Journal of Computer Science

Original Research Paper

Crime Rate Analysis and Mapping from Socio-Economic Data Using Deep Neural Networks

[1]Santhosh Sankara and [2]Nadeson Sugitha

[1]Department of Information Technology, Noorul Islam Centre for Higher Education, Kumaracoil, Kanyakumari, Tamil Nadu, India
[2]Department of Electronics and Communication Engineering, Saveetha Engineering College, Tandalam, Chennai, Tamil Nadu, India

Article history
Received: 19-05-2024
Revised: 30-06-2024
Accepted: 08-07-2024

Corresponding Author:
Santhosh Sankara
Department of Information Technology, Noorul Islam Centre for Higher Education, Kumaracoil, Kanyakumari, Tamil Nadu, India
Email: santhosh.vattapara@gmail.com

Abstract: Crime prediction is the attempt to identify and mitigate future criminal activity. Crime is typically "unpredictable"; it cannot be predicted in advance. Addressing the roots of crime has long been a priority for researchers. Extracting causality from data is difficult if the relevant data aspects are not selected. In this research activity, an innovative classification framework is defined which is the enhanced future crime prediction. The framework consists of 3 major steps, the first step is the pre-processing step which is carried out based on the Lagrange polynomial interpolation method for filling the missing values. Next, the second step is the feature selection process which is employed using the Whale optimization algorithm. Feature selection is often regarded as a crucial step in any pattern identification procedure. Its purpose is to reduce the amount of memory used, the processing time, and the computational overhead of the classification process in order to improve the classification efficiency. The last step is the Classification process, in which the suggested feature selection and Whale optimization algorithm method will be used for selecting the important socioeconomic data based on their influence on crime rate prediction using the deep learning algorithm. Finally, the crime rate is analyzed and categorized as less prone, medium prone, and high prone with regard to crime activities. Several measures are used to analyze the suggested methodology's performance. This newly developed model is compared with existing models like Genetic algorithm, FireFly, and particle swarm optimization in terms of diverse performance metrics like execution time, memory consumed, training and testing time, sensitivity, specificity and accuracy. From the results, this model is proposed as the best crime prediction model compared with the other existing models. In comparison to other methods now in use, this approach effectively retrieves the crime's attributes with a high accuracy of 93.39%.

Keywords: Crime, Deep Learning Algorithm, Lagrange Polynomial Interpolation Method, Mapping, Whale Optimization Algorithm

Introduction

Methods for predicting future crime with location employ historic socioeconomic data and, evaluating it after, forecast future crime with area. In today's world, serial criminal instances occur often, making it difficult to effectively forecast future crime and improve performance. A crime rate has turned into a subject of real concern absolutely to restrict the advancement of good administration and expanding step by step. With improving personal satisfaction, social interest in protection from crime will increase. Salcedo-Gonzalez *et al*. (2023) Regardless of not expressly encountering crimes, fiascos, and mishaps, individuals experience such circumstances vicariously through the media and their groups of friends, prompting a rising trepidation of crime in people. Saeed and Abdulmohsin (2023); and Aziz *et al*. (2023) Numerous crime types display comparable spatial examples, are related with a similar arrangement of hazard factors, and are deciphered utilizing the equivalent biological speculations. William *et al*. (2023) Crime examination is an orderly approach for distinguishing and investigating examples and patterns in crime. Mastrorocco and Minale (2018) Criminal investigation

DOI: 10.3844/jcssp.2024.1203.1213

follows up on criminal cases like homicide cases, kid misuse, dangers, hacking, and monetary crime locations like illegal tax avoidance, psychological oppression financing, extortion, and so forth. So the criminal investigation group should utilize systems with the goal can foreseeing the future crime slants based on accessible verifiable criminal information and thus the future crime rate will diminish (Intravia *et al*., 2017; He and Zheng, 2021; Campaniello and Gavrilova, 2018).

Because there is a large amount of crime information available, crime forecasting and criminal distinguishing proof are important difficulties for the police department. Oguntunde *et al*. (2018) hence the need for innovation so that cases can be resolved more quickly. Lee (2019) Although the expected consequences cannot be guaranteed to be 100 percent accurate, the results show that our app helps to reduce crime rates to a limited extent by providing security in crime-prone areas. Jendryke and McClure (2019). Information mining and AI algorithms are acquainted with buildup spatiotemporal patterns and their algorithm utilizes the lattice cell of 800 by 800 m to foresee private robbery. Vujić *et al*. (2016); Wei *et al*. (2016) Information Mining is an activity that dissects information from different points of view and outlines or sums it up into valuable data or connections. In any case, it doesn't give exact results (Joshi *et al*., 2017).

Lately, they have numerous systems to distinguish crime. Along these lines, the deep neural network can be utilized. Agarwal *et al*. (2016) a deep neural network has demonstrated the capability of playing out a non-straight mapping from an info space to a yield space. Yoon *et al*. (2018) it is an AI approach where the algorithm can remove the highlights from the crude information, conquering the confinements of other AI techniques (Qu *et al*., 2019).

Literature Survey

An intelligent human-focused information science approach to crime pattern investigation has been created by Qazi and Wong (2019). In this research, we used content mining to examine unstructured crime records in order to identify possible affiliations. Qazi and Wong (2019) used this model in conjunction with segment bunching to create an intelligent, human learning disclosure and data mining strategy. This proposed method has a major test of incorporating compelling human connection with the machine learning algorithms through a representation input circle.

Hooghe and de Vroome (2016) examined the connection between ethnic descent variety and the dread of crime through an examination of police files and study information on Belgian people group. Hooghe and de Vroome (2016) the investigation depended on a mix of recently accessible authority police records and review information for neighborhood districts in Belgium. The outcome appeared there was no huge connection between announced crime and dread of crime. The discoveries recommend that uses of gathering risk hypothesis ought to center around financial and social danger, yet additionally on the apparent effect of decent variety on crime and wellbeing.

Information stream examination and representation for spatiotemporal factual information without direction data was created by Kim *et al*. (2018). The nonstop dissemination of the occasions over reality and concentrate stream fields for three-dimensional and temporal change used a gravity model.

Jing *et al*. (2019) clarified security information accumulation and information examination on the web. Jing *et al*. (2019) the creator proposed a few extra prerequisites for security-related information investigation so as to make the examination adaptable and versatile. In view of the utilization of information classifications and the kinds of information investigative strategies, we assessed current location techniques for Distributed Denial of Service (DDoS) flooding and worm assaults by utilizing the recommended prerequisites that assess its exhibition. An investigation of the dread of crime utilizing multimodal estimation was created by Kim and Kang (2018). The trial result demonstrated that the physiological signs were reliant on cognizance of their very own individual dread of crime. The creator found huge contrasts between the two gatherings for all video clasps aside from daytime Commercial Street and evening-time Natural Street; this information recommends that individual qualities are significant in estimating trepidation of crime.

The impact of fierce crime on monetary versatility was broken down by Kim and Kang (2018). The creator concentrated on one explicit element of urban territories, the degree of savage crime. Utilizing longitudinal information and a variety of observational methodologies, we discover solid proof that the degree of fierce crime in a region causally affected the degree of upward financial versatility among people brought up in families at the 25th percentile of the salary appropriation.

Sharkey and Torrats-Espinosa (2017) built up improving crime check estimates utilizing Twitter and taxi information. It assesses the informative and prescient estimation of human movement patterns obtained from taxi excursions, twitter, and foursquare information. Investigation of a six-month time of crime information for New York City demonstrated that these information sources improved prescient precision for property crime by 19% contrasted with utilizing just statistic information. Sharkey and Torrats-Espinosa's (2017) crime forecast was urgent to criminal equity leaders and is a fundamental restriction.

DOI: 10.3844/jcssp.2024.1203.1213

A non-stationary model for crime rate induction utilizing present-day urban information was proposed by Vomfell *et al.* (2018). In this study, the creator utilized an enormous scale of data and taxi flow information in the city of Chicago. In comparison to using standard highlights, we saw significantly better performance in crime rate induction. In the element relevance investigation, we established that these current sources were crucial. The correlations between crime and different watched highlights were not constant over the entire city. We also use the Geographically Weighted Regression on top of the Negative Binomial model to solve this spatially non-stationary characteristic (GWNBR). The test result demonstrated that GWNBR beats the negative binomial model.

Problem Statement

Police everywhere have been handling a large amount of crime information and a huge volume of records. Because there is a large amount of crime information available, crime identification and prediction are important difficulties for the police department. The current crime scenario cannot be satisfied by the conventional approach of maintaining and analyzing criminal records and intelligence. These procedures do not aid with decision support or crime prediction, nor do they offer continuous, accurate, and thorough data. From this perspective, the need for an effective crime prediction model is essential in public safety management.

Novelty of the Research

The current approaches for predicting crime employ socioeconomic data from the past and, following data analysis, forecast future crime with location. Presently, serial crimes occur so regularly that it is challenging to predict future crimes more accurately and precisely with the algorithms available. Extraction of causation from data might be challenging if pertinent data points are not chosen. The process of selecting features is often regarded as crucial to the success of any pattern recognition procedure. Its goal is to decrease the amount of memory used, the time it takes to execute the work, and the computational cost of the classification task in an effort to either improve or maintain classification performance. The aim is to create an efficient feature selection system thereby reducing the memory usage, execution time, and computational cost of the classification tasks when compared with the existing models.

The overall aim of the research is to develop an effective algorithm for crime rate analysis and prediction from socio-economic data. The framework will predict future crime accurately with better performance. The algorithm will achieve high classification accuracy with optimal features and achieve optimal performance metrics better than the existing models, using deep neural networks.

Materials and Methods

The system configuration for this research is Processor® Dual-core CPU running at 2.70 GHz with 1 GB of RAM and a professional version of Microsoft Windows 7. The dataset used are the socio economic data related to crime related documents which are retrieved from internet.

A novel classification framework is defined in this research work by selecting the important social data as shown in Fig. 1. The steps involved are Pre-processing, classification, and feature selection. The pre-processing stage involves using the Lagrange polynomial interpolation method to fill in the missing values. The best features should be chosen to produce good classification results. To choose the optimum characteristics, the Whale Optimization Algorithm (WOA) is used in the step of feature selection. Next is classification, for the training phase Deep Neural Network (DNN) is used and testing phase new DNN is used. With the help of the training and testing phase, DNN classifies the socioeconomic crime data into several classes. Finally, the crime rate is analyzed and categorized as less prone, medium prone, and highly prone to crime activities using the deep learning algorithm.

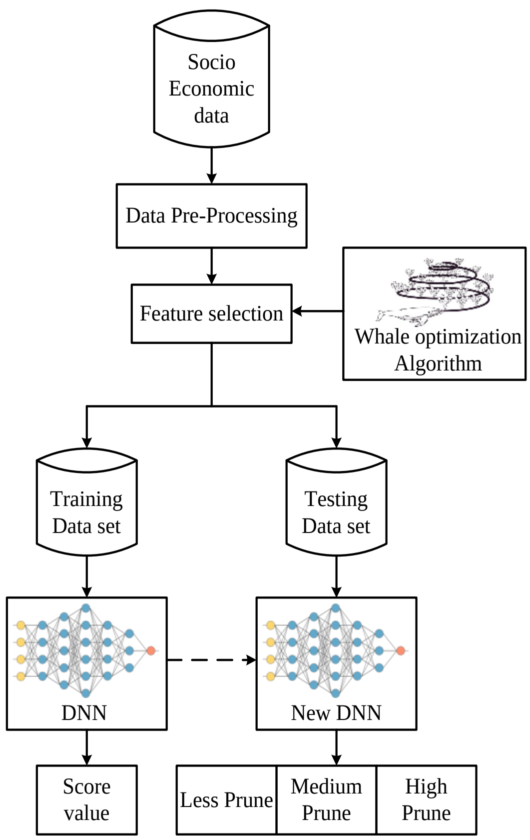

Fig. 1: Overview of a proposed architecture

DOI: 10.3844/jcssp.2024.1203.1213

Pre-Processing Stage

In a pre-processing step, the socio-economic data are selected to precede the further process. The dataset used in this research is annual, state code, administrative unit status, and name of the executive branch, number of murders, crimes, riots, and arson-related crimes; the strength of the civil police, actual armed police strength, and total police strength. Data cleaning, data integration, and data removal can be performed to manage missing values and superfluous data. The pre-processing phase is a crucial step in handling socio-economic data as it prepares the dataset for control and is considered a significant advancement. In this, Lagrange polynomial interpolation method is used to fill the missing values. In this research, the Lagrange interpolation method is used to predict missing values. This procedure is used to transform the data value to the actual value predictor variable. In a dataset, if an attribute depends on other than using known values, then unknown values can be found.

Interpolation

The method of determining unknown values from known ones is known as interpolation. Interpolation is one of the most basic approaches, requiring only two points and a constant rate of change. The cost of storing indexed functions in a system's memory is higher. It's easier to do this by using a method to calculate the value of any arbitrary function, such as sine values of argument. Consider the values (xi, yi) of any function $y = f(x)$, where I = 0, 1,... n. Interpolation is considered an approach to calculating the values of y and the intermediary number of x. The procedure for determining y's value is given below.

Lagrange Interpolation

A notable characteristic of this formula is that Lagrange provides the subsequent interpolation polynomial p (X) with specified degrees n given by n + 1 point (x_i, y_i) and its purpose is to preserve the generalization of x, i (x_i) = 1 and j (x_i) = 0 (j6 = i), giving $y = y_i$:

$$p(x) = \sum_{i=1}^{n} p_j\,(x) \tag{1}$$

$$p_j\,(x) = \prod_{\substack{k=1 \\ k\neq j}}^{n} \frac{x-x_k}{x_j-x_k} \tag{2}$$

Feature Selection

In this, feature selections are used for the crime rate analysis over various locations with the help of the Whale Optimization Algorithm (WOA). The proposed feature selection utilizes the optimization method for selecting important socio-economic data based on their influence on crime rate prediction. Finally, the crime rate is analyzed and categorized as less prone, medium prone, and highly prone to crime activities using the DNN algorithm. Feature selection enhances classification performance by eliminating irrelevant attributes and redundant datasets in current research. It reduces both the training time in addition to dimensionality.

Whale Optimization Algorithm (WOA)

The WOA incorporates a recently developed meta-heuristic that draws inspiration from humpback whales' bubble-net hunting technique. This system explains how humpback whales behave. Two types of uncommon behavior presented to this whale include encircling prey and bubble-net hunting. When whales encircle prey, they try to encircle the prey (small fish) as close to the water's surface as possible while blowing bubbles in a circle. The humpback whales use the bubble-net hunting technique, which involves diving approximately 12 m below the surface and then swimming toward the surface while blowing bubbles in a loop around the prey.

Encircling the Prey Strategy

Initially, when encircling prey, whales kept a close eye on the prey's location (fish). The whales then encircle their prey. The best candidate answer is prey that is quite close to the whales. The other whales adjust their positions in relation to the b hunting agent after the best hunt agent has been found. Equation depicts the surrounding process (4):

$$D = \left|U.Y*(k) - Y\,(k)\right| \tag{3}$$

$$Y(k\,+\,1) = Y*(k) - V.D \tag{4}$$

where, U and V are coefficients, k is the current number of repetitions, $Y*(k)$ s the vector sum of the optimal solution, Y (t) is the vector of the current position, and || is an absolute value. The following method is used to compute the coefficient vectors U and V:

$$V = 2.v.r - v \tag{5}$$

$$U\,=\,2.r \tag{6}$$

where, V is a term that decreases gradually from 2-0 during the period of iteration and r is a random value between 0 and 1.

Bubble-Net Attacking Strategy (Exploitation Phase)

Two enhanced methodologies are created in order to quantitatively predict humpback whale bubble-net behavior:

- Shrinking encircling system
- Spiral updating location

DOI: 10.3844/jcssp.2024.1203.1213

Shrinking Encircling Mechanism

The method was achieved by decreasing the quantity within formula (5). It is important to mention that the variable 'v' reduces the range of fluctuations in the variable 'V'. In other words, V represents a random number within the range [v, v], where v decreases from 2-0 with each repeat. The new position of a search agent can be determined by a randomized number for V in the range of [1, 1], which can be anywhere between the agent's beginning position and the existing optimal agent's position.

Spiral Updating Position

Humpback whales first hunt for prey before computing the difference between them and the prey. The humpback whales then assault the fish herds by spiraling in a circular exponential movement. It is suggested that each humpback whale update its position in accordance with the spiral flight route. This behavior can be stated statistically as follows:

$$Y\,(k\ +\ 1) =\ D'.e^{bt} * cos\,(2\,p\,k) + Y * (k) \tag{7}$$

$$D' = |Y^{*}(k) - Y\,(k)| \tag{8}$$

where, b is a constant that defines the geometry of the logarithmic spiral, t is a randomized value within range [1, 1], and "*" is a multiplication of components by components. Humpback whales employ a dual swimming technique, wherein they encircle their prey in a diminishing circular trajectory while simultaneously following a spiral pattern. In order to account for this simultaneous action, we posit that there is a 50% probability of whales altering their location after optimizing the circling process or the spiral model. The following is the mathematical formula:

$$\underset{X}{\rightarrow}(t+1) = \begin{cases} X^{+}(i) - \underset{V.}{\rightarrow}\underset{D}{\rightarrow}\ if\ R < 0.5 \\ \underset{D}{\rightarrow}.e^{bk}.\cos(2\prod k) + \underset{X^{+}}{\rightarrow}(t)\ \ if\ R \geq 0.5 \end{cases} \tag{9}$$

R is a randomized integer in the interval [0, 1]. Apart from employing bubble nets, humpback whales engage in haphazard hunting for prey.

Search for Prey (Exploration Period)

If their locations are aligned with one another, humpback whales will search for prey at random. We want to concentrate our efforts in this phase on promising portions of the search area and drive the search agency to move far to the desired whale. As a result, during prey exploration, the vector 'V' is used, which has a value higher than or less than 1. In contrast to the exploitation period rather than using the best agents thus far discovered, the exploration phase will update a search agent's position based on a newly selected hunt agent. We use $|V|>1$ for force WOA algorithm investigation in order to discover the global maximum while avoiding local maxima. The theoretical model can be expressed in the following way:

$$D = |C.Xr_{and} - X| \tag{10}$$

$$X\,(t\ +\ 1)\ =\ Xr_{and} - V.D \tag{11}$$

Xr_{and} is a randomly chosen position vector from the existing population.

Search agents evaluate their location in relation to a randomly selected agent or the best solution, after every iteration. For the purpose of making research and exploitation easier, the value 'a' is decreased from 2-0. When the magnitude of vector V is greater than 1, a randomized searching agent is selected. Conversely, when the magnitude of vector V1 is selected, the best solution is chosen to update the locations of the search agents. To determine the value of R, we need to analyze the interplay between a helical and a cyclical motion.

Feature Selection Using Whale Optimization Algorithm (WOA)

Optimum features should be chosen to produce good classification results. The greatest properties are chosen using the whale optimization algorithm. WOA will determine the best global solution with the maximum classification results. In comparison to other state-of-the-art algorithms, WOA is more effective at selecting optimal features and optimizing a range of restricted engineering design issues. We create the WOA algorithm for picking the best features in our research. To choose optimal features the subsequent processing stages are utilized.

Step 1: Initialization

The initialization phase, also known as solution creation, plays a crucial role in the optimization process by facilitating the quick identification of the optimal solution. The database comprises socio-economic statistics. Location-based crime prediction methods utilize historical socioeconomic data to forecast future crime occurrences at specific locations. In this, SF represents the selected features, and the selected features are represented as SF = {I = 1, 2, 3…n}. Achieved resolution is proposed for the following stage, which is fitness evaluation, in order to increase performance and identify an optimal solution.

Step 2: Fitness Calculation

The fitness function evaluates the resolution after it is generated and then selects the best option. The majority of the time, an optimization algorithm's fitness function helps to determine the best alternative. To discover the best solution, the optimization method mostly focuses on its fitness value. The classification accuracy is considered as the solution qualifier in this study using the DNN. The feature data set is split into two halves, one for training and the other for testing. DNN is learned by the input features throughout the training process. The new DNN classifier is provided with feature data after the training is completed. Out of 100 data sets, 80% are used for training and 20% are used for testing. The updation is based on the results of DNN testing and training accuracy. The range of classification accuracy is [0; 1]; each Search Agent represents this range. One of the core components of WOA is fitness selection:

$$Fitness_{,t} = \sum_{K=1}^{N} \frac{accuracy_{gr,t,k}}{N} \tag{12}$$

The function $f(g, t)$ represents the fitness value of whale optimization in iteration t. N is the number of selected features for further processing and accuracy, and t, k is the accuracy resultant. WOA upgrades the underlying arbitrary populace on the test capacities and attractively enhances the accuracy of the approximated optimum is mathematically represented as described:

$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} \tag{13}$$

The true positive is expressed by TP, the true negative by TN, the false positive by FP, and the false negative by FN.

Step 3: WOA-Based Updation Solution

Utilize the WOA algorithm to adjust the answer during the fitness evaluation. By using Eq. (14), we can revise the solution. The mathematical characterization of the whale optimization algorithm involves describing its situation or position as given below:

$$S(I-1) = \vec{S} * (I) - \vec{U}.\vec{V} \tag{14}$$

where, I specifies the current iteration S specifies the vector position and $S * (i)$ specifies the vector position of the best solution. On computing the location of the present optimal solution the algorithm is used to determine a new search position (15):

$$\vec{S}(I+1) = \vec{A}_{rand} - \vec{U}.\vec{V} \tag{15}$$

In the exploration stage, a search agent chosen at random will update the location of the search agents using formula (16):

$$\vec{S}(I+1) = \left|S * \vec{(I)}\right|.h^{st}.cos(2\prod t) + \vec{S} * (I) \tag{16}$$

Step 4: Termination Criteria

We halted the entire process by implementing a maximum iteration limit. The algorithm only continues if the optimum quantity of cycles has been completed and the option with the highest fitness number has been chosen. When the best fitness is achieved using WOA methods, a feature is chosen for classification.

Deep Learning Network (DNN) Based Prediction

DNN is considered one of the most efficient methods for categorization. However, DNN is not suitable for classifying large datasets due to its high dependence on the size of the input, which results in increased complexity. Multi-kernel DNNs are employed to handle data with large dimensions, ensuring accurate classification and optimal performance metrics while minimizing computational costs. The DNN classifier has superior accuracy and demonstrates substantially faster performance compared to other classifiers. DNNs have many hidden layers between their input and output layers. In the midst of the training phase, when there are a lot of samples available, deep learning approaches work well. For training, use a DNN, a deep design and popular feed-forward framework where input passes via more than two hidden layers from the input layer to the output layer. The framework may produce visible openings based on the location of its hidden units, which represent the confidence of the structure, similar to the Deep Belief Network (DBN) model (Hassan *et al.*, 2019). To solve the aforementioned issue, we used a Restricted Boltzmann Machine (RBM) in this instance. The DNN structure is shown in Fig. 2.

Restricted Boltzmann Machine (RBM)

A layer of randomly apparent or perceptible units and a layer of stochastic concealed units generate an RBM, which is a barrier-type Markov random field. The output vector of the network's vectorization and output serves as the input for DNNs.The structure of the RDM is shown in Fig. 3.

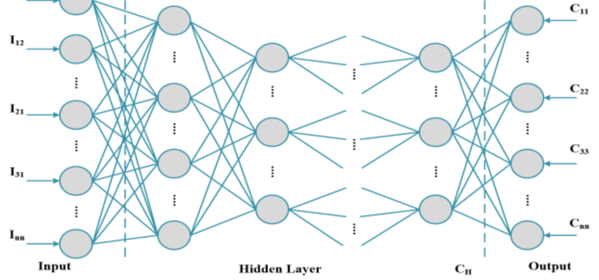

Fig. 2: Structure of DNN

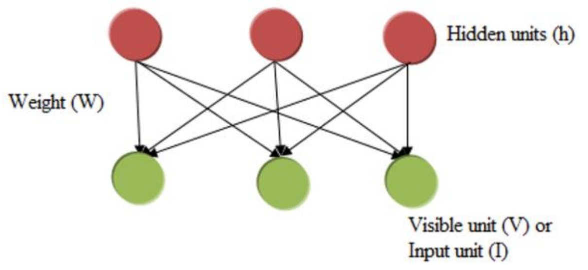

Fig. 3: RBM structure

Consider [R_m] being the input features (positive and negative scores) where $1 \leq m \leq M$ and 'C' is the actual output. The general model of the neural network is 'C' for the output of the entire network and 'C_H' for the concealed layer's output. Similar to DNN, the first hidden layer is multiplied by the element weights. Additionally, the first hidden element's individual outputs are multiplied by a further weight in the second hidden layer, and so forth.

In the first hidden layer, the input weight values are assigned to the neuron function in conjunction with Eq. (17):

$$C_{H\_1}(x=1,2..,K)=\left(\sum_{m=1}^{M} w_{xm}\, R_m\right)+b_x \tag{17}$$

where:
b_x = Bias value
w_{xm} = Interconnection weight
M = Number of inputs
K = Number hidden nodes

The activation function is represented as:

$$F\left(C_{H\_1}(x)\right)=\frac{1}{\left(1+e^{-C_{H\_1}(x)}\right)} \tag{18}$$

where, $F(.)$ is the sigmoid activation function. Therefore, the operation of y^{th} hidden layer can be generalized as:

$$C_{H\_y}(p)=\left(\sum_{z=1}^{K} w_{pz}F\left(C_{H\_(y-1)}(z)\right)\right)+b_p \tag{19}$$

where:
b_p = Bias of p^{th} hidden node
w_{pz} = Interconnection weight

The activation function of the y^{th} hidden layer is given as:

$$F\left(C_{H\_y}(p)\right)=\frac{1}{\left(1+e^{-C_{H\_y}(p)}\right)} \tag{20}$$

The output of the y^{th} hidden layer is multiplied by the interconnection weights once again at the output layer and the bias is then added up. (b_q) as:

$$C(q)=F\left(\sum_{p=1}^{K} w_{qp}\; f\left(C_{H\_y}(p)\right)+b_q\right) \tag{21}$$

where, w_{qp} weight of connections at the output and hidden levels. The output of the entire model is represented by the activation function located in the output layer.

In order to maximize the network output, the current output is compared to the objective, and error is found. The Eq. (22) contains the error calculation:

$$Error(m)=\frac{1}{M}\sum_{m=1}^{M}\left(Actual(C_m)-Target(C_m)\right)^2 \tag{22}$$

where, *Target* (C_m) is the network output estimated and *Actual* (C_m) is the actual output. The error should reduced in order to obtain the optimal network configuration. Therefore, weight values should be maintained until each of the iterations is deceased. By evaluating this error function, input features of records are divided as positive and negative.

Results and Discussion

In this study, the Lagrange polynomial interpolation technique has been implemented for filling missing values in the step of pre-processing and WOA for selecting the important socio-economic data based on their influence in crime rate prediction and for classification DNN techniques have been executed in the operating platform of JAVA. The following specifications apply to the Windows computer used for this procedure: Processor® Dual-core CPU running at 2.70 GHz with 1 GB of RAM and a professional version of Microsoft Windows 7.

With regard to the experimental findings, the effectiveness of all of the comparable algorithms, including our suggested WOA and DNN has been verified in detail. Not all of the characteristics are used for classification in particular. The best features should be chosen to produce better classification results. WOA is used to choose the best characteristics, resulting in the most accurate comprehensive solution. In our experience, DNN is ideal for categorization. DNN is being used to anticipate and classify vital socio-economic data based on their influence on crime rate prediction. Finally, the crime rate is analyzed for the data and categorized as less prone, medium prone, and highly prone to crime activities using the Deep Learning algorithm. Our suggested model is expected to yield superior classification accuracy by using optimal features and achieving optimal performance metrics in comparison to other current models.

The following Figs. 4-10 shows the Execution time, Memory, Training Time, Testing Time, Sensitivity, Specificity, and Accuracy of the proposed approaches. When analyzing Fig. 2 the proposed WOA obtains the less execution time of 85441, 91547, 97858, and 115787. Comparing these existing Genetic Algorithms (GA), FireFly (FF), and Particle Swarm Optimization (PSO), the proposed WOA achieves less execution time. Figure 4 illustrates how our proposed strategy exceeds existing approaches in terms of results.

DOI: 10.3844/jcssp.2024.1203.1213

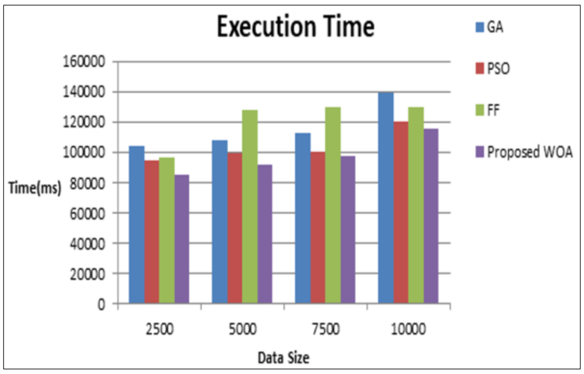

Fig. 4: Performance analysis for execution time

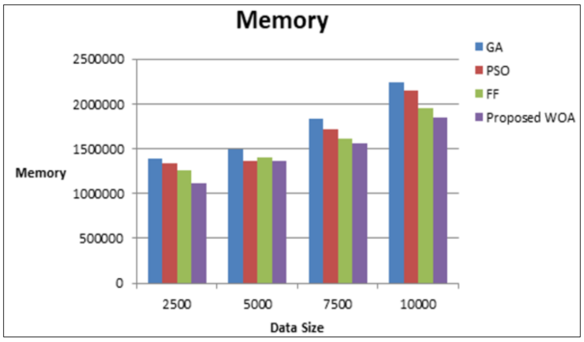

Fig. 5: Performance analysis for memory utilization

Figure 5 represents the comparative examination of the memory usage of a suggested approach in relation to existing methods. When examining Fig. 5 the suggested WOA obtains minimal memory utilization of 1115484, 1364945, 1561475, and 1854456. Comparing these existing GA, PSO, and FF the proposed WOA achieves minimum memory utilization. Figure 5 illustrates how our proposed strategy exceeds existing approaches in terms of results.

In Fig. 6, the proposed WOA obtains the minimum training time of 11547, 16884, 22545, and 26365. Comparing these existing GA, PSO, and FF the proposed WOA achieves minimum training time. Figure 6 illustrates how our proposed strategy exceeds existing approaches in terms of results.

Figure 7 represents the comparison analysis of the testing time of a proposed method with the existing methods. When examining Fig. 5 the suggested WOA obtains the minimal testing time of 23544, 25465, 29658, and 31254. Comparing these existing GA, PSO, and FF the proposed WOA achieves minimum testing time. Figure 7 illustrates how our proposed strategy exceeds existing approaches in terms of results.

The graph depicts a comparative analysis of the sensitivity of a proposed method in relation to existing methodologies. When analyzing Fig. 8, the proposed WOA obtained the maximum True Positive Rate (TPR) i.e., the sensitivity of 90.53, 91.9, 92.96, and 93.79. Comparing these with existing GA, PSO, FF and the proposed WOA achieves maximum sensitivity.

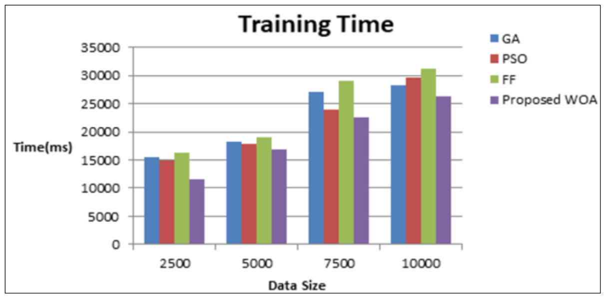

Fig. 6: Performance analysis for training time

Fig. 7: Performance analysis for testing time

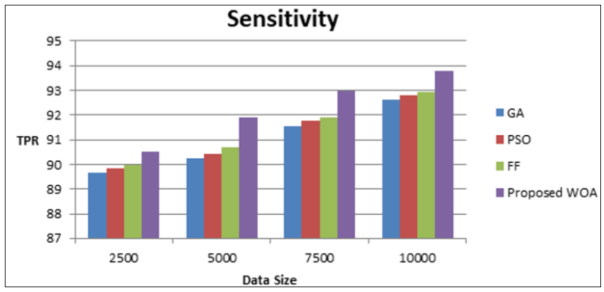

Fig. 8: Performance evaluation for sensitivity

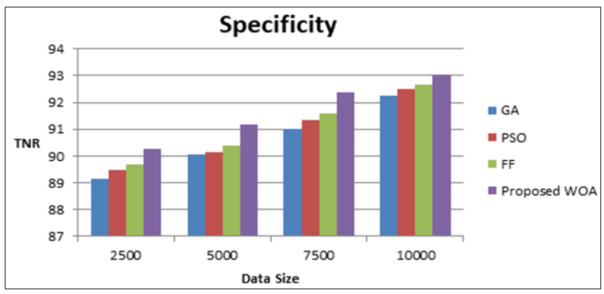

Fig. 9: Performance analysis for specificity

When analyzing Fig. 9 the proposed WOA obtains the maximum specificity of 90.25, 91.19, 92.37, and 93.02. The current methods of GA, PSO, and FF fail to accurately identify the True Negative Rate (TNR). However, the suggested WOA correctly detects the TNR. The comparison of these proposed WOAs demonstrates a greater level of specificity. Figure 9 illustrates how our proposed strategy exceeds existing approaches in terms of results.

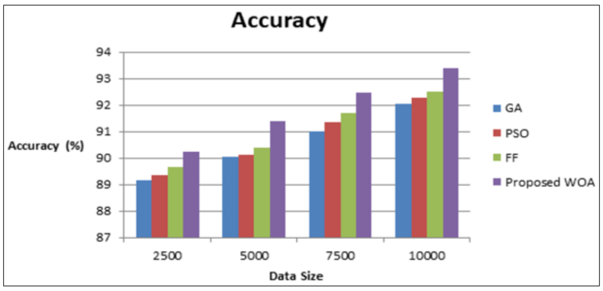

Fig. 10: Performance analysis for accuracy

The Fig. 10 specifies the performance analysis for maximum accuracy. It is clear from Fig. 10 that the proposed whale optimization algorithm achieves the maximum accuracy of 90.23, 91.39, 92.46, and 93.39. Hence the proposed WOA technique achieves greater accuracy relative to the approaches existing in terms of results.

The suggested WOA aims to determine the sensitivity, specificity, execution time, and memory utilization. Once these factors are identified, the WOA will assess the maximum accuracy. The accuracy is determined by dividing the number of correct suggestions by the total number of forecasts and then multiplying by one hundred to obtain a percentage. GA, PSO, and FF have established methodologies that inadequately assess sensitivity, specificity, execution time, and memory application, which is a significant limitation. Upon analyzing Fig. 10, it is evident that the suggested WOA technique achieves the highest level of accuracy when compared to other current techniques.

Conclusion

With today's rapid occurrence of repeated criminal instances, it is a difficult challenge to precisely predict future crime and improve functionality. In order to predict the socio-economic crime data, this research introduces an innovative classification framework consisting of three phases: Pre-processing, feature selection, and classification. The ideal features should be chosen to produce good classification results. Whale Optimization is a technique for selecting the optimal characteristics. The improved classification accuracy will be used by WOA to establish the ideal overall solution. Employing these properties, DNN is employed to categorize the crime data. The suggested model is expected to yield superior classification accuracy by using optimal features and achieving optimal performance metrics in comparison to other currently created models. The proposed WOA model is analyzed and compared with other models like Genetic Algorithm (GA), FireFly (FF), and Particle Swarm Optimization (PSO). One of the main drawbacks of existing techniques (GA, PSO, FF) is parameters like sensitivity, specificity, execution time, and memory utilization are not properly identified. From the experimental results, this model is found as the best crime prediction model in terms of performance metrics; with less execution time, minimal memory, less training time, less testing time, higher sensitivity, higher specificity & high accuracy. In comparison to previous models, this method effectively retrieves the crime's attributes with a high accuracy of 93.39%. Hence the proposed model will aid in decision-making for proposing resources or infrastructure recommendations, like setting up a new police station in a higher crime-prone area.

Future Research and Gaps

The limitation of the proposed model is that our DNN-based strategy for predicting the incidence of crimes cannot be used in situations where there is insufficient input data. It is also suggested to use this prediction model to assess how well a real-world application performs. In the future, a hybrid prediction model is proposed using a combination of Support Vector Machines (SVM) and deep neural networks.

Acknowledgment

The authors are thankful to the Department of Information Technology, Noorul Islam Centre for Higher Education, for the research support.

Funding Information

No funding was received for this research.

Author's Contributions

Santhosh Sankara: Conceptualization, methodology, investigation, data curation, written original drafted preparation.

Nadeson Sugitha: Edited, supervision, project administration.

Ethics

There are no ethical issues or conflicts to declare.

References

Agarwal, A., Saxena, R., Jaiswal, K., & Malhotra, S. (2016). Application for analysis and prediction of crime data using data mining. *International Journal of Advanced Computer Engineering and Networking*, *4*(5), 9–12.

Aziz, R. M., Hussain, A., & Sharma, P. (2023). Cognizable crime rate prediction and analysis under Indian penal code using deep learning with novel optimization approach. *Multimedia Tools and Applications*, *83*(8), 22663–22700. https://doi.org/10.1007/s11042-023-16371-0

Campaniello, N., & Gavrilova, E. (2018). Uncovering the gender participation gap in crime. *European Economic Review*, *109*, 289–304. https://doi.org/10.1016/j.euroecorev.2018.03.014

Hassan, M. M., Alam, Md. G. R., Uddin, Md. Z., Huda, S., Almogren, A., & Fortino, G. (2019). Human emotion recognition using deep belief network architecture. *Information Fusion*, *51*, 10–18. https://doi.org/10.1016/j.inffus.2018.10.009

He, J., & Zheng, H. (2021). Prediction of crime rate in urban neighborhoods based on machine learning. *Engineering Applications of Artificial Intelligence*, *106*, 104460. https://doi.org/10.1016/j.engappai.2021.104460

Hooghe, M., & de Vroome, T. (2016). The relation between ethnic diversity and fear of crime: An analysis of police records and survey data in Belgian communities. *International Journal of Intercultural Relations*, *50*, 66–75. https://doi.org/10.1016/j.ijintrel.2015.11.002

Intravia, J., Wolff, K. T., Paez, R., & Gibbs, B. R. (2017). Investigating the relationship between social media consumption and fear of crime: A partial analysis of mostly young adults. *Computers in Human Behavior*, *77*, 158–168. https://doi.org/10.1016/j.chb.2017.08.047

Jendryke, M., & McClure, S. C. (2019). Mapping crime Hate crimes and hate groups in the USA: A spatial analysis with gridded data. *Applied Geography*, *111*, 102072. https://doi.org/10.1016/j.apgeog.2019.102072

Jing, X., Yan, Z., & Pedrycz, W. (2019). Security Data Collection and Data Analytics in the Internet: A Survey. *IEEE Communications Surveys & Tutorials*, *21*(1), 586–618. https://doi.org/10.1109/comst.2018.2863942

Joshi, A., Sabitha, A. S., & Choudhury, T. (2017). Crime Analysis Using K-Means Clustering. *2017 3rd International Conference on Computational Intelligence and Networks (CINE)*, 33–39. https://doi.org/10.1109/cine.2017.23

Kim, S., Jeong, S., Woo, I., Jang, Y., Maciejewski, R., & Ebert, D. S. (2018). Data Flow Analysis and Visualization for Spatiotemporal Statistical Data without Trajectory Information. *IEEE Transactions on Visualization and Computer Graphics*, *24*(3), 1287–1300. https://doi.org/10.1109/tvcg.2017.2666146

Kim, S.-K., & Kang, H.-B. (2018). An analysis of fear of crime using multimodal measurement. *Biomedical Signal Processing and Control*, *41*, 186–197. https://doi.org/10.1016/j.bspc.2017.12.003

Lee, A. W. (2019). A time-sensitive analysis of the work-crime relationship for young men. *Social Science Research*, *84*, 102327. https://doi.org/10.1016/j.ssresearch.2019.102327

Mastrorocco, N., & Minale, L. (2018). News media and crime perceptions: Evidence from a natural experiment. *Journal of Public Economics*, *165*, 230–255. https://doi.org/10.1016/j.jpubeco.2018.07.002

Oguntunde, P. E., Ojo, O. O., Okagbue, H. I., & Oguntunde, O. A. (2018). Analysis of selected crime data in Nigeria. *Data in Brief*, *19*, 1242–1249. https://doi.org/10.1016/j.dib.2018.05.143

Qazi, N., & Wong, B. L. W. (2019). An interactive human centered data science approach towards crime pattern analysis. *Information Processing & Management*, *56*(6), 102066. https://doi.org/10.1016/j.ipm.2019.102066

Qu, L., Li, W., Li, W., Ma, D., & Wang, Y. (2019). Daily long-term traffic flow forecasting based on a deep neural network. *Expert Systems with Applications*, *121*, 304–312. https://doi.org/10.1016/j.eswa.2018.12.031

Saeed, R. M., & Abdulmohsin, H. A. (2023). A study on predicting crime rates through machine learning and data mining using text. *Journal of Intelligent Systems*, *32*(1), 20220223. https://doi.org/10.1515/jisys-2022-0223

Salcedo-Gonzalez, M., Suarez-Paez, J., Esteve, M., & Palau, C. E. (2023). Spatiotemporal Predictive Geo-Visualization of Criminal Activity for Application to Real-Time Systems for Crime Deterrence, Prevention and Control. *ISPRS International Journal of Geo-Information*, *12*(7), 291. https://doi.org/10.3390/ijgi12070291

Sharkey, P., & Torrats-Espinosa, G. (2017). The effect of violent crime on economic mobility. *Journal of Urban Economics*, *102*, 22–33. https://doi.org/10.1016/j.jue.2017.07.001

Vomfell, L., Härdle, W. K., & Lessmann, S. (2018). Improving crime count forecasts using Twitter and taxi data. *Decision Support Systems*, *113*, 73–85. https://doi.org/10.1016/j.dss.2018.07.003

Vujić, S., Commandeur, J. J. F., & Koopman, S. J. (2016). Intervention time series analysis of crime rates: The case of sentence reform in Virginia. *Economic Modelling*, *57*, 311–323. https://doi.org/10.1016/j.econmod.2016.02.017

Wei, X., Yan, J., Chen, Z., & Shi, T. (2016). Analysis of Crime Rate Distribution Based on TPML-WMA. *2016 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery (CyberC)*, 157–160. https://doi.org/10.1109/cyberc.2016.39

DOI: 10.3844/jcssp.2024.1203.1213

William, P., Shrivastava, A., Shunmuga Karpagam, N., Mohanaprakash, T. A., Tongkachok, K., & Kumar, K. (2023). Crime Analysis Using Computer Vision Approach with Machine Learning. In *Mobile Radio Communications and 5G Networks* (pp. 297–315). Springer. https://doi.org/10.1007/978-981-19-7982-8_25

Yoon, J., Gong, E., Chatnuntawech, I., Bilgic, B., Lee, J., Jung, W., Ko, J., Jung, H., Setsompop, K., Zaharchuk, G., Kim, E. Y., Pauly, J., & Lee, J. (2018). Quantitative susceptibility mapping using deep neural network: QSMnet. *NeuroImage*, *179*, 199–206. https://doi.org/10.1016/j.neuroimage.2018.06.030