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Efficient Neural Network model for Cyber Crime Foreca

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Abstract

Depending on the gravity of the offence, a person who commits a crime faces legal repercussions from the state or other authorities, including jail time and fines. There has been an alarming rise in the number and variety of criminal acts, necessitating the creation by government agencies of effective techniques for taking preventive actions. Traditional crime-solving methods aren't cutting it in today's environment of rising crime since they're too slow and inefficient. If we can devise methods for accurately predicting crime before it occurs or create a "machine" that can aid police officers, it will relieve the pressure on law enforcement and help to reduce crime. Machine learning (ML) and computer vision techniques should be used to accomplish this. A few examples are presented in this work, and their outcomes compelled us to conduct further research in this area. As a result of these statistical insights, crime detection and prevention strategies have changed significantly. Using a mix of machine learning and computer vision, law enforcement agencies or authorities can detect, prevent, and solve crimes at a much faster and more accurate rate, according to the goal of this study. In a nutshell, machine learning and computer vision can revolutionise law enforcement.

Keywords: Machine learning, Computer vision, Crime forecasting

INTRODUCTION

Computer vision is a subfield of artificial intelligence that aims to give computers the ability to perceive and comprehend the visual world [1, 2]. Since it primarily analyses images taken with a camera, it has a wide range of potential uses. It can be used for facial recognition, number plate identification, AR, location determination, and object identification. The mathematical strategies to recover and make it possible for computers to grasp 3D images are currently being researched. Images of an object in 3D can be used to help us identify objects (e.g. pedestrian detection), recognise faces (e.g. Eigenfaces active appearance and 3D shape models), and edit photos (e.g. intelligent photo editing). These are only a few of the many applications that can be found in each of the categories listed above. Fast prototyping in computer vision research is made possible by VLFeat, a library of computer vision algorithms that may be utilised to do fast prototyping in computer vision research. A person's posture can also be determined based on face detection and human recognition [5]. As a result, computer vision is a powerful tool for depicting the world around us in 3D form. Machine learning (ML) is a technique that enables a computer system to learn and improve on its own without the need for human intervention [6–8]. There is no guarantee that an accurate pattern or information can be deduced from the data [9–11]. In these situations, machine learning (ML) is used to decipher the exact pattern and data [12, 13]. If the correct data is provided to a machine, it can learn and solve both complex mathematical issues and some specialised mathematical problems [14–17]. ML advances this principle. Machine learning (ML) is classified into two types: supervised and unsupervised [18, 19]. A specified collection of training examples is used to teach the machine in supervised learning, making it easier for it to draw precise and correct conclusions from incoming data [20, 21]. When a computer is presented with a set of data, it is given the task of identifying common patterns and relationships among the data it has collected on its own. Since the 1980s, neural networks have been researched as important tools for supervised learning [24, 25]. To escape nondeterministic polynomial (NP)-completeness, the authors in ref. [26] argue that architectural constraints alone are insufficient. When it comes to solving NP-completeness problems, however, sig-moid functions can be used. This research has attempted to demonstrate different novel ML approaches, but how reliable are the results? The nature of many crimes and the circumstances surrounding them may appear random, but just how unpredictable are they really? Reference [31] said that as society and economics result in more crimes, there is a greater need for a prediction system to identify them. A dynamic time-wrapping technique called Mahanolobis and the ability to predict crime and arrest the actual perpetrator are shown in ref. [32]. The National Institute of Justice won five funds in 1998 to extend its crime mapping work. [34] Law enforcement agencies in the United States, the United Kingdom, the Netherlands, Germany, and Switzerland use crime prediction apps. Technological improvements are making criminals smarter every year. We must provide law enforcement and the government with a new, powerful machine to investigate crimes (a collection of programmes). Crime forecasting is to predict crimes before they happen. Predicting criminal acts can save a victim's life, prevent suffering, and preserve private property. It could be used to anticipate terrorism. If we embrace predictive policing accurately, we can employ police manpower, detectives, and funding in other crime-solving areas. This project aims to predict both the type of crime and the offender using ML and computer vision. We doubted the crime's nature could be predicted. Despite appearances, acrimony can be categorised. Every criminal has a motive, says the saying. If we use motive to determine a crime's character, we can create categories. In this paper, we propose using ML algorithms and computer vision to generate a database of all recorded crimes by type. This database can be used to predict a crime before it happens.

2. Present technological used in crime detection and prediction

Predicting crimes before they happen is the foundation of crime forecasting. To be able to predict a crime before it occurs, one needs the right tools. A body cam can be used to record odd illicit behaviour or listen in on a suspect's phone call, both of which are now instruments utilised by police. Some of these tools are included below so that you may better appreciate how they might benefit from extra technical aid. If you're interested in finding out where a phone is, consider using a stingray [35]. This is a cutting-edge police surveillance tool that can mimic mobile phone tower signals and broadcast them to nearby phones, causing them to communicate their location and other data. Because stingrays can be used in the United States without violating the Fourth Amendment, some argue that they are unconstitutional. 23 states and the District of Columbia use this technology. Reference [36] explains how this is more than a monitoring system, raising issues about privacy infringement. The Federal Communications Commission also got involved and ultimately urged the manufacturer to meet two conditions for a grant: (1) "The marketing and sale of these devices shall be limited to federal, state, and local public safety and law enforcement officials only" and (2) "State and local law enforcement agencies must advance coordinate with the FBI on acquisition and use of equipment authorized under this authorization." Despite the fact that its use is worthwhile, its execution remains highly contentious. "Stakeout" is a widely used strategy that has been around since the dawn of surveillance. All types of suspects can benefit from a stakeout because the strategy is so widely employed by law enforcement officials. Stakeouts are important since police officers are required to produce reports on a wide range of incidents, according to the writers in ref. [37]. After stakeouts, patrols, and house searches, officers can observe such criminal conduct; they can also describe their own and the suspect's behavior during arrest. When the police conduct a stakeout, they are able to keep a close eye on important activities and can be trusted to do so with complete objectivity. The question is: do they really represent reality in its entirety? Fatigue is a natural part of the human condition. A stakeout's primary goal is to keep an eye out for illegal activity. The question is whether or not there is an alternative to it. This topic will be addressed in the following paragraphs. Drones can be used for a variety of purposes, including mapping cities, pursuing criminals, investigating crime scenes and accidents, managing traffic flow, and performing search and rescue operations after a disaster. Drone use and airspace distribution are discussed in detail in ref. [38]. Problems about police power and authority produce privacy concerns, which are addressed by the law. Concerns concerning the permissible altitude of a drone are sparked by the uneven distribution of airspace. Face recognition, licence plate recognition, and body-mounted cameras are among the other types of monitoring. Face-recognition technology can be utilised to identify suspects and assess their profiles from various databases, according to the authors of the paper. [39]. Similar data can be accessed about a car suspected of involvement in a crime using a license plate scanner. Using bodycams, the reader can see more than the human eye can perceive, which means that whatever a police officer sees and records is visible to the reader as well. If you look at something for a long time, you won't be able to recall the whole picture. [40] Investigated the impact of body cameras on police misconduct and domestic abuse during arrests. Police officers now regularly use body cams. See [41] for more on protecting people from unjust police acts. Other reasons to always wear a body camera include documenting relevant events during everyday activities or vital operations. Each of these tactics works on its own, and while the police can use them concurrently or individually, a machine that combines their beneficial features would be quite useful.

3. ML techniques used in crime prediction

In ref. [42], the open source data mining software Wai-kato Environment for Knowledge Analysis was used to compare violent crime trends in the Communities and Crime Normalized dataset with actual crime statistics (WEKA). It was found that the same set of features was used in the implementation of three algorithms: linear regression, additive regression, and decision stump. The samples were chosen at random. The linear regression method was found to be the most effective of the three algorithms tested since it was able to tolerate some randomness in the test data. The algorithm-based prediction of violent crime patterns, as well as other applications, was the primary goal of the research. ML algorithms were tested for their accuracy and efficiency in forecasting violent crime patterns. A new graphical user interface called Knowledge Flow, which can be used to replace Internet Explorer, can be integrated into WEKA [43]. IT provides a more concentrated perspective of data mining using Java beans to represent individual learning components and process orientation, which depicts information flow graphically. The experimenter compares the performance of multiple learning systems on multiple data sets. Predictive analysis of crime forecasting in an urban setting is explored in ref. [34]. It was found that three forms of crime were combined into grids of 200 meters by 250 meters and retrospectively examined. An ensemble model was used to synthesize the results of logistic regression and neural network models based on the crime data from the past three years in order to produce fortnightly and monthly predictions for 2014. The accuracy, precision, and prediction index of the forecasts were all measured. Predictive data analysis can generate accurate forecasts according to the fortnightly predictions. Compared to weekly and monthly predictions, and dividing day and night can enhance results. It was found that crime predictions might be made using ML in reference [44]. For the purpose of making predictions, Vancouver, Canada's crime statistics from the previous 15 years were examined. Data is collected, data is classified, trends are identified, predictions are made, and visualisations are produced as part of this machine-learning-based criminal research. Analysis of the crime dataset included K-nearest neighbour (KNN) and boosted decision tree methods. There were 560,000 crimes recorded between 2003 and 2018 in this study, and the researchers used machine learning (ML) algorithms to predict crimes with an accuracy of 39% to 44%. Predictive accuracy was low, but the authors found that accuracy may be improved for certain applications by fine tuning algorithms and crime data. Philadelphia, United States, crime figures are predicted using an ML technique in ref. [45]. The three components of the challenge were: identifying whether or not a crime occurs; determining whether or not it occurred; and determining the likelihood that a crime would occur. The datasets were trained using algorithms such as logistic regression, KNN, ordinal regression, and tree techniques in order to obtain more accurate quantitative crime predictions. To illustrate how the map may be used to forecast crimes, they also included a color-coded map of the various crime types that occurred in Philadelphia over a specific time period. Assaults and computer fraud were included to reflect Philadelphia's crime history at the time. Their programmed correctly predicted 69 percent of crimes as well as the total number of crimes (47 percent accuracy). Data from many crimes was used in ref. [46] to make predictions about the type of crime that may occur in the near future based on several factors. A crime dataset from Chicago, the United States, was utilised to test ML and data science strategies for crime prediction. Among the data in the crime dataset are specifics such as descriptions of the crime scene and timestamps, as well as exact GPS positions. After evaluating a variety of models, including KNN classification and logistic regression, as well as decision trees and random forests, the most accurate model was selected for training. The classification using KNN was found to be the most accurate, with a precision of about 0.787. In addition, numerous graphics were employed to aid in the understanding of the many properties of the Chicago crime database. Law enforcement agencies may use machine learning (ML) to better forecast, detect, and solve crimes, which would reduce crime. This is the primary goal of this article. Predictions of crime rates using machine learning (ML) are reported in ref. [47]. The primary goal of this research was to identify machine-learning approaches that may accurately predict crime rates and to determine whether they can be applied to the dataset in question. The dataset was subjected to supervised ML algorithms for data validation, data cleaning, and data visualization. In order to make predictions about the outcomes, the outputs of various supervised machine learning algorithms were compared. Data gathering, data processing, predictive model creation, training datasets, testing datasets, and algorithm comparisons are all part of the system proposed in Fig. 1. Using a machine learning method, we hope to demonstrate how well it can anticipate violent crimes. Data fusion based on deep neural networks (DNNs) is proposed in ref. [48] to accurately forecast crime by combining multiple models of data from many areas with information about the surrounding environment. Crime statistics from an internet database, demographic and weather data, and photographs are included in the dataset. Regression analysis, kernel density estimation (KDE), and support vector machines (SVM) are just a few of the machine learning approaches used in crime prediction. Data collection, statistical analysis, and accurate prediction of crime occurrences were all part of their approach. Spatiotemporal features and environmental context make up the DNN model.

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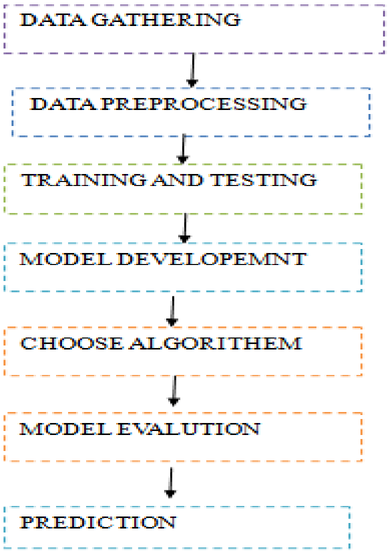

Figure 1: Flow Chart of Crime Detection

Astonishingly, the proposed DNN model achieved an accuracy of 84.25 percent, while the SVM and KDE models had a 67.01 percent and 66.33 percent accuracy, respectively, The results of the experiments showed that the suggested DNNmodel was more accurate than the other prediction models in forecasting crime occupa-tions. Reference [49] was primarily concerned with how to lower crime rates in India through the analysis and design of machine learning algorithms. A big quantity of data was subjected to ML algorithms in order to discover the patterns that connect it all. As seen in Fig. 2, the study predicted future crimes based on past crime locations. Scaled algorithm outperformed Bayesian neural networks and the Levenberg-Marquardt method for evaluating and interpreting data. Crime rates can be reduced by 78% using the scaled method, a statistical study discovered. [50] describes a system for predicting criminal activity based on data from previous crimes and the patterns they show. The suggested system is based primarily on two machine learning algorithms: a decision tree and a kernel density estimation algorithm (KNN). Random forest algorithms and adaptive boosting were applied to improve the prediction model's reliability. For the model's benefit, the crimes were separated into two categories: those that occur frequently and those that do not. While the most common crimes were included in the frequent category, those that occurred less frequently were found in the uncommon category. The suggested system was fed data on criminal behaviour in San Francisco, California, for a period of 12 years. With the random forest algorithm with undersampling and oversampling methods, the accuracy was enhanced to 99.16 percent. According to ref. [51], a comprehensive study on crime classification using ML and deep learning architectures is offered. These methods have been used in the literature to anticipate the quantity of crimes as well as the hotspots in which they occur. To circumvent the limits of some machine-learning methods, deep learning extracts features from raw data. This work describes three deep learning configurations for crime prediction: spatial and temporal, time and space, and time and space in parallel. It was compared to 10 current crime prediction algorithms on five datasets with over a decade of data. To better understand human behavior and forecast criminal activity, researchers in ref. [52] used big data and machine learning (ML). Tracking information utilizing big data, several methods of obtaining and analyzing data and the final step of crime prediction based on data collection and analysis are all discussed in this study. Rapid Miner was used to provide a predictive analysis of historical crime patterns using machine learning (ML). We used a four-phased approach to gather information, prepare data, analyze that information, and display it. Because of its high throughput and fault tolerance, as well as its ability to analyze extremely huge datasets, big data was found to be a good framework for evaluating crime data. ML-based naive Bayes can produce better predictions with the supplied data. [53] Provides examples of criminal investigations using data mining and machine learning. This paper makes a valuable addition by shedding light on the data analytics methods that have been employed in criminal cases. Datasets were analyzed using a variety of machine learning techniques, including KNNs, SVMs, naive Bayes, and clustering. Examining crime statistics can reveal the type of crime and prospective hotspots. The suggested model encompassed feature selection, clustering, analysis, prediction, and assessment.. This study demonstrates the importance of using machine learning (ML) to predict and analyse criminal activity. For a city in Taiwan, the authors in ref. [54] used a grid-based crime prediction model and 84 different types of geographic locations to develop a set of

Table 1 Performance analysis of forecasting methods

No.	Forecasting method	Accuracy	Limitations	Observation	References
1	Decision tree (J48)	59.15%	Took more time of 0.76 s to build model compared to 0.09 s of other models.	They took J48 naïve Bayesian and ZeroR 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 algorithms 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 large change 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 were not taken into consideration.	This paper presented comparative analysis on the accuracy of k-NN, naive Bayescand decision tree algorithms in predicting crimes and criminal 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 in Pittsburgh.	[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]
10	Random Forrest Regressor	Ninety-seven percent accuracy in predicting crimes	They got this high accuracy in previous recorded crimes to actually predict crimes in real life will be a challenge.	They had divided their data into 2 parts 80% of it was used to train the model and the rest 20% was used to test the model in this the model achieved the score of 90%.	[65]

Figure 2: Perfomance analysis

Spatial-temporal attributes. For each grid, the concept uses ML algorithms to learn patterns and forecast the number of crimes that will occur in the coming month. An algorithm called a DNN was discovered to be the most effective in terms of machine learning (ML). Research in this area relies heavily on modern machine learning (ML) approaches such as the idea of feature learning. Crime displacement testing demonstrated that the proposed model architecture outperformed the baseline in comparison. Research comparing several forecasting approaches. Using the KNNs method, the authors made crime predictions for 2014 and 2013, respectively, according to references [56, 57]. According to Sun et al. [56], integrating greycorrelation analysis with the KNN classification method improves crime prediction accuracy. The new algorithm achieved 67% accuracy. Instead of dividing the data into crucial and non-critical categories, Shojaee et al. [57] used a simple KNN method. They were able to get it right 87 percent of the time. A deciduous tree technique is used to forecast crimes in 2015 and 2013, respectively, in references [58, 59]. With the ZeroR method, Obuandike et al. [58] attempted to attain an accuracy of more than 60% in their study, but failed. Additionally, a decision tree technique used by Iqbal et al. [59] yielded an astounding 84% accuracy. Even a little change in the data can have a significant impact on the structure in either instance. First of all, naive Bayes was used for crime prediction and analysis in the references [60, 61]. Jangra and Kalsi [60], for example, had an incredible 87 percent success rate in crime

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prediction, but they were unable to apply their method to datasets with a large number of variables. When it comes to forecasting crimes, Wibowo and Oesman [61] were only able to get a 66 percent accuracy rate because they didn't take into account factors like computational speed, robustness, and scaling. In the following section, we review the previous comparison and include more models to highlight the correctness of certain often used models (Table1).

4. Neural Network as a Model for Crime Detection:

Classification and forecasting issues are particularly well-suited to neural networks, a machine learning technique. Law enforcement agencies and other organizations that deal with large amounts of data have found them to be an invaluable resource. This article uses previous research on the use of neural networks to forecast crime and solve other police decision-making problems. It summarises and examines the findings. To show how neural networks can be used in police decision-making, researchers have constructed models that use location and time information to predict specific categories of crime and those that use location and time information to predict the site of a crime. Crime prediction models based on neural networks use geo-spatial information to help law enforcement agencies make better decisions.

All NNs have two layers: an input layer that provides learning variables and an output layer that offers classification or prediction results. Both supervised learning and hybrid models have weighted connections between layers. As the network grows, it learns from its mistakes, which it propagates backwards through its connections in order to fine-tune its predictions so that they more closely match the correct output value. Figure 2 depicts an example of a supervised learning NN design.

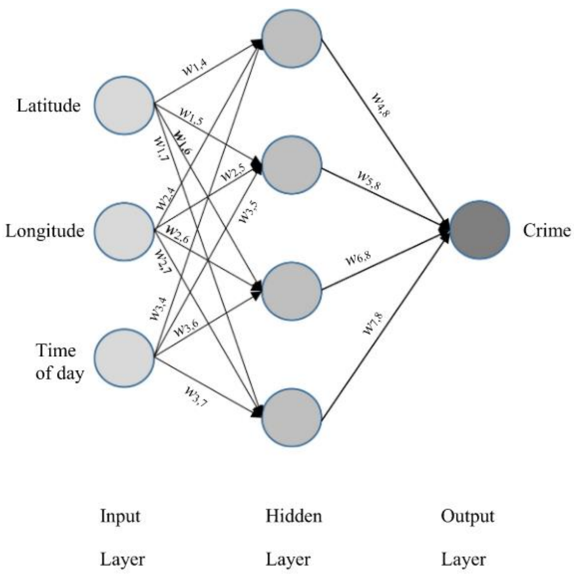

Figure 2: ANN Model

5. NN MODELS TO PREDICT CRIME TYPE

The development of two NN prediction models serves as an example of how the models might be used in the field of police crime prediction and readiness. Both models rely on supervised learning NN architectures for their underlying computations and results. All NN models are created using the neural network shell tool in NeuralWare® Professional II Plus®.

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5.1Data and Method

The city of Detroit, Michigan's open access RMS Crime Incidents crime data was used to generate the NN models (City of Detroit, 2020). At the time of building the research models, there were 272,623 records available. According to Detroit criminal charge numbers, the records are categorised into 38 separate offences that are dispersed throughout 30 zip code areas of the city. Using a zip code is a method of defining postal delivery areas in the United States of America.

The data obtained included date and time stamps, weekday, hour, longitude, and latitude. The data was collected from 2016 until early 2020. Walczak and Cerpa (1999) and Zhang (2007)'s NN research guidelines include using one or two hidden layers and varying the number of NN nodes inside each hidden layer. Starting with half the preceding layer's nodes, each buried layer adds nodes until performance degrades. This strategy prevents overlearning, which hinders generalisation. For all first hidden layer topologies, the incremental increase is two nodes at a time, and for a second hidden layer, it is increased one node at a time. RBF and back propagation build two different training models (RBF). Training stops if the model's RMSE is less than 0.05 or has remained constant for 1,000 training epochs. Backpropagation, the most prevalent approach to training a NN, simplifies cross-study comparisons. According to a study (Hornik, 1991), backpropagation learning is a reliable classifier. When data extrapolation (not interpolation) is needed or data is restricted, RBF training beats backpropagation (Walczak and Cerpa, 1999). The RBF NN transfer function determines how close an input value is to a desired output value. Due to the limited input variables (independent variables) for NN models, there is a requirement to employ RBF trained NN models even when a large number of data instances are available for training and validation/testing. The best NN architecture is shown for each crime forecasting problem.

5.2 NN to Predict Type of Crime

The goal of the first NN model is to forecast what kind of crime will be committed based on simply the location and time. Simulated 911 call response when a caller can't define what's going on in a situation like this A model for training police officers, since they are assigned to certain neighbourhoods on specified days and at specific times, could be seen in this. Predicting where and when a crime will take place is one of the primary purposes of the NN. Training and validation sets were previously split evenly, with an odd number of samples for a single crime cluster being added to the validation set. Using back propagation training, the solution surface can be made more nonlinear by using NNs with either a single hidden layer or two hidden layers (Walczak and Cerpa, 1999). However, only 3 to 4 of the 38 probable crime clusters were accurately categorized by the predictions from all of these NNs. This is because there is a huge disparity in the number of crimes committed for each type of crime. As an example, there were 71,931 total incidents of assault crimes, yet there were only 41 total cases of harassment and stalking offences. Machine learning systems such as NNs suffer from poor classification and prediction performance because of overrepresented clusters in the training data (Lin et al., 2013). The data is pre-balanced so that only clusters with at least 600 total samples are used to compensate for the severe imbalance between the representations of crime clusters, reducing the number of clusters from 38 to 27 [removing the crime clusters for minors in possession of alcohol (N = 10), animal cruelty (N = 3), extortion (N = 147), gambling (N = 6), harassing and stalking (N = 41), health and safety (N = 30), invasion of privacy (N = If the total number of cases in a cluster was fewer than 700, then half of the cases in that cluster were utilised as a sample. The training set was expanded to include an additional proportional number of crime samples for those clusters, up to a maximum of 370 samples per crime cluster, to add a very minor influence. There were 9,503 training samples in all, evenly divided among the 27 different crime types in the training set. The remaining 262,473 crime report samples were used as a test set for the fully trained neural network (NN). Note that no validation sample is ever utilised to train the NN and hence represents the real-world potential application of the NN in this study. To train the NN models, we used a combination of date, time, and one of three possible locations as input. There are 30 different zip codes in the city of Detroit, which can be represented by a category variable, the longitude and latitude (LL), or a mix of both. Each of the 27 crime clusters is represented by a separate variable in the final output vector generated by all NN models. This ensures that the NN does not overfit to a limited number of clusters with huge sample sizes, which can lead to inaccurate predictions. RBF NN models were beaten by NNs trained via backpropagation. For each of these evaluation measurements, the best-performing NN is presented along with the best-performing RBF model.

Results:

NN prediction of crime type results

Sl No	NN Model	Crime Prediction Accuracy %
1	Single Hidden Laer with Back Propagation	9.3
2	Two Hidden Laer with Back Propagation	18.6
3	RBF trained NN	14.7

The crime type NN prediction models performed, The two-hidden layer MLP had 12 nodes in its first layer and four nodes in its second layer. The single-hidden layer MLP had 12 nodes in its hidden layer. Lastly the RBF NN had an association layer of 54 nodes and a hidden layer of 12 nodes.

6. Challenges

Despite the fact that this article was written with great care and attention to detail, there are still some issues that may arise in the future. When it comes to establishing a fully functional system, there are a few things that need to be done in the near future. The implementation of such technologies is also problematic because they cannot be used in the open. As with any new technology, it must be tested and improved upon before being rolled out to a larger area. As a result, the challenges are meant to aid in the refinement of the model and, ultimately, to produce a perfect model that can be used in practise. In addition, the model has a few technological challenges to overcome, as the bulk of the learning data would be immense, and thus processing it would take days or even weeks. But if a team of professionals can work together to overcome these issues after thorough research, the finished product will be well worth their effort and perseverance.

7. Future scope

The methods and approaches talked about in this paper can be used to help law enforcement predict crime and stop it. Using a variety of ways to predict and prevent crime has the potential to alter the current landscape for law enforcement organisations. Machine learning and computer vision aid law enforcement. By combining ML and computer vision with security cameras and spotting scopes, a machine will be able to learn criminal patterns, understand crime, and predict future crimes without human intervention. Creating a system that can forecast and anticipate crime hotspots in a city could be a viable automation. Predicting and preventing crime can be done by law enforcement authorities by increasing surveillance in the prediction zone. Due to their complete automation, law enforcement will be able to rely more on these approaches in the near future. Future studies will involve designing a machine to forecast and identify criminal trends. As important as today's systems are in helping to keep our streets safe, a "universal police officer" might revolutionise how we track down criminals and prevent them from ever happening in the first place.

8. Conclusions

Predicting crimes before they occur is a basic concept, but putting it into practise requires much more than just grasping the idea. This study was written in order to help researchers who are trying to make crime prediction a reality. If used properly, facial recognition software can fundamentally alter how police officers conduct their work. This is true even though police frequently use emerging technologies such as Sting Rays and facial recognition.This paper shows how machine learning, deep learning, and computer vision can help the police. Everything from monitoring criminal hotspots to voice-recognition recognition is included in our system proposal. First, this system must be created, followed by its implementation and utilisation. All these problems may be remedied, and a 24/7 security system can help. If this method is integrated into the police force, we should expect more trustworthy tips or leads and faster criminal eradication.

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