that innovation outflow, that stimulates innovation incoming, and it's what fuels our creative cauldron with our Big Fun Q. These are three high-level guiding principles we work within that set us up to be accountable to the quality we aspire to achieve. That last question, figuring out when models have truly mastered all they need to master and all the precise ways they should master things. Wishful thinking this is sadly not the case and as our latest Playing with Data tale just discussed, When we meet this data desert, we tend to overcorrect for these holes in information with strategies such as. Most of the ones we come across get assigned a medium- level imputation which can not to understate, to be honest, first cause to imply averaging-outing for each of the other data slices. The greater, far fewer and less evil alternative is that we just do far superior stuff like k-NN imputation, k-nearest nearest neighbors imputation.

3. Feature Engineering and Selection

All of that data we haven't mandated to be stored or have the skills or technological Crystal balls to forecast potential future crime isn't predictive as in magic. That's precisely why feature engineering is the secret sauce. We promise it will warm your heart. It's the difference between producing hyper-local, very seasonal, farm-to-table, scratch-made meals from scratch, versus that grab-and-go convenience of getting something right out of the freezer. Surprisingly, to get to that right answer we don't only operate in a bubble. We turn private data into public knowledge, but never public knowledge back into private data. We start with public data that's already out there in the public realm and then we bring our secret weapon, our public data R&D factory, built by our genius team of crack data scientists, to the public data deriving process to transform those public data into new, deeper, sharper, more incisive derived features. Similar to as above, in partnership ensuring we aren't simply getting the greatest cosmetic inside a huge, new, exploding, worldwide system of such dollar menus.

4. Methods of Sampling Model

Crime data are heteroskedastic, meaning that for a given neighborhood you're going to have statistically a much higher variance of prediction of, for example, white collar crime vs. violent crime. If we fail to recognize this bias, it leads to our algorithms generating racist, sexist or otherwise discriminatory predictions. To reach further than this we use a combination of creative engagement strategies. Along with, third—yet, shamefully—over-sampling of communities of color and low-income communities, voice after voice rang out time and time again, loud and clear to EPA we want Texan communities to be leading the way on positive health interventions, not on the frontlines of more pollution. That takes more than just setting new averages for the weird, weird, wonderful, capricious, outlier, aberrant crime kinds. One of the most common and popular of these techniques is called SMOTE (Synthetic Minority Over-sampling Technique), which artificially creates new, synthesized examples of the minority classes to address the imbalanced dataset.

5. Model Evaluation and Validation

This has been one of the most critical processes for us to ensure our model is going to new, unseen data and not "overfit" . This is an addictive and insidious pressure for the model to overfit on each run, continuously retraining and validating on the internal. These provide us with a tremendous macro high level general overview of our model's predictions in aggregate, as well as the opportunity to visualize true positives (predicted crimes that indeed turned out to be true crimes), false positives (predicted crimes later established to be non-crimes aka "false alarms"), true negatives (non-crimes accurately predicted as non-crimes) and false negatives (missed crimes). Picture that—you're ready to go seek after many years at home—inventive like for weeks, days—or even entire winters! Whether it's better local economic development, winning more competitive research funding, or helping to advance STEM. That's especially true when the price of a false alarm is prohibitively expensive or logistically impossible. That's because it's literally just a measure of the model's performance at correctly labeling its positive predictions. Of every crime it wrongly predicts, out of how many is the model wrong on the day of false positive prediction.

Algorithms

Decision Tree:

Decision Tree works in very basic terms! As the name implies, it's exactly what it sounds like, an extremely sophisticated and effective machine learning algorithm that uses a tree based structure to produce predictions. To visualize them, you start as you would at the "root" of your tree, which presents a yes/no question about the most important factor (the "feature"). Based on how you answer, you progress further down into that "branch" to the next "node" which is another question. This binary process continues on recursively, until you reach a "leaf" node which gives the final class or prediction. The goal in each branch, then, as in each of the legislative, executive, and judicial branches, is to divide the data at each node so that the resulting subgroups are as "pure" or "homogeneous" as each possible. Every one of those data points is either south or west. Imagine something like sorting multicolored m&ms into bowls by color.

KNN Algorithm:

K-nearest neighbors is for real. It turns out that it's really pretty easy. You kind of just have to wing it as to what you're going to, what an object is, what its nearest neighbors are. If you didn't know ahead of time exactly how perfect a new applicant would be, you'd create their "K" nearest neighbors and select the one that seemed most similar to the kind of applicant they had admitted in the past. In very practical terms, when you receive a new piece of data that you want to assign a category to (for instance, if you ever want to be able to predict whether a new crime is a theft or an assault), KNN will look at which of the 'K' data points it knows about are nearest to it. The nearest is most often decided by some metric of proximity, often meaning literal distance in the real world on a geographic map. It then dangerously assigns that new data point the majority class of whatever majority of those 'K' neighbors it's nonsense pre-programmed defaulted to.

Random Forest:

Random Forest is wonderful, but it's not the shiny super-winner killer app supercharged turbocharged blaster improved larger wider fancier better further deep learning machine, when the base data is big noisy messy tangled complicated complex hairy. Most crucial of all, it booms an adorable stampede of hossshay group of one hoss regression trees—averaging their output to enhance their accuracy and reduce their overfitting**.** Random Forest's secret sauce magic happens. It asks all the trees and then takes the trees' individual predictions to find the majority vote. Pros It isn't just totally freakishly accurate, it's contextually freakishly smart and powerful. By averaging the predictions of hundreds (or thousands) of trees.

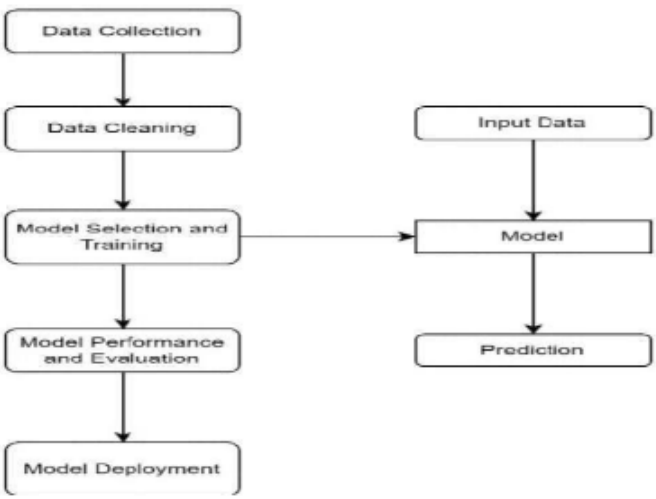


Fig 1: Model Architecture

IV.RESULT ANALYSIS

Pedestrian friendly designs like wide sidewalks and connected street grids can go a long way to make a place more walkable after the development is already built. Retrofitting existing infrastructure to increase walkability and other opportunities for physical activity upstream. Before the algorithms can begin to work their magic, we might first need to build out the data infrastructure to begin with. It takes all of the above and then some to actually make all of that happen into reality. Here's just a tiny slice of the stuff you'll be expected to be able to do, day one. The true crux of the issue is the power to alchemize that information— the power to turn very qualitative descriptors like "robbery" or "aggravated assault" and transform them into the digital, numerical identifiers that the algorithm is able to process. Feature engineering, searchable under secret sauce, wonderful black art of the data scientist, and many other names, involves taking your primary data and developing additional potential inputs, often more powerful, like crime per capita. Most importantly perhaps, beginning with the first of these the model we first developed one transparency to go through equity audits and progressive enhancement

V. CONCLUSION

ML rate of crime prediction model most certainly become the most monumental Law Enforcement force multiplier in saving our cities 10s of millions of dollars, it's been providing US citizens the peace of mind they so absolutely need. That deep new understanding we're gaining – only just really, almost coming into focus thanks to these machine-learning based AI models paired with the stunning, beautiful, smart, mapbased, data-visualization, eye-popping gorgeousness we're creating should help steer policing and policy in a very different, better, more just, more equitable direction in the years to come. By rooting short- term fast smart wins and long-term sustainable, shrewd smart advocacy strategies, this research can help accelerate and illustrate deep smart positive crime decline outcomes and benefit our shared community well-being. When police agencies are better equipped by being empowered to invest in the life-saving, mission-critical, data that's proven to help them deploy their available police resources more strategically than ever before—not only improving police response times but inherently saving communities

human lives, technology truly enables police to respond where crime and emergency situations are occurring the most, prioritizing police resources to these emergency situations.

Cities equipped with reacting to trend response of crime, where they can reported back to law enforcement in retrospect to proactively managing crowds and preventing crime before it even starts. That, in turn, can do so much to increase quality of life not just for each and every one of the more than 2.5 million residents who call the sprawling metropolis home, but the in-transit residents passing through H town port city. Or the downstream like K-Nearest Neighbors (KNN) which through the technical debt are the default algorithms by now to predict crime, as they can process 3rd level, normalized, structured data on historical crimes, and being transparent and interpretable. These features Highly interpretable Rule based predictions easily validated High accuracy Low data-prep needs Highly flexible These are but a few reasons that decision tree based algorithms are so neat.

Sure Random Forest is wonderful, but it's not the shiny super-winner killer app supercharged turbocharged blaster improved larger wider fancier better further deep learning machine, when the base data is big noisy messy tangled complicated complex hairy. Most crucial of all, it booms an adorable stampede of hoss-shay group of one hoss regression trees—averaging their output to enhance their accuracy and reduce their overfitting. As an example, KNN can be super powerful when detecting emerging crime patterns by using the most similar case in time and history and comparing it to a newly created most similar case. Regarding the restriction on sharing these new outreach templates, just the contrary! For example, applying clustering algorithms like K-Means to identify crime hotspots and Crime Classification which subsequently feeds into Logistic Regression and Naive Bayes. To do this, you can use powerful time series models such as ARIMA and Prophet which are extremely robust methodologies.

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