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An Optimization of Multimodal Deep Crime Detection Network Using Osprey Optimization Algorithm

Sundari Palanisamy[1], Malathi Arunachalam[2]

[1]PG and Research Department of Information Technology, Government Arts College (Autonomous), Coimbatore- 641018, Tamil Nadu, India
Email: *sundaripalanisamyphd[at]yahoo.com*

[2]PG and Research Department of Computer Science, Government Arts College (Autonomous), Coimbatore- 641018, Tamil Nadu, India
Email: *malathi.arunachalam[at]yahoo.com*

Abstract: ***Crime detection helps law enforcement to prevent future crimes by identifying their patterns. However, evolving criminal behaviors and rapid crime occurrences makes the future crime classification difficult. Various Deep Learning (DL) models are made to predict crime accurately. Among them, Social media information enriched Multimodal Diversified Deep Crime detection network (SMDDCnet) was proposed for crime prediction using historical dataset and social media (twitter) image and video information. This model uses enhanced recursive self-attention mechanism (ERSAM) to capture long term dependencies, Convex Function Information Entropy (CFIE) quantifies the uncertainty in crime patterns and Convolutional Bidirectional Long Short Term Memory (ConvBiLSTM) to forecast the crime effectively. But, the hyperparameters of ConvBiLSTM are not optimally selected causing lower accuracy result and higher computational complexity. Also, hyperparameter tuning is typically performed manually, making the process time-consuming and work-intensive. Hence, Social media information enriched Optimized Multimodal Diversified Deep Crime detection network (SMODDCnet) is proposed in this paper for tuning hyperparameters of the ConvBiLSTM network to enhance the crime prediction performance. The Osprey Optimization technique (OOA) is a novel metaheuristic optimization technique is employed in this study. It is based on how ospreys seek fish in the sea. The OOA involves two stages such as exploration and exploitation, wherein ospreys identify their prey's location and move it to an appropriate location to eat it. Based on these processes, the optimal hyperparameters of the ConvBiLSTM model are determined for the prediction of crime from both historical and social media information data. By utilizing the OOA, this model effectively fine-tunes the hyperparameter of ConvBiLSTM, resulting with high accuracy and lower computational complexity. Finally, the results of the experiment indicate that the SMODDCnet model is more accurate than other crime prediction models on the Crime in India dataset, with an accuracy rate of 98.42%.***

Keywords: Deep Learning, Social Media, Crime Detection, Osprey Optimization

1. Introduction

Crime is a major problem in society, with regular events making individuals apprehensive. Crime patterns are continually changing, making it difficult to analyze and forecast behavior [1]. Law enforcement organizations use information technology (IT) to gather crime data, but forecasting crime remains difficult owing to variables like poverty and employment, both of which influence crime rates [2]. Crime occurrences are neither constant or random and the growing number of crimes challenges forecast attempts [3].

Traditional crime prediction systems estimate several crime categories based on past socioeconomic data and demographic information from hotspot maps [4]. However, these maps may not always fully show all incidents, such as taxicab robberies with victims spread over numerous areas. Furthermore, the absence of generalizable data across areas impedes prediction models, since these approaches mostly depend on previous crime records, neglecting socio-behavioral data from communities [5].

Public chats and posts using social media sites like Facebook, Instagram, and Twitter give a new source of information in which individuals express their views and ideas. [6]. This user-generated information contains socio-behavioral markers that may be used for crime prediction [7]. Sentiment Analysis (SA), that is often called opinion mining, collects and classifies subjective information from unstructured text by determining emotional tone using contextual word hints [8]. It has become an important instrument for law enforcement to evaluate public opinion on crime by monitoring social media postings, news and reviews [9]. SA makes it easier to anticipate crime by sorting content into positive, negative, or neutral categories, providing insights into public safety attitudes for improved resource allocation [10]. However, SA has challenges with high-dimensional crime data, lexical variety and dataset imbalances, which may limit its accuracy.

Data mining in crime prediction effectively extracts patterns from crime reports, social media and surveillance data to detect trends and predict crimes [11]. It aids law enforcement in proactive measures by analyzing historical data and forecasting future occurrences [12]. However, it raises ethical and legal concerns, potential biases, computational power requirements and the constant change in criminal behavior, making past data patterns less useful for predicting new crimes. To solve these issues, Deep Learning (DL) models, a kind of Artificial Intelligence (AI), have been developed. DL algorithms may improve crime detection and prediction by studying surveillance film and categorizing illegal acts including theft, mischief and assault [13]. It may also be used with smart prediction technologies like as drones and Internet of Things (IoT) sensors for better monitoring [14]. Some of the DL models used to assess geographic and temporal crime data to effectively anticipate crime trends and hotspots in cities are Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks [15].

Several DL algorithms have been created to minimize crime and anticipate trends for early intervention. Among other things, multimodal DL crime prediction models use tweets and past crime data to develop predictive models. The ConvBiLSTM [16] model generates independent vectors from twitter and crime data and combines them to provide relevant information. Word embedding vectors use convolution and pooling layers to summarize this data. However, these models continue to confront obstacles, such as a lack of semantic comprehension, which may affect prediction accuracy.

As a result, Social Media Information Enriched Multimodal Deep Crime Detection Network (SMDCnet) [17] was created to address the aforementioned concerns by integrating multimodal social media data and criminal databases. Text vectors are generated using Latent Dirichlet Allocation (LDA) to identify crime-related subjects such as theft and murder. Features from twitter images and videos are retrieved using Mask Regional CNN (MASK-RCNN) combined with Multi-Feature Pyramid Network (MFPN) and Non-Maximum Suppression (NMS). ConvBiLSTM [16] enhances crime prediction accuracy by combining text and images picture information. However, in ConvBiLSTM, CNN recovers local features easily but has difficulty with sequential correlations. While Bi-LSTM captures bidirectional context, it does not allow for parallel feature extraction. As a result, these concerns are handled by merging CNN with Bi-LSTM. However, while processing varied multimodal input (text, images and structured data), Bi-LSTM may experience information redundancy and gradient explosion.

To solve this, Social Media Information Enriched Multimodal Diversified Deep Crime Detection Network (SMDDCnet) [18] was developed to address the issue of BiLSTM in crime prediction. Two key enhancements are proposed to improve BiLSTM performance. First, BiLSTM employs an enhanced recursive self-attention mechanism (ERSAM) to compress feature representation by analyzing data in both forward and backward directions, improving representation across time steps without adding parameters. Multi-Scale Self-Attention (MSSA) is applied to focus on different feature regions, efficient feature similarity computation across recursive layers, reducing computational cost without sacrificing accuracy. Second, an enhanced Loss Function using CFIE enhances the optimization and convergence speed, especially with limited crime data. ConvBiLSTM [16] enhances crime prediction accuracy by combining text and images information for reliable crime prediction. But, selecting the right hyperparameter for ConvBiLSTM is challenging because it involves choosing the optimal combination of layers and its connections which impacts the network's accuracy. Since, each hyperparameter affects the performance differently, it is difficult to find the best configuration directly often leads to computational complexity. Also, hyperparameter is usually done manually, making the process time-consuming and labor-intensive.

Hence, in this paper, SMODDCnet model is proposed to lower computational complexity and enhance the accuracy performance for crime prediction. The Osprey Optimization technique (OOA) is a novel metaheuristic optimization technique that is used in this model is applied for fine-tuning the hyperparameter of ConvBiLSTM. This OOA depends on the behavior of osprey and its core idea is the ospreys' method for catching fish in the sea, which has two parts: exploration and exploitation The osprey hunts by finding prey and moving it to a place to eat. This OOA policy indicates that selecting the optimal hyperparameters for training the ConvBiLSTM model is straightforward. Then, the ConvBiLSTM is trained and validated to predict the crime intensities. By exploiting OOA, the hyperparameters of ConvBiLSTM are properly adjusted, resulting in improved accuracy and reduced computing efficiency in crime prediction.

The structure of the research is: In section 2, various papers related to crime categorization and identification models are provided. Section 3 describes the suggested SMODDCnet model, whereas Section IV shows its validity. Section V contains an overview of the model as well as plans for future improvements.

2. Literature Survey

Rayhan and Hashem [19] presented an Attention based Interpretation Spatio-Temporal model (AIST) for crime detection. The adaptive spatio-temporal relationship correlations were applied to analyze the crime classes using the external factors such as crime vehicular movement and location data, repeated crime patterns and real crime records. The characteristics were inputted into AIST in order to capture the complex and dynamic and non-sequential connections of environmental reliance and temporal aspects for predicting a certain type of crime. Overfitting problems have merged as a result of insufficient data interpretation.

Singuluri et al. [20] devised a Modified Capsule Network with Crisscross Optimization (MCN-CCO) for the cyber-crime prediction. By combining the outputs of both networks to optimize their strengths and boost the detection rate, the approach combines MCN with Multilayer Perceptron (MLP) using a rule based strategy. Next, the CCO method was used to improve and optimize the capsule network's hyperparameters for finding crimes. Unfortunately, F1-Score and training time were both negatively affected by this model.

Escobar et al. [21] created an Agent-Based Model (ABM) for law enforcement using crime trend prediction. The technique predicts crime trends by examining offender behavior, escape trajectories and stealing frequency. It detects crime trends and pinpoints conflicting areas for safety enhancement. The approach also creates defender positions and crime factors based on environmental data,

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enabling for more efficient patrol sites to combat city crime. However, significant computer resources and complex emotional models were needed to enhance the accuracy values.

Hashi et al. [22] developed a transfer learning based CNN for crime perceptive prediction by entity detection. The gathered information was pre-processed and inputted into ResNet VGG-19, and GoogleNet to forecast the corruption scenarios. Also, the YOLO was merged to detect the entities in support to crime prediction. However, optimizing algorithms were necessitated to refine the pre-trained CNN's parameter causing uncertainty issues and lower accuracy performance.

Mithoo & Kumar [23] presented a Spizella Swarm Optimization based Bidirectional LSTM (SSO-BiLSTM) using twitter data to find out the crime rate. The pre-processed and augmented data were inputted to BiLSTM to forecast the crime patterns in related to time period. The hyper-parameter of BiLSTM were fine-tuned by SSO for convergence enhancements and lowering the models complexity. But, the models performance was hindered due to limited training data which restricts the accuracy and sensitivity rate.

Butt et al. [24] constructed a Transfer Learning (TL) with BiLSTM for crime prediction. In this model, this model reviews statistical modeling techniques for time series prediction by Weighted Moving Averages (WMA), Simple Moving Averages (SMA) and Exponential Moving Averages (EMA). Then, DL models like LSTM, BiLSTM and CNN-LSTM for analyzing time-series data. Finally, BiLSTM with TL addresses data and training challenges, improving efficiency and reducing resource and time needs for crime prediction. But, this model fails to account for temporal effects like trends, lags and periodicity.

Selvan & Sivakumaran, [25] utilized Bi-LSTM model to anticipate the criminal activities and forecast high-risk crime regions in the city. This model uses machine learning (ML) to forecast crime spots and DL to verify the alignment among predicted and actual crime incidents for analyzing crime incident data. ML algorithms process voice-based emotion data for detection, while DL methods like convolutional stacked bidirectional LSTM to handle crime scene data like audio/video, geographic coordinates and timestamps. But, this model struggled with capturing contextual information and word relationships.

Zhou et al. [26] created a Hybrid Dynamic Multi-Perspective Graph Neural Network (HDM-GNN) to detect the crime actions. This approach leverages Spatio and temporal interactions using varied urban data and incorporates the inter-regional relations across various perspectives. The compressive spatial trends and extensive temporal interactions were obtained using the Gated CNN and Graph Attention model. But, this model struggles with training spatiotemporal features from diverse sequences and effectively fusing complementary features.

Shan et al. [27] devised an adaptive urban crime spatial and temporal forecasting technique dubbed Ada-GCNLSTM. This model used graph convolutional networks (GCN) to find spatial patterns in crime data, with a focus on greatest mean discrepancy and spatial interdependence. After that, LSTM was utilized to find temporal features, and relational mechanism units (RMUs) were concatenated to the LSTM to guess the hidden connections between different forms of crime. However, the model uses normal crime data distribution might misrepresent extreme crime patterns leading to increased prediction errors.

Wang et al. [28] developed a Multi-Type Relations Aware Graph Neural Networks (MRAGNN) is a model that predicts when crimes will happen by acquiring the skills different types of crimes are related to each other. This model builds a spatial/type graph structure of crime data on the fly and uses dynamic graph networks to find both spatio-temporal and type-temporal connections in the data. They employed a cross-modal gated fusion approach to combine the representations of two dependencies. Finally, an enhanced multi-label classification focal loss was used to fix the problems that the uneven distribution of crime data caused for classification results. Still, the model was incapable to fully the imbalance issues leads to lower accuracy results.

Tuarob et al. [29] created a CRIMe and accident Surveillance from online news articles (CRIMSON) to monitor and predict the crime and accident trends using large-scale online news. This model crawls on online news articles, cleans text and removes irrelevant content for analysis. It compares crime/accident statistics with official police reports using correlation analysis. Features are extracted using TF-IDF. Multi-label Classification was performed using pre-trained cross-lingual language model to categorize news articles into multiple crime/accident types. But, this model solely relies on online news, leading to reporting bias that skews crime monitoring accuracy.

2.1 Research Gap

Various crime prediction models have been developed but faces different challenges. Some models were faces challenges in overfitting due to limited data, inability to fully address data imbalance and ineffective to handle the spatiotemporal dependencies in crime trends. Many models rely on static crime data distributions which might misrepresent the extreme crime patterns leading to inaccurate predictions. Mostly, the hyperparameters of some models were not optimized properly leads to lower accuracy and complexity issues. In this framework, a metaheuristic model i.e., OOA [30] is applied to fine-tune the hyper parameter to make it more accurate and lower the complexities in crime prediction.

3. Proposed Methodology

This part explains the suggested SMODDCnet model for crime prediction in detail. A pipeline of the proposed study is portrayed in Figure 1.

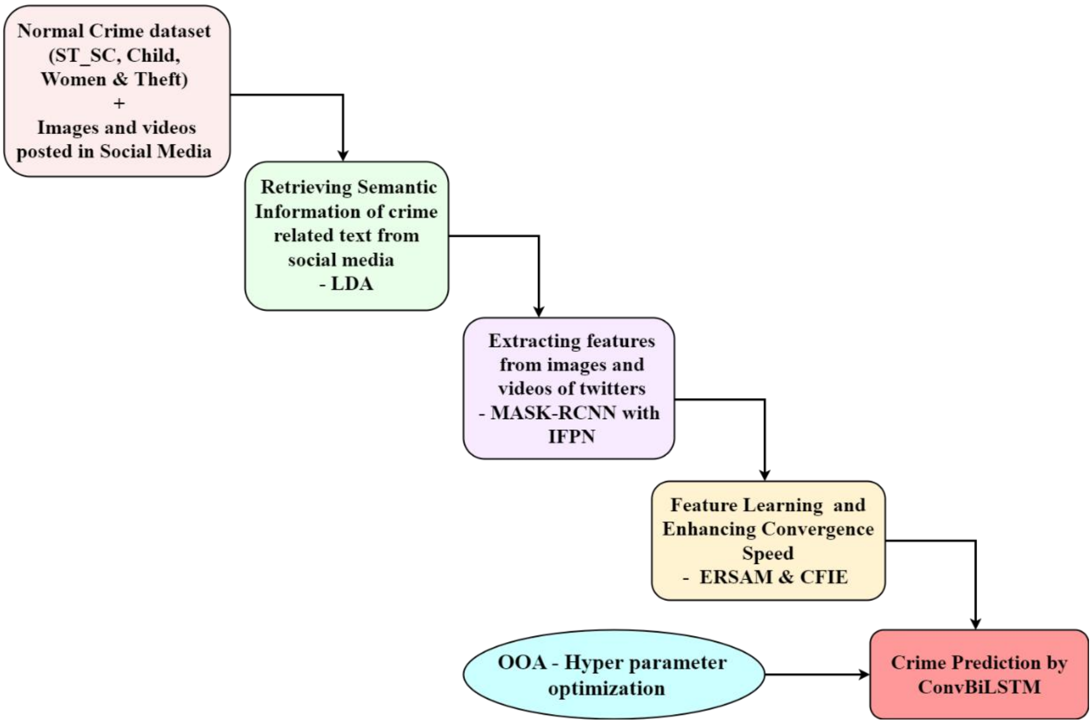

Figure 1: Pipeline of the suggested technique

3.1 Model Overview

Initially, the historical data and social media (twitter) data regarding crime perspective have been collected. Then, semantic information related to crime were extracted from text using LDA. Next, it extracts features from Twitter images and videos using Mask R-CNN. The structures of LDA and Mask R-CNN are detailed in SMDCnet [17]. Further, ERSAM and CFIE were used to prevents gradient explosion issues caused by information redundancy, as illustrated in SMDDCnet [18]. The extracted features are then fed to the ConvBiLSTM for crime prediction, in which the OOA finds the best values for the model's hyperparameters to make the predictions more accurate. The ConvBiLSTM model's hyperparameters include the size of the word embedding, the number of filters, the activation function, the learning rate, the dropout rate, the weight decay, the number of epochs, the batch size, the momentum rate, and the loss function. The suggested OOA sets the values of these hyperparameters in the best way for training the model properly. Figure 2 depicts the detailed layer of optimized ConvBiLSTM structure using OOA. The detailed description of this OOA is presented below section.

3.2 Osprey Optimization-based Hyperparameter Tuning

The osprey is a nocturnal bird of prey that can inspire a new optimization algorithm by showing the way it can catch fish and move them to a better location. The mathematical modeling of the OOA is explained below.

3.2.1 Initialization

The OOA comes under population-based approach that uses an iterative procedure to discover an suitable response based on the search power of its members. Every osprey in the OOA population decides whatever the problem variables are based on the location it is in the search space, which means that each osprey is a possible solution. They start by modelling the OOA population with a matrix, as shown in Eq. (1):

$$P = \begin{bmatrix} P_1 \\ \vdots \\ P_x \\ \vdots \\ P_N \end{bmatrix}_{N\times z} = \begin{bmatrix} p_{1,1} & \cdots & p_{1,y} & \cdots & p_{1,z} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ p_{x,1} & \cdots & p_{x,y} & \cdots & p_{x,z} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ p_{N,1} & \cdots & p_{N,y} & \cdots & p_{N,z} \end{bmatrix}_{N\times z} \quad (1)$$

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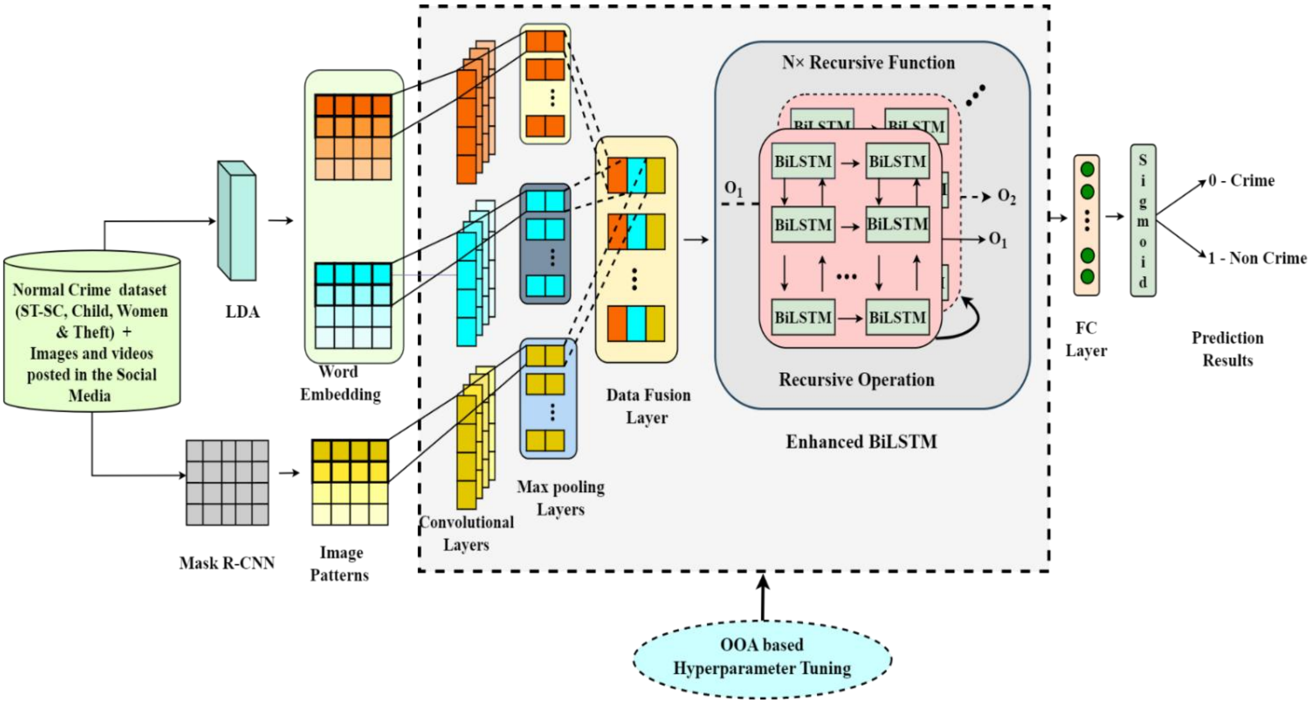

Figure 2: Optimized ConvBiLSTM model using OOA

Then, the ospreys' locations in the search space are set up randomly by

$$p_{x,y} = lb_y + rand_{xy} \cdot (ub_y - lb_y), x = 1, \dots, N;\ y = 1, \dots, z \quad (2)$$

In Eq. (1) & Eq. (2), P is the population matrix of osprey positions, P_x is the x^{th} osprey (a candidate solution), $p_{x,y}$ is its y^{th} dimension (a problem variable), N is the number of ospreys, z is the number of problem variables (the number of hyperparameters of the ConvBiLSTM model), and $rand_{x,y}$ is a random value between [0,1]. lb_y and ub_y are the lower and upper bounds of the y^{th} problem variable, respectively.

The evaluation may involve assessing the objective (fitness) function of a problem, such as prediction accuracy, by considering each osprey as a potential solution and utilizing a vector to display the results:

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_x \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_x) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \quad (3)$$

In Eq. (3), F denotes the vector containing the fitness function values and F_x stands for the fitness function value that was found for the x^{th} osprey. The values that were evaluated for the goal function are very important for figuring out if possible solutions will work. The best value is the best possible solution, and the worst value is the worst possible solution. Updating the ospreys' position in the search space is necessary for each iteration of the search process, which in turn requires updating the best candidate solution.

3.2.2 Exploration – Searching Location and Hunting Prey

Ospreys can see fish underwater and attack them because they have good eyesight. This natural behavior is used to model the first step of the population update in OOA. This simulation moves the osprey's position in the search space in a big way, making it easier for OOA to find the best places and avoid local optima. The OOA design looks at undersea fish that have greater fitness function values for each osprey's location in the search space. The group of fish that each osprey has is shown by

$$S_x = \{P_k | k \in \{1, \dots, N\} \land F_k < F_x\} \cup \{P_{best}\} \quad (4)$$

In Eq. (4), S_x denotes the collection of fish sites for the x^{th} osprey and P_{best} indicates the best candidate solution, or the best osprey. The osprey picks one of these fish at random and attacks it. Based on the osprey's movement toward the fish, the osprey should move to a different place. is determined as in Eq. (5),

$$p_{x,y}^{S_1} = p_{x,y} + rand_{xy} \cdot (CS_{x,y} - I_{x,y} \cdot p_{x,y}) \quad (5)$$

$$p_{x,y}^{S_1} = \begin{cases} p_{x,y}^{S_1}, & lb_y \le p_{x,y}^{S_1} \le ub_y \\ lb_y, & p_{x,y}^{S_1} < lb_y \\ ub_y, & p_{x,y}^{S_1} > ub_y \end{cases} \quad (6)$$

This new location alters the previous position of the osprey when the fitness function value is present:

$$P_x = \begin{cases} P_x^{S_1}, & F_x^{S_1} < F_x \\ P_x, & Otherwise \end{cases} \quad (7)$$

In Eqns. (5), (6) and (7), $P_x^{S_1}$ refers to the different position of the x^{th} osprey based on the initial phase of OOA. The y^{th} dimension of the osprey is $p_{x,y}^{S_1}$, the fitness function value is $F_x^{S_1}$, the chosen fish for the x^{th} osprey is CS_x, the y^{th}

dimension is $CS_{x,y}$, and $I_{x,y}$ is a random value between {1,2}.

3.2.3 Exploitation – Moving the Fish to the Safe Location

The osprey carries the fish to a safe place to eat after catching it. This natural behavior is used to plan the second step of updating the OOA population. This makes the osprey's position in the search space vary somewhat, which gives the OOA more power to find better solutions near the ones that have already been found. It is modeled by finding a new random place for each member of the group to eat fish that is safe by

$$p_{x,y}^{S_2} = p_{x,y} + \frac{lb_y + rand_{xy} \cdot (ub_y - lb_y)}{t}, x = 1, \dots, N; y = 1, \dots, z; t = 1, \dots, T \quad (8)$$

$$p_{x,y}^{S_2} = \begin{cases} p_{x,y}^{S_2}, & lb_y \le p_{x,y}^{S_2} \le ub_y \\ lb_y, & p_{x,y}^{S_2} < lb_y \\ ub_y, & p_{x,y}^{S_2} > ub_y \end{cases} \quad (9)$$

If the fitness function value goes up in this new location, it moves the osprey to a new identify that is closer to the previous one:

$$P_x = \begin{cases} P_x^{S_2}, & F_x^{S_2} < F_x \\ P_x, & Otherwise \end{cases} \quad (10)$$

In Eqns. (8), (9) and (10), $P_x^{S_2}$ refers to the second stage of OOA determines the new placement of the x^{th} osprey. The y^{th} dimension is shown by $p_{x,y}^{S_2}$, the fitness function value is shown by $F_x^{S_2}$, and t is the iteration number and T denotes the maximum iterations.

Thus, the OOA is an iterative method that changes the positions of ospreys in the first iteration, compares the values of the fitness function, and then updates the best candidate solution in the next iteration. The algorithm changes the positions of ospreys in the last iteration. After the full implementation, the best candidate solution (best hyperparameters) that was stored during the iterations is used to solve the problem (hyperparameter tuning). The pseudocode of OOA for hyperparameter tuning is described in Algorithm 1 and an overall workflow of the OOA is shown in Figure 3.

Algorithm 1: Hyperparameter tuning using OOA

Input: A group of hyperparameters for the ConvBiLSTM technique

Output: Ideal hyperparameters

1) **Begin**
2) **//Initialization stage:**
3) Initialize the OOA population size N and the total number of iterations T;
4) Define the fitness function (prediction accuracy);
5) Create the initial population matrix randomly using Eqns. (1) & (2);
6) Evaluate the fitness function using Eq. (3);
7) $\boldsymbol{for}(t = 1{:}T)$

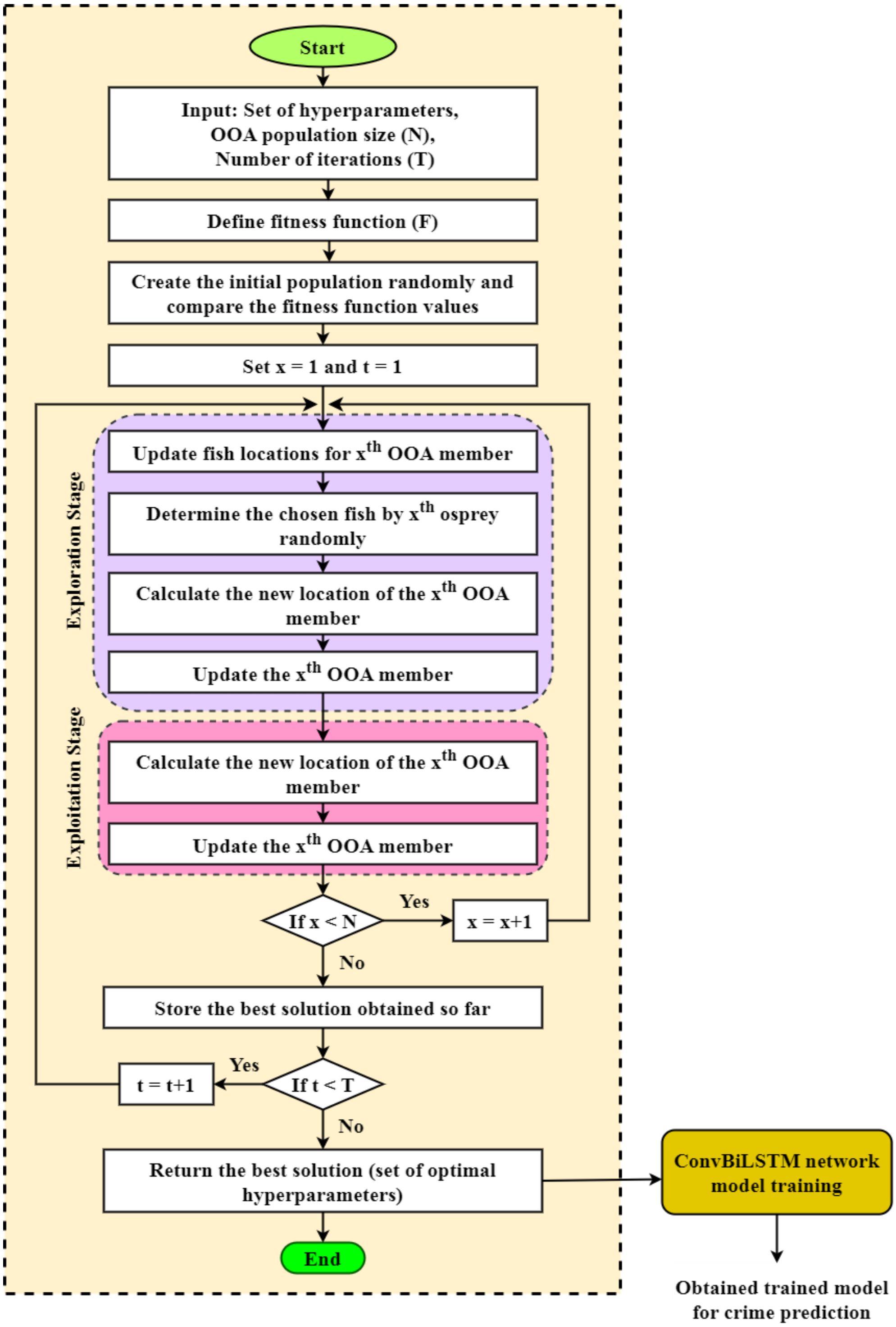

Figure 3: Flow Diagram of SMODDCnet Model based on Osprey Optimizer

1. $\boldsymbol{for}(x = 1{:}\,N)$
2. **//Exploration Stage:**
3. Update fish locations for the x^{th} OOA member using Eq. (4);
4. Determine the chosen fish by the x^{th} osprey randomly;
5. Determine the new location of the x^{th} OOA member using Eq. (5);
6. Verify the boundary criteria for the new location of OOA members using Eq. (6);
7. Update the x^{th} OOA member using Eq. (7);
8. **//Exploitation Stage:**
9. Compute the new location of the x^{th} OOA member of OOA using Eq. (8);
10. Verify the boundary criteria for the new location of OOA members using Eq. (9);
11. Update the x^{th} OOA member using Eq. (10);
12. $\boldsymbol{end\ for}$
13. $\boldsymbol{end\ for}$
14. Return the best solution (i.e., optimal hyperparameter selection in ConvBiLSTM)
15. $\boldsymbol{end}$

3.3 Model Training

Table 1 shows the best hyperparameters for training the ConvBiLSTM technqiue to predict crime using the Adam optimizer. Also, the trained model can be used to make accurate predictions about the crime by using the historical data (registered information) and twitter information (posted data).

Table 1: List of Optimal Hyperparameters for ConvBiLSTM Model

Parameters	*Search Space*	*Optimal Range*
Word Embedding Size	[50, 100, 200, 300]	200
Kernel Size	[2, 3, 4, 5]	3
Convolutional Layers	[2, 4, 6]	4
Filter Size	[4,8,16]	8
Pool Size	[1, 3, 5, 7]	3
No. of BiLSTM layers	[1, 2, 3]	2
BiLSTM Output Size	[16, 32, 64]	32
Kernel Normalization	[Batch Norm, Layer Norm]	Batch Norm
Dropout	[0.2, 0.3, 0.4]	0.3
Activation Operation	[Tanh, Sigmoid, ReLU]	ReLU
Momentum	[0.6, 0.7, 0.8]	0.7
Batch size	[32, 64, 96]	64
Training rate	[0.01, 0.001]	0.001
Length	[25, 50, 100]	50
Optimizer	[Adam, NAdam, RMSprop, Stochastic Gradient Descent]	NAdam
Epochs	[50, 100, 150, 200]	100
Loss Function	[Cross-entropy, Mean Squared Error]	Cross Entropy

Thus, the proposed model effectively enhances the model accuracy and lowers the computational complexity for efficient crime prediction.

4. Result and Discussion

4.1 Dataset Description

The dataset used in this framework is "Crime in India" [31], which has all the necessary details on many facets of crimes carried out in India during 2001. This dataset allows one to investigate various elements. This dataset enables the people to have better knowledge about Indian crime statistics. There are forty-three parts of crimes from India in this collection. Few statistics provide district-level data, including police departments and special police agencies, which could vary from revenue districts. Most of the data falls between 2001 and 2010; other files provide information from 2011 and 2001–14. For the experimental purposes, four important crime classes are considered i.e., "ST_SCcrime", “Childcrime", "Womencrime" and “Theftcrime". In addition to this, image and video data associated with crime terminologies from the social media tweets of the above listed four crime classes are taken. By matching each crime data with image and video details, totally 9794 crime instances are determined for the experiment.

4.2 Experimental Setup and Performance Metrics

This part looks at the extent that the SMODDCnet technique works in Python 3.11, comparing it with existing models like AIST [19], TL-BiLSTM [24], HDM-GNN [26], ConvBiLSTM [16], SMDCnet [17] and SMDDCnet [18]. The tests were done on a Windows 10 64-bit machine with an Intel® CoreTM i5-4210 CPU running at 3GHz, 4GB of RAM, and a 1TB HDD. Both proposed and existing models were tested using datasets as described in Section 4.1. From the acquitted data, an overall sample of 9794 are determined where 7834 are used for training and 1960 are used for testing in split of 80:20 proportions. Figure 4 shows the confusion matrix for the suggested technique.

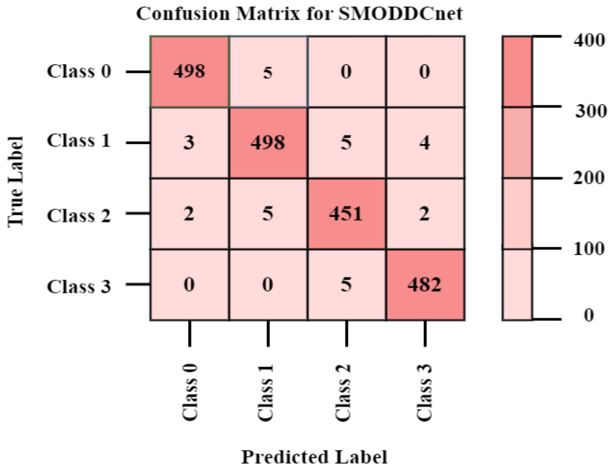

Figure 4: Confusion Matrix for the suggested technique

The efficiency of the suggested method is evaluated with following evaluation measures.

Accuracy: It is figured out by dividing the number of accurately anticipated cases by the total number of instances, as shown in Eq. (11):

$$Accuracy = \frac{TP + TN}{TP+TN+FP + FN} \tag{11}$$

Where, **True Positive (TP):** The system accurately identifies crime occurrences as crimes. False Positive (FP): It incorrectly detects a non-crime incident as crimes. True Negative (TN): It correctly identifies the non-crime occurrence as not a crime. False Negative (FN): It wrongly predicts that a crime event is the same as another event.

Precision: The formulation is defined in Eq. (12)

$$Precision = \frac{TP}{TP+FP} \tag{12}$$

Recall: The derivation is given in Eq. (13)

$$Recall = \frac{TP}{TP+FN} \tag{13}$$

F1-score: It refers to the harmonic mean of recall and precision as defined by Eq. (14)

$$F1 - score = \frac{2\times Precision\times Recall}{Precision+Recall} \tag{14}$$

Figure 5 compares the efficiency of various crime prediction algorithms on Crime in India dataset. The precision of SMODDCnet model is 18.21%, 13.05%, 8.46%, 4.04%, 1.96% and 0.89% higher over the AIST, TL-BiLSTM, HDM-GNN, ConvBiLSTM and SMDDCnet and SMDDCnet models, respectively. In terms of recall, SMDDCnet shows

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improvements of 19.98%, 14.26%, 9.89%, 3.88%, 2.014% and 0.91% over the same models. Additionally, the F1-score of SMDDCnet is higher by 19.08%, 13.65%, 9.17%, 3.93%, 2.12% and 1.12% over the same models, respectively. These enhancements are due to an efficient optimization of hyperparameter in ConvBiLSTM enabling effective feature extraction and sequential pattern learning in crime prediction.

Figure 6 illustrates the accuracy of various models evaluated on the crime data prediction dataset. The SMODDCnet model achieves accuracy that is 18.71% higher than AIST, 15.81% higher than TL-BiLSTM, 10.19% higher than HDM-GNN, 3.74% higher than ConvBiLSTM, 1.82% higher than SMDCnet and 0.85% higher than SMDDCnet. This enhancement is due to which the SMODDCnet model maximizes the prediction accuracy compared to the other models by optimizing the model hyperparameters to learn more complex features from the historical and social media information to predict crime intensities precisely.

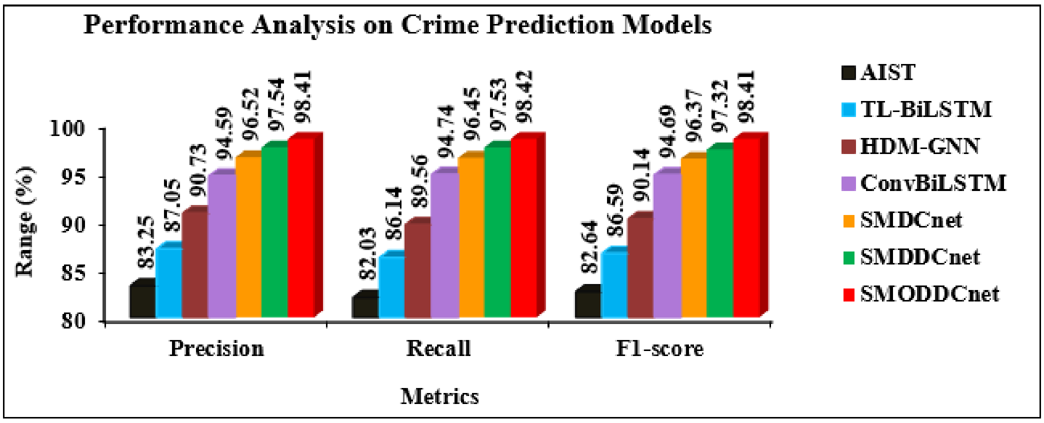

Figure 5: Evaluation of Various Crime Prediction Models using the Collected Dataset

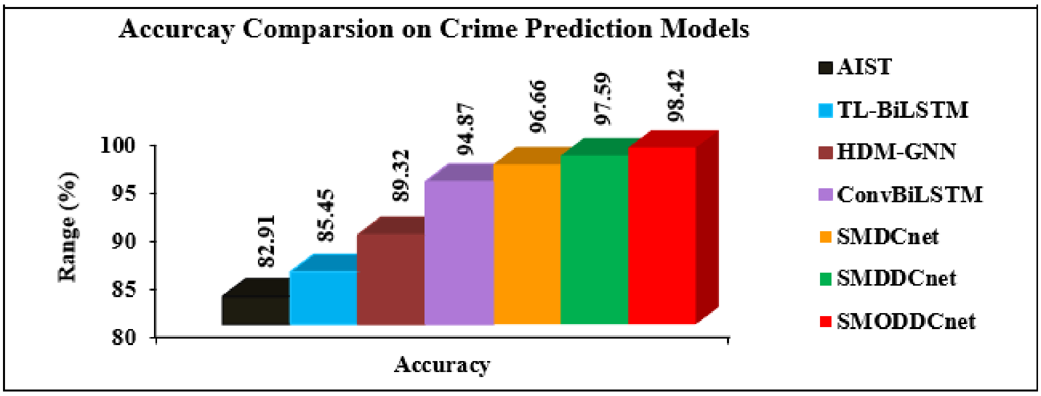

Figure 6: Accuracy Examination of Various Crime Prediction Algorithms Using Derived Datasets

5. Conclusion

In this paper, SMODDCnet is suggested for modifying hyperparameters of the ConvBiLSTM network to improve crime prediction accuracy while reducing computational complexity. This model employs OOA and focuses on the behavior of ospreys when hunting fish in the oceans. The OOA has two stages: exploration and exploitation, in which ospreys locate their prey and transfer it to an opportune spot to devour it. Based on these procedures, the ConvBiLSTM model's best hyperparameters for predicting crime using historical and social media information data are identified. Using the OOA, this model successfully fine-tunes the hyperparameter of ConvBiLSTM, resulting in excellent accuracy and minimal computing cost. The findings reveal the SMODDCnet technique is better than older crime prediction models of 98.42% on the Crime in India dataset.

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