IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

An Innovative Approach To Crime Forecasting: Predicting And Preventing Crimes Using Computer Vision And Machine Learning Techniques

1Dr.Yazdani Hasan, 2Sumbul Afroz
1Associate Professor, 2Assistant Professor
1IIMT University-Meerut,
2IIMT University-Meerut

ABSTRACT

The topic of crime and the demand for effective deterrents are covered in the work. The rising issue of criminal activity has shown that conventional crime-solving methods are ineffectual. Consequently, there is a growing need to foresee crimes in advance or develop a "machine" that might help law enforcement personnel avoid crime. The suggestion is to use algorithms and techniques from computer vision and machine learning to overcome this problem. The paper provides concrete examples of applications of these strategies, providing motivation for additional investigation in this area. This investigation's main goal is to examine how combining ML and computer vision can enable law enforcement organisations to identify, stop, and solve crimes with unmatched precision and quickness. By utilising these cutting- edge technologies, law enforcement organisations might undergo a revolution and efficiently battle crime.

KEYWORDS

Machine Learning,computer vision,Artificial Intelligence,3D shape Model,Neural Network

1. PURPOSE

Regarding computer vision, it is astonishing how it makes it possible for computers to comprehend and interpret the visual world, making it useful in a variety of applications, including face recognition and object identification. Computer vision's skills may be further improved by ongoing research in 3D image interpretation. The ability of machine learning, on the other hand, enables systems to learn and improve automatically from prior experiences, making it beneficial in resolving difficult issues and spotting data trends. Machine learning is divided into two categories: supervised and unsupervised learning. Each has advantages and disadvantages. The correctness of the outcomes is still up for debate despite the vast study of neural networks. Crime forecasting approaches using machine learning algorithms and computer vision techniques provide great prospects for crime prevention and investigation. These techniques can save lives, lessen trauma, and safeguard private property by foreseeing and stopping crimes before they happen. Additionally, efficient resource allocation can aid governments in fighting crime more successfully. This is achieved through precise predictive policing.

2. ML TECHNIQUES IN CRIME PREDICTION

Utilising data analysis and statistical techniques, crime forecasting—also known as predictive policing or crime prediction—aims to predict the locations and times of criminal activity. Advanced analytics and machine learning algorithms are used to analyse historical crime data as well as other relevant data sources to identify patterns, trends, and potential hotspots for criminal activity.

Crime forecasting models frequently examine data from a variety of sources, including demographic data, geographic data, socioeconomic data, and data on past crimes. Machine learning algorithms are used to analyse the data, look for trends and correlations, and predictfuture criminal conduct.
Crime forecasting has several benefits, including better resource management, situational awareness, and the potential to prevent and reduce crime. However, there are additional concerns including bias, privacy, and the potential for overpolicing specific communities. It is imperative to carefully evaluate the effectiveness and fairness of crime predicting systemsin order to use them ethically and fairly.
In the discipline of crime forecasting, criminal activity is predicted and prevented through data analysis and predictive modelling methods. Some significant developments in crime prediction include the following:

Predictive analytics is the process of examining past crime statistics, demographic data, and other pertinent information to spot trends and forecast criminal activity in the future. To find connections, trends, and hotspots for particular crimes, machine learning techniques and statistical models are used.

Real-time data analysis and big data: These developments have greatly improved the ability to predict crime. Authorities now have access to a tremendous amount of data from a variety of sources, including social media, sensor networks, surveillance systems, and public records.

Geographic Information Systems (GIS): By combining geographic information such as maps, crime locations, and socioeconomic indicators, GIS technology plays a significant role in crime forecasting. Law enforcement organisations can use this data to overlay high- crime areas, comprehend the underlying causes of criminal activity, and create specialised measures to reduce crime.

Criminal activity frequently involves networks of people, according to social network analysis. Using social network analysis, it is possible to spot important players, criminal connections, and prospective crime patterns by looking at interactions between people, criminal organisations, and groups.
Software for predictive policing: Law enforcement agencies are now better able to predict crime thanks to the development of specialised software programmes. These software programmes combine several data sources, forecasting formulas, and visualisation tools to produce prediction models and actionable insights.

It is significant to emphasise that developments in crime predicting also bring up moral issues with bias, privacy, and potential technology exploitation. Therefore, great thought must be given to the legal, moral, and social ramifications before these tactics are implemented responsibly.

Different data mining and machine learning (ML) techniques are illustrated in reference [53] for application in criminal investigations. This paper makes a contribution by outlining the approaches employed in crime data analytics. For the categorization, comprehension, and analysis of datasets based on predetermined conditions, various ML techniques including a KNN, SVM, naive Bayes, and clustering were used. It is possible to identify the type of crime and the potential hotspot for future criminal activity by comprehending and analysing the data included in the crime record. The suggested model was made to carry out a number of tasks, including feature selection, clustering, analysis, prediction, and assessment of the provided datasets. This study demonstrates the need for machine learning techniques for forecasting and analysing criminal activity.

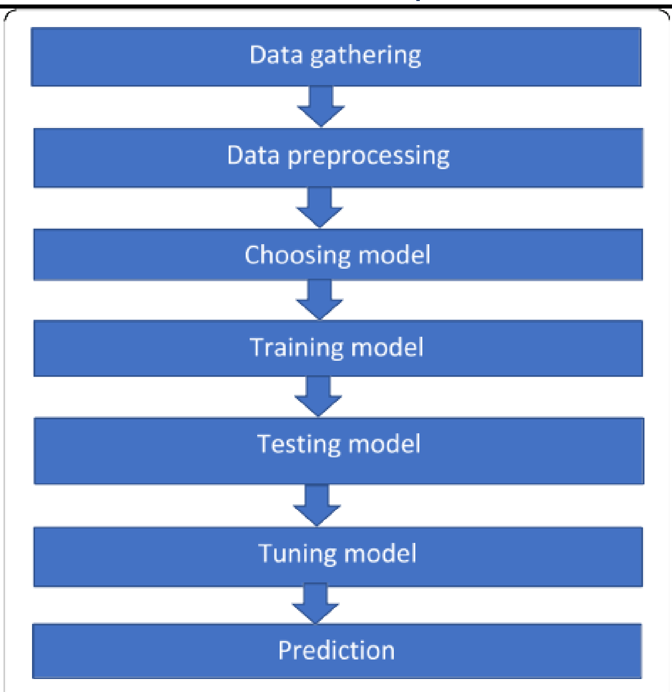

Fig 1 Data Flow Diagram

Crime forecasting is a proactive strategy that anticipates crimes before they happen and necessitates the creation of tools for proactive crime prevention. Currently, law enforcement uses a variety of methods for specialised purposes, including listening in on suspect phone calls, tracking smartphones with stingray devices, performing stakeouts, employing drones for surveillance, and using facial recognition, licence plate recognition, and body cameras.

However, some of these instruments, like stingrays and drones, have been used in ways that have sparked concerns about possible invasions of privacy and violations of the fourth amendment. It is crucial to take these legal issues into account and make sure that using these technologies complieswith the law.

Fig 2 Functionality of Proposed Approach

3. CONTRIBUTION

These examples show the efficacy and precision of machine learning algorithms in identifying crime trends and projecting crime in various cities. The studies analysed crime data and produced predictions using a variety of methods, including decision trees, linear regression, and K-nearest neighbour. The studies' predictions' level of accuracy varied, with some obtaining a higher level of accuracy than others. However, the authors came to the conclusion that tailoring the algorithms and crime data for particular applications might greatly increase the forecasts' accuracy. The research also emphasised the value of information gathering, categorization, and visualisation in predicting and analysing crime.

It is accurate to say that WEKA now features a new graphical interface called Knowledge Flow that enables a more streamlined view of data mining activities. The visual representation of the information flow in this interface is done using separate learning components represented by Java beans. In addition, WEKA offers another graphical user interface called the experimenter that was created specifically to examine the effectiveness of various learning strategies on distinct data sets. For those using WEKA, these interfaces may make the process easier to utilise. Please let me knowif you have any more queries or worries.

Predictive analysis can be used to forecast crime in metropolitan settings, according to the study cited in [44]. The study examined three categories of crime—home burglary, street robbery, and battery—and did so retroactively using information from the preceding three years' worth of crime statistics. The findings were compiled and the 2014 fortnightly and monthly crime rates were forecasted using an ensemble model that incorporated logistic regression and neural network algorithms. Direct hit rate, precision, and prediction index were used to assess how accurate the forecasts were. According to the study, predictive analysis may accurately anticipate crime, and the outcomes can be enhanced by contrasting fortnightly and monthly projections and by accounting for day and night.

The study cited in [46] claims that a machine learning (ML) strategy was utilised to forecast crime-related statistics in Philadelphia, United States. The issue was broken down into three parts: figuring out whether a crime happens, forecasting when one will happen, and figuring out which kind of crime is most likely to happen. In order to train the datasets and produce precise quantitative crime predictions, the study used a variety of techniques, including logistic regression, KNN, ordinal regression, and tree approaches. A map was also provided, showing various crime categories for a certain time period in various Philadelphia neighbourhoods, with various colours denoting each sort of crime. The ML system had a 47% accuracy in forecasting the number of crimes and a 69% accuracy in predicting if a crime will occur.

It's noteworthy that machine learning and data science techniques were used in reference[47] to forecast crime in Chicago, United States. The dataset used included data on the location's description, the crime's category, the date, the time, and its exact locations. KNN classification, logistic regression, decision trees, random forests, SVM, and Bayesian techniques were some of the models investigated. It was discovered that the KNN classification model had the highest accuracy,averaging about 0.787.

locating, tagging, and searching for objects and events in camera feeds. Although the potential impact of computer vision on the criminal justice system is optimistic, relying only on this technology may not be dependable.

4. COMPARATIVE STUDY OF DIFFERENT FORECASTINGMETHODS

It is noteworthy that automated visual surveillance systems utilising Knight have produced high accuracy detection, tracking, and classification results. However, the authors also noted significant difficulties such shifting lighting, concealment, boring moving objects, and shadows. This emonstrates how crucial it is for computer vision models to consider real-world scenarios.

The issue of low-quality security surveillance system footage and how it interferes with gathering forensic evidence is raised in reference[72]. It is troubling that even skilled forensic identification officers struggle when confronted with unknown targets in subpar films. The study also emphasises the value of recognising targets with a clear head because obscuring the target's head significantly affected crime detection.A reference[73] presented an automatic number plate recognition (ANPR) model. It required the image of the car to be captured, preprocessed, the licence plate to be extracted, character segmentation, and character recognition. Preprocessing of the photograph included grayscale conversion, noise removal, and border enhancement. Deep learning techniques were usedby the ANPR system to identify licence plates.

In reference[74], it was described how to alter a spatial temporal residual network in order to forecast the distribution of crime in Los Angeles on an hourly basis. The proposed model performed more accurately than tried-and-true techniques like ARIMA, KNN, and historical average. The inclusion of a ternarization technique solved worries regarding resource utilisation.

The importance of non-crime data for crime prediction was stressed by the authors of reference[75]. A fine-grained metropolis's crime was predicted using deep neural networks (DNNs).

Using the brightness of headlights and taillights, Reference[77] focused on traffic control and nighttime vehicle identification. The system developed by the scientists demonstrated the potential for nighttime surveillance by accurately detecting cars and bicycles with high scores.

Forecastingmethod	**Accuracy**	**Limitations**	**Observation**	**Ref**
1 Decision tree (J48)	59.15%	Took more time of 0.76 s to build model compared to 0.09 s of othermodels.	They took J48 naïve Bayesian andZeroR and compared them by running tests.	[58]
2 KNN (K = 5)	66.6939%	Data filling algorithms needs to be added to increase the accuracy.	In their research they try to prove that higher accuracy can be achieved if GBWKNN filling algorithm and KNN classification algorithm is combined.	[56]
3 KNN (K = 10)	87.03%	Naïve Bayesian has slightly higher accuracy.	They essentially divided data into critical and non-critical and then compared it in 5 classification algo-rithms and noted that naïve Bayesian, neural networks, and KNN predict better than the SVM and decision tree.	[57]
4 Naïve Bayes classifier	87.00%	Cannot be applied to the dataset having large number of features.	They implemented a novel crime detection naïve Bayes method for crime prediction and analysis.	[60]
5 Decision tree	83.9519%	As they are unstable, a small change in data can lead to a largechange in the structure.	They showed that decision tree performed better than the naïve Bayesian with the same crime dataset, using WEKA.	[59]
6 Naïve Bayes	65.59%	Computational speed, robustness, scalability, and interpretability werenot taken into consideration.	This paper presented comparative analysis on the accuracy of k-NN, naive Bayescand decision tree algo-rithms in predicting crimes and crim-inal actions.	[61]
7 Autoregressive integrated moving average (ARIMA)	The mean absolute error and standard deviation of the model are (1) Test average test standard deviation is 0.0867 ± 0.0293; (2) Training average training standard deviation is 0.0413 ±0.0084.	They have described this model as quite complex compared to others.	This paper is about the cons of fuzzy cognitive maps with respect to time series prediction. The ARIMA uses the auto-correlation parameters.	[62]
8 Regression model	They first took 10 crimes per month the expected forecast for absolute percent error (APE) was 42%. When 20 crimes were taken the expected forecast APE was 28%, and at 25 crimes per month the expected forecast APE was 25%. After 30 crimes they 13.5% error.	This research date backs 20 years.	They aim at predicting crimes 30 days ahead. They conduct the experiment inPittsburgh.	[63]
9 SVM	Over 10 months of experiment its accuracy was 84.37%.	The challenge that they indicated that we may face in the future could be to locate the best point at which spatial knowledge is available.	They compare different model to analyze which has the best chance at predicting hotspots.	[64]

5. PROPOSED IDEA

After researching and evaluating the various police surveillance methods, we assessed the significance of each strategy. Every surveillance technique has the potential to be effective on its own, yielding results that are adequate but limited to certain qualities. For instance, the use of a Sting Ray hinges on having accurate knowledge of the location of the stakeout because it can only be used when the suspect has a phone that is turned on. This is an example of how advances in technology have led to the development of intelligent monitoring technologies based on computer vision, machine learning, and deep learning approaches. Once trained, these systems mimic human behaviour by completing tasks regularly and reliably every day, 365 days a year.

Even though we've already discussed computer vision and machine learning's successes, let's take a closer look at their fundamental components. the inclusion of essential Sting Ray components like body cameras, facial recognition, number plate identification, and stakeouts. Additionally, there are features for computational linguistics, voiceprint recognition, natural language processing, gait analysis, biometric recognition, pattern mining, intelligence interpretation, threat detection, and threat categorization. Additional features include Bayesian networks, neural networks, heuristic engines, recursion processors, and core analytics. These features are primarily reliant on computer systems and demand human involvement from the beginning of creation. However, once formed, they work on their own, freeing humans to do other tasks. Let's look into the drivers behind each function:

1. Core analytics: This involves applying statistical techniques to predict a range of outcomes, from behavioural patterns to potential retail thefts.

2. Neural networks: These networks imitate the function of the human brain and enable comprehension and prediction of crime scenes by employing algorithms to establish connections between data.

3. Heuristic engines: By identifying and eliminating known dangers, these engines increase system security by leveraging knowledge and data from antivirus software.

4. Cryptographic algorithms: These algorithms do two tasks: encrypt recently discovered potential criminal data, and encode hidden illicit content.5. Recursion processors: By repeatedly carrying out duties to maintain surveillance, these processors guarantee the continuing execution of our machinefunctions.

6. Bayesian networks: These probabilistic models aid in thinking, diagnostics, automated insight, and time series prediction.

7. Data gathering: This crucial phase involves compiling details about previous crimes in order to learn from them and predict criminal activity in the future.

8. Document processors: To aid in learning, these processors organise, classify, and extract information from obtained information.

9. Computational linguistics: Using algorithms and learning models, this method aims to teach computers how to understand spoken human language, allowing them to recognise and understand human speech.

10. Natural language processing: This technique aids computers in better understanding human languages.

11. Voiceprint identification: This application uses mathematical algorithms to analyse factors such as mouth and throat shape to categorise persons based on their distinctive voice characteristics.

14. Data mining has a subset called pattern mining that can assist identify patterns in routine behaviour. With the use of this technology, anomalies can be found, such as a person who always appears behind a drugstore window at a specific hour.

15. Intel interpretation: This process involves comprehending and making sense of the information acquired by combining the outcomes of multiple aspects.

16. Threat detection: A threat is recognised during the intel processing stage if specific checkboxes are

checked.

17. risk categorization: When a threat is detected, it is classified and categorised into several levels of criminal crimes, such as burglary, murder, and potential terrorist attacks. It is now possible to make a forecast.

6. CHALLENGES

Although the basic idea behind crime prediction is straightforward, doing so requires much more than just understanding the idea. In order to make crime prediction a realistic possibility, this book aims to support researchers who are working to apply cutting-edge technologies in practical settings. The use of such software has the ability to fundamentally transform how law enforcement functions and significantly boost their effectiveness, even though the police do occasionally use new technologies like facial recognition and Sting Rays. In order to create a system that is particularly helpful to law enforcement, this study suggests a framework for merging computer vision, deep learning, and machine learning. From identifying criminal hotspots to keeping an eye on them, our recommended strategy includes a number of tools.

7. FUTURE PROSPECTS

This article has provided a variety of strategies and methods to aid law enforcement organisations and anticipate crime. As a result of the potential application of numerous techniques for crime prevention and prediction, law enforcement may alter. Combining machine learning (ML), computer vision, and security systems like surveillance cameras and spotting scopes can significantly increase the productivity of law enforcement organisations. By combining ML and computer vision with security tools and learning from patterns of previous crimes, machines will soon be able to predict future crimes with accuracy without human intervention. One potential use is the development of a system that forecasts and locates crime hotspots in a city, assisting law enforcement.

8. CONCLUSION

It is simple to understand the idea of foreseeing crimes before they happen, but to make it a reality, much more is needed. This study was written to assist academics who are attempting to apply such advanced technologies in practical settings and make crime prediction a reality. However, deploying such software can fundamentally transform how police work in a much better way. Every few years, police use new technologies like facial recognition and sting rays. This study provided a paradigm for how computer vision, machine learning, and deep learning may combine to create a system that is significantly more useful to law enforcement. Our proposed system's technology can do everything from locate criminal hotspots to recognise individuals based on Our proposed system includes technologies that can perform everything from locate crime hotspots to recognise people based on voice notes. The system's creation itself will present the biggest challenge, which will thereafter be followed, among other things, by problems with its use and implementation. We can fix all of these problems, and we could benefit from a security system that constantly scans the entire city. To put it another way, envision a day in the future where a police department employs a technology that greatly increases the reliability of tips and leads.

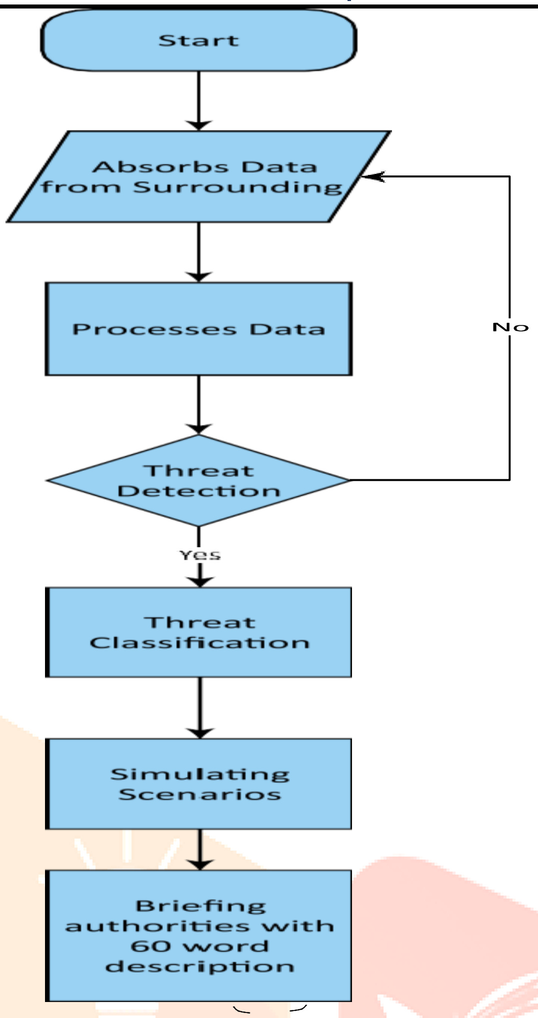

Fig 3 Flow chart of our proposed Model

There are still some concerns that could arise later, despite the careful study and writing that went into this article. The entire system must first be developed precisely and thoroughly in the near future in order to guarantee proper and speedy implementation. In addition, the implementation of such technologies itself creates important issues because they cannot be immediately used in the real world. The system must be trialled in a small section of a metropolitan area before being employed on a larger scale, and it must then go through continuing modifications and improvements. Because of this, these challenges offer opportunities for steady model development that will eventually lead to a flawless system that can be applied in real-world situations.

REFERENCES:

[1] M. Cahill and G. Mulligan, ''Using geographically weighted regression to explore local crime patterns,'' Social Sci. Comput. Rev., vol. 25, no. 2, pp. 174–193, May 2007, doi: 10.1177/0894439307298925.

[2] J. M. Caplan, L. W. Kennedy, and J. Miller, ''Risk terrain modeling: Brokering criminological theory and GIS methods for crime forecasting,'' Justice Quart., vol. 28, no. 2, pp. 360–381, Apr. 2011, doi:10.1080/07418825.2010.486037.

[3] A. Almehmadi, Z. Joudaki, and R. Jalali, ''Language usage on Twitter predicts crime rates,'' in Proc. 10th Int. Conf. Secur. Inf. Netw., Oct. 2017, pp. 307–310, doi: 10.1145/3136825.3136854.

[4] V. K. Borooah and N. Ireland, ''Deprivation, violence, and conflict: An analysis of Naxalite activity in the districts of India,'' Int. J. Conf. Violence, vol. 2, no. 2, pp. 317–333, 2008, doi: 10.4119/UNIBI/ijcv.42.

[5] A. Babakura, M. N. Sulaiman, and M. A. Yusuf, ''Improved method of classification algorithms for crime

prediction,'' in Proc. Int. Symp. Biometrics Secur. Technol. (ISBAST), Aug. 2014, pp. 250–255, doi: 10.1109/ISBAST.2014.7013130.

[6] P. Pławiak, M. Abdar, and U. R. Acharya, ''Application of new deep genetic cascade ensemble of SVM classifiers to predict the Australian credit scoring,'' Appl. Soft Comput., vol. 84, Nov. 2019, Art. no. 105740, doi: 10.1016/j.asoc.2019.105740.

[7] Z. Li, T. Zhang, Z. Yuan, Z. Wu, and Z. Du, ''Spatio-temporal pattern analysis and prediction for urban crime,'' in Proc. 6th Int. Conf. Adv. Cloud Big Data (CBD), Aug. 2018, pp. 177–182, doi: 10.1109/CBD.2018.00040.

[8] A. Almaw and K. Kadam, ''Survey paper on crime prediction using ensemble approach,'' Int. J. Pure Appl. Math., vol. 118, no. 8, pp. 133–139, 2018. [Online]. Available: https://internal-pdf://107.93.182.66/18. pdf%0Ahttp://www.ijpam.eu

[9] T. B. Hyde, H. Dentz, S. A. Wang, H. E. Burchett, S. Mounier-Jack, and C. F. Mantel, ''The impact of newvaccine introduction on immunizationand health systems: A review of the published literature,'' Vaccine, vol. 30, no. 45, pp. 6347–6358, 2015, doi: 10.1016/j.vaccine.2012.08.029

[10] S. Yadav, M. Timbadia, A. Yadav, R. Vishwakarma, and N. Yadav, ''Crime pattern detection, analysis & prediction,'' in Proc. Int. Conf. Electron., Commun. Aerosp. Technol. (ICECA), Apr. 2017, pp. 225–230, doi: 10.1109/ICECA.2017.8203676.

[11] N. H. M. Shamsuddin, N. A. Ali, and R. Alwee, ''An overview on crime prediction methods,'' in Proc. 6th ICT Int. Student Project Conf. (ICTISPC), May 2017, pp. 1–5, doi: 10.1109/ICT-ISPC.2017.8075335.

[12] S. S. Roy, V. M. Viswanatham, P. V. Krishna, N. Saraf, A. Gupta, and R. Mishra, ''Applicability of rough set technique for data investigation and optimization of intrusion detection system,'' in Proc. Int. Conf. Heterogeneous Netw. Quality, Rel., Secur. Robustness, in Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol. 115, 2013, pp. 479–484, doi: 10.1007/978-3-642-37949- 9_42.

[13] L. Acion, D. Kelmansky, M. D. Van Laan, E. Sahker, D. S. Jones, and S. Arndt, ''Use of a machine learning framework to predict substance use disorder treatment success,'' PLoS ONE, vol. 12, no. 4, pp. 1– 14, 2017, doi: 10.1371/journal.pone.0175383.

[14] V. Ingilevich and S. Ivanov, ''Crime rate prediction in the urban environment using social factors,'' Procedia Comput. Sci., vol. 136, pp. 472–478, Jan. 2018, doi: 10.1016/j.procs.2018.08.261.

[15] G. R. Sinha, K. S. Raju, R. K. Patra, D. W. Aye, and D. T. Khin, ''Research studies on human cognitive ability,'' Int. J. Intell. Defence Support Syst., vol. 5, no. 4, pp. 298–304, 2018.

[16] F. A. Anifowose, J. Labadin, and A. Abdulraheem, ''Ensemble model of non-linear feature selection- based extreme learning machine for improved natural gas reservoir characterization,'' J. Natural Gas Sci. Eng., vol. 26, pp. 1561–1572, Sep. 2015, doi: 10.1016/j.jngse.2015.02.012.

[17] F. Anifowose, J. Labadin, and A. Abdulraheem, ''Predicting petroleum reservoir properties from downhole sensor data using an ensemble model of neural networks,'' in Proc. Workshop Mach. Learn. Sensory Data Anal., 2013, pp. 27–34, doi: 10.1145/2542652.2542654.

[18] F. Anifowose, J. Labadin, and A. Abdulraheem, ''Ensemble learning model for petroleum reservoir characterization: A case of feed-forward back-propagation neural networks,'' in Proc. Pacific–Asia Conf. Knowl. Discovery Data Mining, in Lecture Notes in Computer Science: Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, vol. 7867, 2013, pp. 71–82, doi: 10.1007/978-3-642- 40319-4_7.

[19] F. Anifowose, J. Labadin, and A. Abdulraheem, ''Ensemble model of artificial neural networks with randomized number of hidden neurons,'' in Proc. 8th Int. Conf. Inf. Technol. Asia (CITA), Jul. 2013, pp. 1– 5, doi: 10.1109/CITA.2013.6637562.

[20] S. S. Roy, P. V. Krishna, and S. Yenduri, ''Analyzing intrusion detection system: An ensemble based stacking approach,'' in Proc. IEEE Int. Symp. Signal Process. Inf. Technol. (ISSPIT), Dec. 2014, pp. 307– 309, doi: 10.1109/ISSPIT.2014.7300605.

[21] F. Anifowose, J. Labadin, and A. Abdulraheem, ''Improving the prediction of petroleum reservoir characterization with a stacked generalization ensemble model of support vector machines,'' Appl. Soft Comput.,

vol. 26, pp. 483–496, Jan. 2015, doi: 10.1016/j.asoc.2014.10.017.

[22] D. Wolpert, ''Stacked generalization,'' Neural Netw., vol. 5, no. 2, pp. 241–259, 1992.

[23] X. Zhou, Y. Peng, and B. Liu, ''Text mining for traditional Chinese medical knowledge discovery: A survey,'' J. Biomed. Inform., vol. 43, no. 4, pp. 650–660, 2010, doi: 10.1016/j.jbi.2010.01.002.

[24] B. Zhai and J. Chen, ''Development of a stacked ensemble model for forecasting and analyzing daily average PM2.5 concentrations in Beijing, China,'' Sci. Total Environ., vol. 635, pp. 644–658, Sep. 2018, doi: 10.1016/j.scitotenv.2018.04.040.

[25] Y. Hu, J. Li, and L. E. Holloway, ''Towards modeling of resilience dynamics in manufacturing enterprises: Literature review and problem formulation,'' in Proc. IEEE Int. Conf. Automat. Sci. Eng., 2008, pp. 279–284, doi: 10.1109/COASE.2008.4626539.

[26] H. Mouratidis, M. Ouedraogo, E. Dubois, and D. Khadraoui, ''Information systems security criticality and assurance evaluation,'' in Advances in Computer Science and Information Technology (Lecture Notes in Computer Science), vol. 6059, T. Kim and H. Adeli, Eds. Berlin, Germany: Springer, 2010, doi: 10.1007/978-3-642-13577

[27]R. McCafferty and U. C. Action, "Murder in South Africa: a comparison of past and present," United Christian Action, pp. 1–24, 2003.

[28] Business Insider South Africa, South Africa Climbed the Ranks to Become One of the Most Murderous Countries in the World, Business Insider South Africa, Cape town, South Africa, 2019, https://www.businessinsider.co.za/south-africa-crime-2019-

[29] Statistics South Africa, South Africa's Crime Statistics for 2018/ 19, https://citizen.co.za/news/south-frica/crime/2178462/ factsheet-south-africas-crime-statistics-for-2018-19/2019.

[30] Statistics South Africa, South African Annual Crime Report 2017/2018, RP NUMBER: 299/2018, ISBN NUMBER: 978-0- 621-46552-5, Crime Registrar, 2019.

[31] G. Otieno, E. Marinda, T. Barnighausen, and F. Tanser, "High ¨ rates of homicide in a rural South African population (2000- 2008): findings from a population-based cohort study," Population Health Metrics, vol. 13, no. 1, p. 20, 2015.

[32] M. R. Lindegaard, Homicide in South Africa, the Handbook of Homicide, F. Brookman, E. R. Maguire, and M. Maguire, Eds., John Wiley & Sons, New Jersey, NJ, USA, First edition, 2017.

[33] Statistics South Africa, Crime Statistics for South Africa, https://www.kaggle.com/slwessels/crime- statistics-for-southafrica. Accessed December 2020.

[34] S. Hossain, A. Abtahee, I. Kashem, M. M. Hoque, and I. H. Sarker, "Crime prediction using spatio- temporal data," 2020, https://arxiv.org/abs/2003.09322.

[35] S. Ramasubbareddy, T. Aditya Sai Srinivas, K. Govinda, and S. S. Manivannan, "Crime prediction system," in Innovations in Computer Science and Engineering, H. Saini, R. Sayal, R. Buyya, and G. Aliseri, Eds., vol. 103, Singapore, Springer, 2020, Lecture Notes in Networks and Systems.

[36] S. Kim, P. Joshi, P. S. Kalsi, and P. Taheri, "Crime analysis through machine learning," in Proceedings of the 2018 IEEE 9th Annual Information Technology, Electronics and MobileCommunication Conference (IEMCON), Vancouver, BC, Canada, November 2018.

[37] E. Ahishakiye, E. O. Omulo, D. Taremwa, and I. Niyonzima, "Crime prediction using decision tree (J48) classification algorithm," International Journal of Computer, and Information Technology, vol. 6, no. 3, ISSN: 2279 – 0764, 2017.

[38] G. Saltos and M. Cocea, "An exploration of crime prediction using data Mining on open data," International Journal of Information Technology & Decision Making, vol. 16, no. 5, pp. 1155–1181, 2017.

[39] P. Isha, Exploratory Data Analysis and Crime Prediction in San Francisco, Master's Projects. 642, https://scholarworks. sjsu.edu/etd_projects/642, 2018.

[14] A. Kumar, A. Verma, G. Shinde, Y. Sukhdeve, and N. Lal, "Crime prediction using K-nearest neighboring algorithm," in Proceedings of the 2020 International Conference on Emerging Trends in Information Technology and Engineering (Ic-ETITE), pp. 1–4, Vellore, India, February 2020.

[40] K. Sukhija, S. N. Singh, and M. Kumar, "Using Linear Regression to investigate parameters associated with Rape crime in Haryana," in Proceedings of the 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence), pp. 107–111, Noida, India, January 2020.

[41] J. J. Gonzalez and A. Leboulluec, "Crime prediction and sociodemographic factors: a comparative study of machine learning regression-based algorithms," Journal of Applied Computer Science and Mathematics, vol. 13, no. 27, 2019.

[42] P. Chen, H. Yuan, and X. Shu. Forecasting crime using the arima model. Proceeding of the 5th IEEE International Conference on Fuzzy Systems and Knowledge Discovery., 5:627–630, 2008.

[43] X. Chen, Y. Cho, and S. Jang. Crime prediction using twitter sentiment and weather. Systems and Information Engineering Design Symposium., pages 63–68, 2015.

[44] S. Chetlur, C. Woolley, P. Vandermersch, J. Cohen, J. Tran, B. Catanzaro, and E. Shelhamer. cuDNN: Efficient primitives for deep learning. arxiv 1410.0759, 2014.

[45] F. Choillet. Keras. https://github.com/fchollet/keras, 2015.

[46] M. Courbariaux, Y. Bengio, and J. David. Binaryconnect: Training deep neural networks with binary weights during propagations. In Advances in Neural Information Processing Systems, page 3123C3131, 2015.

[47] M. Courbariaux, I. Hubara, D. Soudry, R. El-Yaniv, and Y. Bengio. Binarized neural networks: Training neural networks with weights and activations constrained to +1 or -1. CoRR, 2016.

[48] S. Dieleman, J. Schlter, C. Raffel, E. Olson, S. K. S?nderby, D. Nouri, et al. Lasagne: First release., Aug. 2015.

[49] M. Gerber. Predicting crime using twitter and kernel density estimation. Decision Support System., 61:115–125, 2014.

[50] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. CVPR, 2016.

[51] S. Hochreiter and J. Schmidhuber. Long short-term memory. Neural Comput, 9:1735–1780, 1997.

[52] D. Holden, T. Komura, and J. Saito. Phase-functioned neural networks for character control. Siggraph,2017.

[53] S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. arXiv:1502.03167, 2015.

[54] A. Jain, A. R. Zamir, S. Savarese, and A. Saxena. Structural-rnn: Deep learning on spatio-temporal graphs. CVPR, 2016.

[55] H. Kang and H. Kang. Prediction of crime occurrence from multi-modal data using deep learning. PLos ONE., 12, 2017.

[56] D. Kingma and J. Ba. Adam: A method for stochastic optimization. ICLR, 2015.

[57] Y. LeCun, Y. Bengion, and G. Hinton. Deep learning. Nature, 521:436–444, 2015.

[58] F. Li, B. Zhang, and B. Liu. Ternary weight networks. NIPS Workshop, 2016.

[18] H. Li, S. De, Z. Xu, C. Studer, H. Samet, and T. Goldstein. Training quantized nets: A deeper understanding. arXiv:1706.02379, 2017.

[59] Y. Li, R. Zemel, M. Brockschmidt, and D. Tarlow. Gated graph sequence neural network. ICLR, 2016.

[60] G. Mohler, M. Short, P. Brantingham, F. Schoenberg, and G. Tita. Self-exciting point process modeling of crime. Journal of Americal Statistical Association, 106(493):100, 2011.

[61] G. O. Mohler, M. B. Short, and P. J. Brantingham. The concentration dynamics tradeoff in crime hot spotting. Connecting Crime to Place: New Directions in Theory and Policy., in press.

[62] M. Rastegari, V. Ordonez, J. Redmon, and A. Farhadi. Xnor-net: Imagenet classification using binary convolutional neural networks. ECCV, 2016.

[63] M. Short, G. Mohler, P. J. Brantingham, and G. Tita. Gang rivalry dynamics via coupled point process network. Discrete and Continuous Dynamical System B, 34(1459), 2014.

[64] M. B. Short, A. L. Bertozzi, and P. J. Brantingham. Nonlinear patterns in urban crime: hotspots, bifurcations, and suppression. SIAM J. Appl. Dyn. Syst., 9(2):462–483, 2010.

[65] M. B. Short, P. J. Brantingham, A. L. Bertozzi, and G. E. Tita. Dissipation and displacement of hotspots in reactiondiffusion models of crime. Proc. Nat. Acad. Sci, 107(9):3961–3965, 2010.

[66] M. B. Short, M. R. D'Orsogna, V. B. Pasour, G. E. Tita, P. J. Brantingham, A. L. Bertozzi, and L. Chayes. Persistent heat signature for pose-oblivious matching of incomplete models. M3AS: Mathematical Models and Methods in Applied Sciences, 18:1249–1267, 2008.

[67] A. Stomakhin, M. B. Short, and A. L. Bertozzi. Reconstruction of missing data in social networks based on temporal patterns of interactions. Inverse Problems, 27(115013), 2011.

[68] Theano Development Team. Theano: A python framework for fas computation of mathematical expressions. Arxiv 1605.02688, 2015.

[69] B. Wang, D. Zhang, D. Zhang, P. J. Brantingham, and A. L. Bertozzi. Deep Learning for Real Time Crime Forecasting. arxiv 1707.03340, 2017.