Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol.14 , Issue 33s (2025)
https://www.jneonatalsurg.com

An Automated Crime Prediction Model using Artificial Bee Colony Optimizer with Deep Learning on FIR Data

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Cite this paper as: Dr. S. Jeya Selvakumari, Dr. V. Roseline (2025) An Automated Crime Prediction Model using Artificial Bee Colony Optimizer with Deep Learning on FIR Data. Journal of Neonatal Surgery, 14, (33s) 1317-1331

Received – 21 Nov 2025 Accepted – 03 Dec 2025 Published – 17 Dec 2025

ABSTRACT

The increasing complexity of modern law enforcement demands sophisticated tools for crime prediction using FIR (First Information Report) data. Crime prediction uses machine learning (ML) and data analysis techniques to predict or forecast the likelihood of a particular kind of crime being committed in the future. Crime prediction model utilizes different data sources such as demographic information, historical crime data, socioeconomic factors, weather conditions, and even geographic data. Predicting crime time and location based on FIR data is a very important research content and application in the fields of public safety and law enforcement. The ability to forecast when and where crime events occur holds great potential for more effectively addressing and preventing crime events. This task includes using machine learning techniques, historical FIR data, and advanced data analysis to make informed predictions. With this motivation, this study designs an artificial bee colony optimization with a deep learning-based crime prediction (ABCODL-CP) technique. The purpose of the ABCODL-CP technique is to investigate the FIR data to forecast the location and time of the crime incidents. To accomplish this, the ABCODL-CP technique undergoes detailed data pre-processing to convert the FIR data into a useful format. Moreover, the Term Frequency-Inverse Document Frequency (TF-IDF) vectorizer can be used to convert unstructured FIR narratives into structured numerical representations, thereby capturing the importance of terms within the reports. Besides, the ABCODL-CP technique uses the Attention Convolutional BiLSTM Neural Network (AC-BiLSTM) model for crime location and time prediction. Finally, the ABC algorithm is applied for hyperparameter tuning, ensuring the classifier's accuracy and reliability in forecasting crime location and time. The experimental evaluations performed on the real-time FIR dataset underline the effective performance of the ABCODL-CP technique, thereby assisting law enforcement in resource allocation, patrol planning, and proactive intervention..

Keywords: Crime prediction; FIR Data; Deep learning; Law enforcement; Machine learning; Artificial bee colony optimizer..

INTRODUCTION

Crime is a violation against humankind that is frequently indicted and punishable by legislation [1]. Criminology is an analysis of crime and it is an interdisciplinary science that gathers and analyzes information on crime and crime implementation. Currently, crime actions are improved and it is the accountability of police administration to control and decrease crime events [2]. Criminal detection and Crime forecast have been a serious issue for the police force as it is massive information of crime occurs. Accordingly, we have required techniques to forecast and avoid crime [3]. Data Mining offers classification and clustering algorithms for this determination.

Machine learning (ML) is a sub-category of artificial intelligence (AI) that employs statistical paradigms and methods for analyzing and producing forecasts depending on information [4]. Alternatively, deep learning (DL) has a sub-section of ML algorithms, which employ artificial neural networks (ANNs) with several layers to method complex correlations among outputs and inputs [5]. Both ML and DL methodologies can be the ability that implemented to the issue of crime forecasting in numerous methods. ML models are employed in crime forecasts for detecting crime information and forecasting upcoming crime forms [6]. For instance, techniques such as support vector machines (SMVs), random forests (RTs), and decision trees (DTs) are trained on crime information from particular cities for accurately forecasting crime patterns. Besides, forecasting crime patterns, the above-mentioned techniques provide useful data on crime patterns and developments [7]. These abilities permit employment strategies and resources for efficiently combating crime.

Moreover, the ML method is also utilized for detecting relationships between crime activities and different demographic and environmental conditions namely period of day, position, and meteorological situations. This data is employed for making crime forecast and anticipation approaches appropriate to an offered community's particular requirements[8]. Deep learning (DL) methods like recurrent neural networks (RNNs) and convolution neural networks (CNNs) also represented potential in crime forecasting. These techniques are trained on crime information with both a temporal and spatial module for accurately evaluating crime patterns in given cities [9]. For instance, DL techniques are utilized to detect crime information comprising the variety of crime activities, positions, and time periods. These data are exploited for making a prediction framework, which could be implemented to analyse prospective crime hotspots and forecast potential crime activities [10].

This study designs an artificial bee colony optimization with a deep learning-based crime prediction (ABCODL-CP) technique. The ABCODL-CP technique undergoes detailed data pre-processing to convert the FIR data into a useful format. Moreover, the Term Frequency-Inverse Document Frequency (TF-IDF) vectorizer can be used to convert unstructured FIR narratives into structured numerical representations, thereby capturing the importance of terms within the reports. Besides, the ABCODL-CP technique uses the Attention Convolutional BiLSTM Neural Network (AC-BiLSTM) model for crime location and time prediction. Finally, the ABC algorithm is applied for hyperparameter tuning, ensuring the classifier's accuracy and reliability in forecasting crime location and time. The experimental evaluations performed on the real-time FIR dataset underline the effective performance of the ABCODL-CP technique.

The rest of the paper is organized as follows. Section 2 offers a brief review of existing crime prediction models. Section 3 elaborates the proposed crime prediction process and section 4 offers the performance validation of the proposed model. Finally, section 5 concludes the study with key findings and possible future works.

2. Related Works

Lv et al. [11] introduced a technique that removes crime components and forecasts legacy crime activities. This method includes 2 DL algorithms. The primary algorithm is Bi-LSTM + CRF built to automate and remove crime components and execute spatial-temporal examination of crimes depending on them. According to these determinations, the secondary algorithm is LSTM+SD made for forecasting excavation-category legacy crimes. Safat et al. [12] implemented various ML techniques such as the SVM, logistic regression (LR), multilayer perceptron (MLP), KNNs, Naïve Bayes (NBs), DT, XGBoost, and RF, and autoregressive integrated moving average (ARIMA) algorithm and time-series examination by LSTM to improved fit the crime information. In [13], a link forecasting technique that combines a fusion of metadata was introduced. The deep reinforcement learning (DRL) algorithm is employed to enhance the training of methods with the self-produced database achieved for developing the technique. In this study, a purely time-developing DRL methodology (TDRL-CNA) with no metadata incorporation was made as a baseline for evaluation with the meta-data integration framework (FDRL-CNA).

Wang et al. [14] presented a work that makes the crime situation awareness network (CSAN) an innovative standard predicting method by combining frameworks of variational AE and context-based sequence generative neural networks. The last analysis indicates that CSAN frequently exceeds other widely-utilized spatial-temporal predictive methods like Conv-LSTM, in regional multitype crime frequency forecasting. Gandapur [15] suggested a DL technique dependent upon Bi-directional gated recurrent unit (Bi-GRU) and CNNs. The CNN extracts the spatial features from video frames while temporal and local motion features have been extracted by the Bi-GRU from multi-frames CNN extracted features. Besides, the ranking-related loss was exploited for identifying and classifying suspicious actions.

Vimala Devi and Kavitha [16] developed a modified DRQN method for designing a robust crime forecasting architecture. This technique comprises the use of GRU rather than LSTM components for storing the important features for efficiently classifying crime information. Adaptable agents depending on the MDP were implemented for adjustably learning the input data and providing better forecasts. The RL algorithm was executed in this technique for choosing the optimum state values and detecting the better return values. In [17], a crime forecasting technique was presented. In this method, the Python programming language must be employed, because of their adaptability and extensive accessibility of libraries oriented to ML technique. This can be potential to produce a crime predictive technique depending on the Sample, Explore, Modify, Model, and Assess (SEMMA) algorithm, and then data manipulation, normalization, and cleaning; clustering was implemented by utilizing K-means and then the NN was designed.

3. The Proposed Model

In this study, a new ABCODL-CP technique was introduced for automatic crime prediction techniques. The major intention of the ABCODL-CP technique is to investigate the FIR data to predict the location and time of the crime events. To accomplish this, the ABCODL-CP technique undergoes four major operations namely pre-processing, TF-IDF feature extractor, AC-BiLSTM-based prediction, and ABC-based parameter tuning. Fig. 1 depicts the workflow of the ABCODL-CP system.

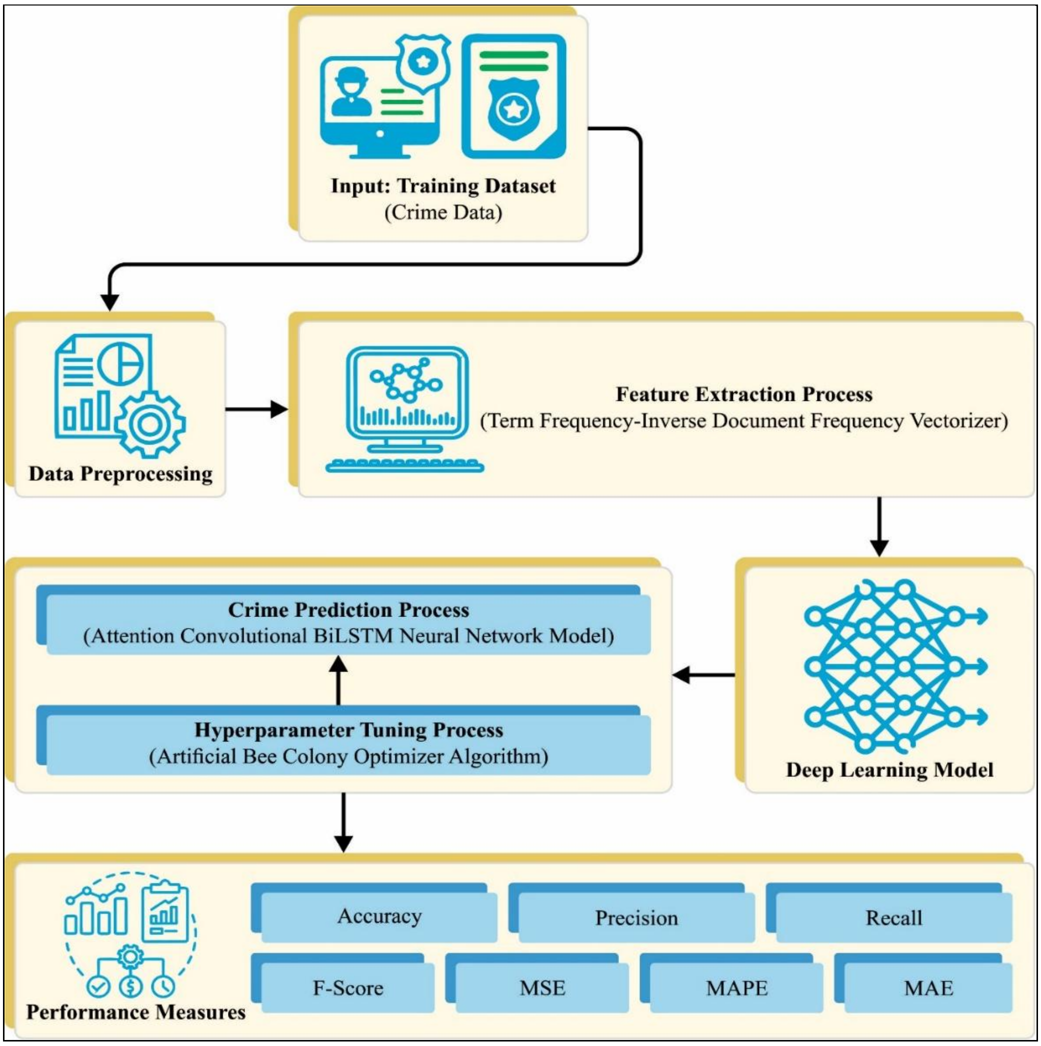

Fig. 1. Workflow of ABCODL-CP algorithm

3.1. Data Pre-processing

Text preprocessing is a fundamental step in preparing text data for analysis and ML techniques for predicting crimes. The steps commonly used for text pre-processing to normalize and clean the textual data are shown below:

- To Lower Case: All texts are converted into lowercase thereby ensuring consistency in the textual data. This prevents the model from treating the similar words in dissimilar cases as dissimilar words.
- Removing Punctuations: Punctuations including exclamation points, commas, and periods are removed typically to improve the efficiency of text analysis and simplify the text.
- Removing Stopwords: Stopwords are commonly used words such as "and," "the," "in," etc., that typically don't carry relevant meaning and can be safely removed to reduce noise in the data.
- Removing Extra Spaces: Whitespace or extra spaces are removed to prevent variations in spacing from affecting text analysis and to ensure uniform formatting.
- Removing Numbers: Numbers can be removed to focus on the text content that contains information about the cases and crimes and may not be relevant in this context.
- Stemming: Stemming is a more aggressive word reduction method that chops off prefixes and suffixes to attain a word's root form. It would be a bit more aggressive than lemmatization and might lead to words that are not actual words but are still related.

- Lemmatization: Lemmatization is used to reduce words into a dictionary or base form, which makes it easier to analyze variations of a similar word.

The textual data must be in a more standardized and cleaner format after applying these preprocessing steps are best fitted for ML techniques. Then, this data can be used for tasks like sentiment analysis, text classification, or crime prediction.

3.2. TF-IDF Word Vectorizer

Next, the TF-IDF model is used in this study. TF-IDF is a probabilistic approach used for evaluating the word relevance in the text [18]. The word meaning reduces in inverse proportion to the frequency of its occurrence in the corpus, but simultaneously, it increases in proportion to the number of times it would appear in the document. TF-IDF model more effectively identifies different words. This word would occur more often in a particular text but occur less often in other texts.

Eq. (1) is used to evaluate the IDF scores of all the words in a particular text in the dataset:

$$idf(w_i) = \log \frac{|D|}{|\{j|w_i \in D_j\}|} \tag{1}$$

Where $\{j|w_i \in D_j\}$ shows the overall amount of text samples having words w_i. D refers to the set of text samples, $|D|$ denotes the overall amount of text samples, D_j shows the j^{th} texts in the text sample, and w_i indicates the i^{th} words in the vocabulary.

Eq. (2) is used to measure the word occurrence in the text sample. If the word occurs in a higher degree of text samples without considering IDF, then the word could possess a wide range of contributions and discrimination to these text samples:

$$tf(k,i) = \frac{count(w_{k,i})}{\sum_j count(w_{k,i})} \tag{2}$$

Where $w_{k,i}$ denotes the i^{th} word frequency of the vocabulary at k^{th} texts, $count\ (w_{k,i})$ implies the frequency of the i^{th} word at k^{th} text sample, and $\sum_j c\ ount(w_{k,i})$ refers to the sum of word occurrences in the vocabulary at k^{th} texts. Eq. (3) is used to evaluate the TF-IDF values of all the words according to the above two equations:

$$TFIDF_{k,i} = idf(w_{k,i})(f,i) \tag{3}$$

The above equation is used to extract the various scores of words in the text.

3.3. Prediction using AC-BiLSTM Model

The AC-BiLSTM can be used for predicting crime location and time. The LSTM model is developed to overcome the gradient vanishing and exploding problems inherent in classical FFNN models [19]. Fig. 2 represents the architecture of AC-BiLSTM. The proposed model includes forgetting gate f_t, input gate i_t, and output gate o_t. Also, it has a memory cell $that$ allows it to learn long-term dependency and a hidden state h_t. The equation is given below:

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \tag{4}$$

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \tag{5}$$

$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \tag{6}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(w_c[h_{t-1}, x_t] + b_c) \tag{7}$$

$$h_t = o_t \odot \tanh\ (c_t) \tag{8}$$

Now σ indicates the logistic sigmoid function, $and\ w_i$, w_f and w_o symbolize the neuron weight. $\odot$ denotes element-wise multiplication and $tanh()$ indicates the hyperbolic tangent function. b_i, b_f and b_o indicate the bias to be learned during training. Bi-LSTM is a kind of classical LSTM that includes two LSTMS that are simultaneously running forward and backwards on the input series. The backward LSTM captures the prior context data whereas the forward LSTM captures the future context data. In this work, the input series is either from the set of features extracted directly from the word embedding of an opinionated sentence or the convolution layer. Therefore, the last hidden state can be attained as follows:

$$h_t = \mu(\overrightarrow{h_t}, \overleftarrow{h_t}) \tag{9}$$

In Eq. (9), μ indicates the average of two hidden states. The Bi-LSTM with trained parameter θ_{bilstm} captures the contextual and sequential data. The output is a hidden representation of the input as shown below:

$$[h_1, \dots, h_n] = BiLSTM([e_{w_1}, \dots, e_{w_n}], \theta_{bilstm}) \tag{10}$$

The last target-specific representation for the s sentence of n length is represented as z:

$$z_s = \sum_{i=1}^{n} \alpha_i h_i \tag{11}$$

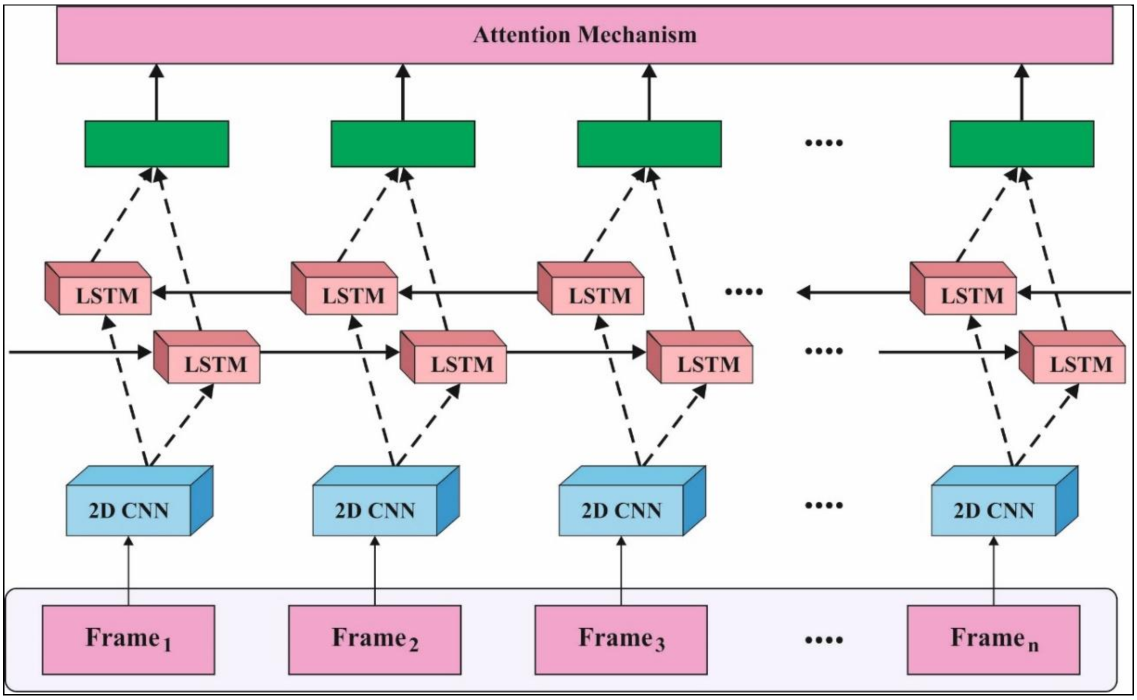

Fig. 2. Structure of AC-BiLSTM

In Eq. (11), h denotes the hidden depiction of the sentence and α shows the attention layer that allocates weight to all the words in the sentence:

$$\alpha = \frac{exp(b_i)}{\sum_{j=1}^{n} exp(b_j)} \tag{12}$$

$$b_i = f_{score}(h_i, t_s) \tag{13}$$

$$t_s = \frac{1}{m}\sum_{i=1}^{m} h_{a_i} \tag{14}$$

Based on the semantic and contextual relations between h_i and t_s, the function f_{score} calculates the weight of all the words w_i in sentence s. t_s refers to the average hidden depiction of the target. Using the softmax activation function, the sentence representation z is given as input to the output layer for predicting the likelihood distribution P over the sentiment label as follows:

$$P = softmax\,(w_o z + b_o) \tag{15}$$

In Eq. (15), w_o and b_o denote the output weight and bias correspondingly. By using the cross-entropy minimization, the attention module was trained as follows:

$$J = -\sum_{i \in D} \log P_i(C_i) \tag{16}$$

Now D denotes the training data, C_i shows the true label for i^{th} samples and $P_i(C_i)$ indicates the likelihood of a true label given sample i. In the AC-BiLSTM model, the input sequence (for example, a sentence) is initially processed by the CNN to extract relevant patterns or features. Then, the output of CNN is fed into Bi-LSTM th, which captures contextual information and processes the sequence bidirectionally. The attention module is used to evaluate the various parts of the sequence, which helps the model focus on the essential data. The last output of the network can be used for crime prediction.

3.4. ABC-based Hyperparameter Tuning

Lastly, the ABC algorithm is used for the optimum hyperparameter selection of the AC-BiLSTM model. ABC technique is stimulated by the foraging behaviors of honey bees while searching for rich food sources [20]. Consider a population of food position and the artificial bee modifies the food position over time. The model exploits a group of computational agents named Honeybee to search for the optimum outcome. Employed, onlooker, and scout bees are the three classes of honey bees. The employed bees are used to investigate the food source (fitness value) and share the data to recruit the onlooker bees. The amount of onlookers or deployed bees is equivalent to the count of solutions from the population (SN). All the food sources (solution) $x_i(i = 1,2, \dots, SN)$ is a D-dimensional vector. Based on this information, the onlooker bees decide to elect a food source. This procedure of bee swarm seeking, advertising, and ultimately choosing the rich food source to search for the optimum solution. Based on the probability value related to the p_i, the onlooker bee chooses a food source evaluated as follows:

$$p_i = \frac{fit_i}{\sum_{q=1}^{SN} fit_q}, \tag{17}$$

In Eq. (17), SN shows the number of food sources which is equivalent to the number of employed bees and fit_i denotes the fitness values of solution i estimated by its employed bee that is proportional to the nectar quantity of food source in location i. Thus, the employed bees interchange the data with the onlooker bees. The ABC makes use of the subsequent formula to generate a candidate food location from the older one:

$$x_{ij}^* = x_{ij} + \varphi_{ij}(x_{ij} - x_{lj}), \tag{18}$$

Where $l \in \{1,2, \dots, SN\}$ and $j \in \{1,2, \dots, D\}$ are random indices, and φ_{ij} is a randomly generated integer within $[-1, 1]$ to alter the older food source to be the newer food source in the following iteration. x_{ij}^* shows the new potential food sources chosen by comparing the randomly selected food sources and the prior food sources x_{ij}.

The fitness optimal is a major factor in the ABC method. An encoded solution is used for assessing the goodness of candidate performance. At this point, the accuracy values are the primary condition used to design an FF.

$$Fitness = \max(P) \tag{19}$$

$$P = \frac{TP}{TP + FP} \tag{20}$$

Where TP and FP represent the true and the false positive values.

4. Results and Discussion

In this section, the performance validation of the ABCODL-CP methodology is tested utilizing a set of FIR collected by our own. A sample CaseGist is illustrated in Table 1. In addition, the dataset includes eight classes of Sub-Divisional Office (SDO). The SDO Classes include “Town": 0, "Rural": 1, "TDR": 2, "SVM": 3, "MNI": 4, "KVP": 5, "VKM": 6, and "SKM": 7

Table 1 Sample CaseGist

Samples	CaseGist
1	case murder deceas subbiah murder brother law raja raja selvakumar associ sathish babi saravanan attack aruv due land disput deceas accus an occur took place abat accus tamilselvi chitra wife mother law deceas subbiah accus person a arrest sent remand aruv use occurr recov
2	case murder occur hr hr accus victim rent hous thavasi perum road muthiahpuram accus karuppasami murder wife shanmugalakshmi attack knife stone lock hous went hous hr owner hous open door anoth key found shanmuga lakshmi dead blood injuri head face complaint karuppasami case regist hr
3	case reveng murder occur accus antoni vinodh vinodha restrain deceas valvangi age ebanez prasath prasatha kaliraj kattakalia attack deceas big knife aruv murder deceas valvangi age conspiraci made anoth two accus person anand marikumara sugunthan suganthan michaela accus anand marikumar a stand aruv northern side occurr place occurr taken place murder took place retali murder one saravanan jinda saravanan central p crno kaliraj kattakalia arrest ananda antoni vinoth vinotha surrend jm no i kovilpatti respect accus ebanez prasath prasath a arrest
4	case murder occur hr front complain hous thangammalpuram th street muthiahpuram accus muthuraja age so mayaperum assault mother gnana kani iron rod head instig younger brother selvakumara age due separ land name father accus person muthuraja selvakumara arrest remand
5	deceas habitu drunkard separ complain mother live muthiahpuram meanwhil wordi alterc aros deceas accus intox mood share beedi due motiv accus murder deceas use iron rod caus multipl injuri die spot accus mariswaran arrest remand

Fig. 3. Confusion matrix of ABCODL-CP appro ach

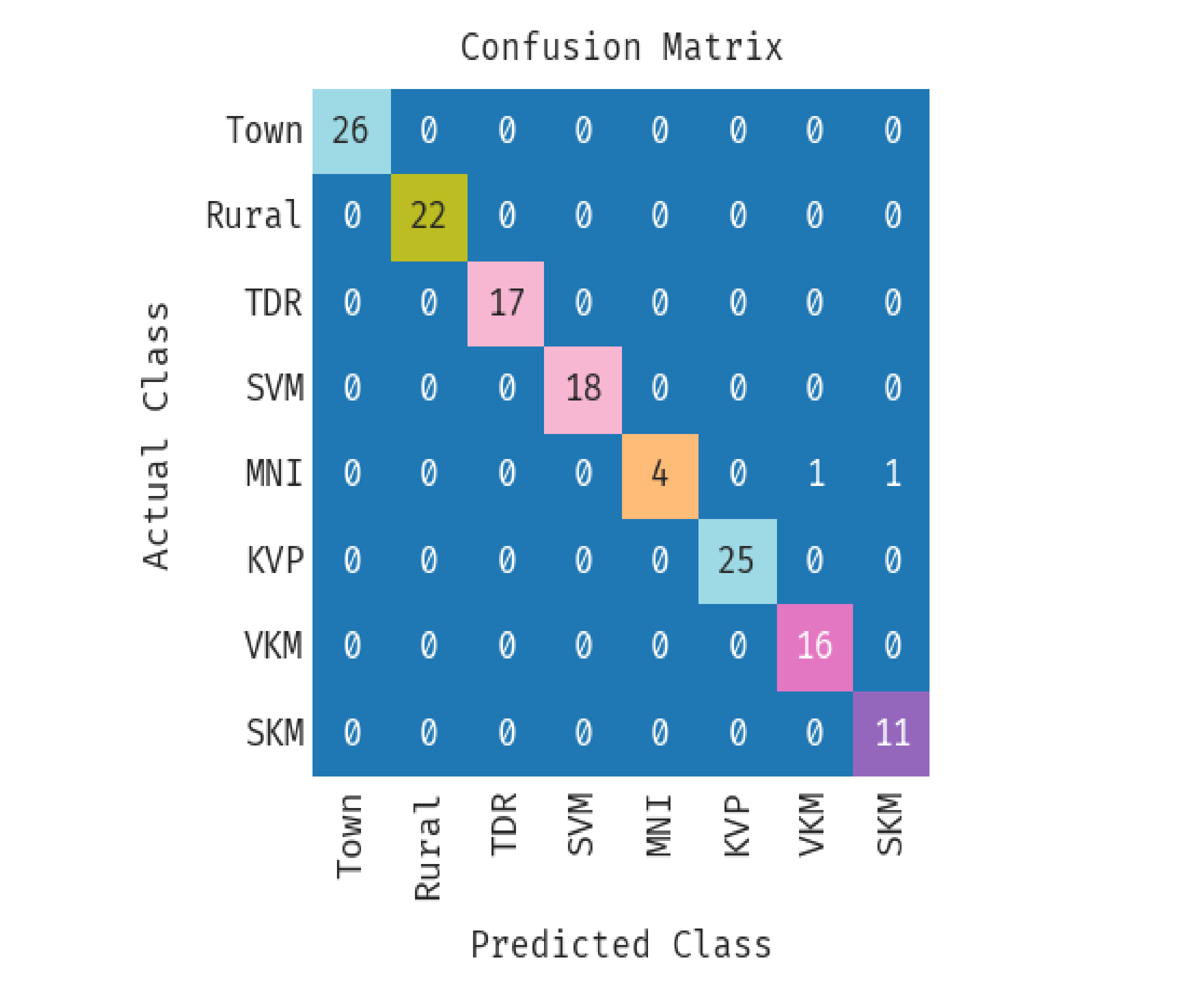

Fig. 3 represents the confusion matrix attained by the ABCODL-CP approach. The simulation values inferred that the effective detection and classification of all 8 classes were accurate.

Table 2 and Fig. 4 represent an overall SDO prediction result of the ABCODL-CP approach. The results indicate that the ABCODL-CP technique properly identifies all the classes of SDO. It is also observed that the ABCODL-CP methodology accomplishes an accuracy of 99.65%, precision of 98.22%, recall of 95.83%, and F-score of 96.58%.

Table 2 SDO prediction outcome of ABCODL-CP system with varying measures

Metrics	**Values**
Accuracy	99.65
Precision	98.22
Recall	95.83
F-Score	96.58

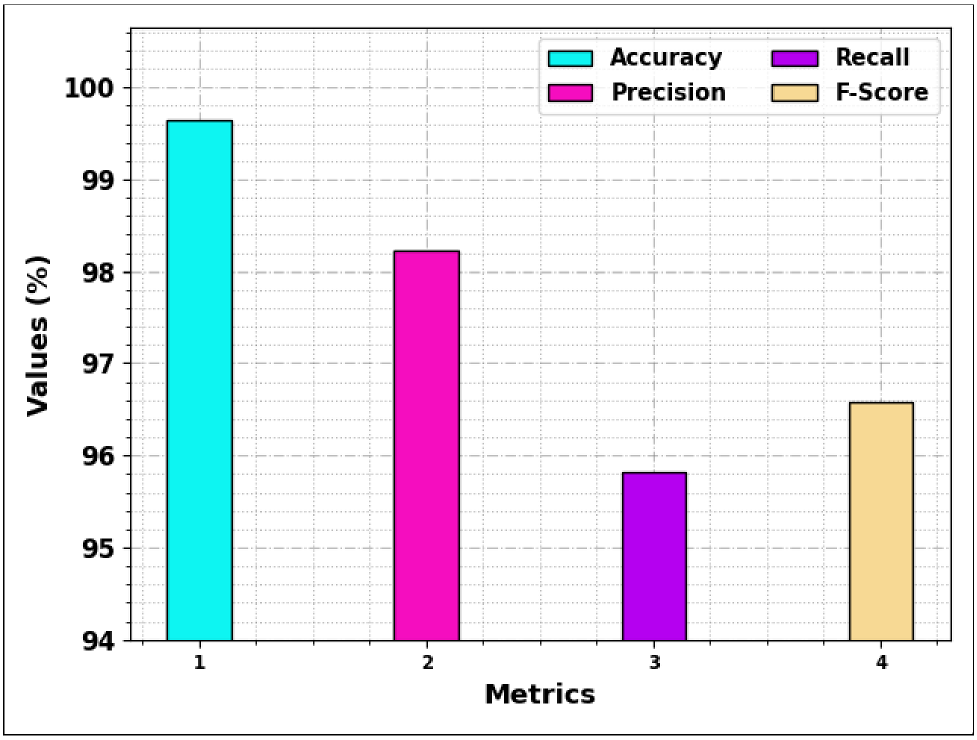

Fig. 4. SDO prediction outcome of ABCODL-CP technique

The precision-recall curve of the ABCODL-CP algorithm is exposed by plotting precision against recall as defined in Fig. 5. The results confirm that the ABCODL-CP approach gains higher precision-recall values under all classes. The figure depicts that the model learns to recognize various classes. The ABCODL-CP system accomplishes improved outcomes in the recognition of positive samples with minimal false positives.

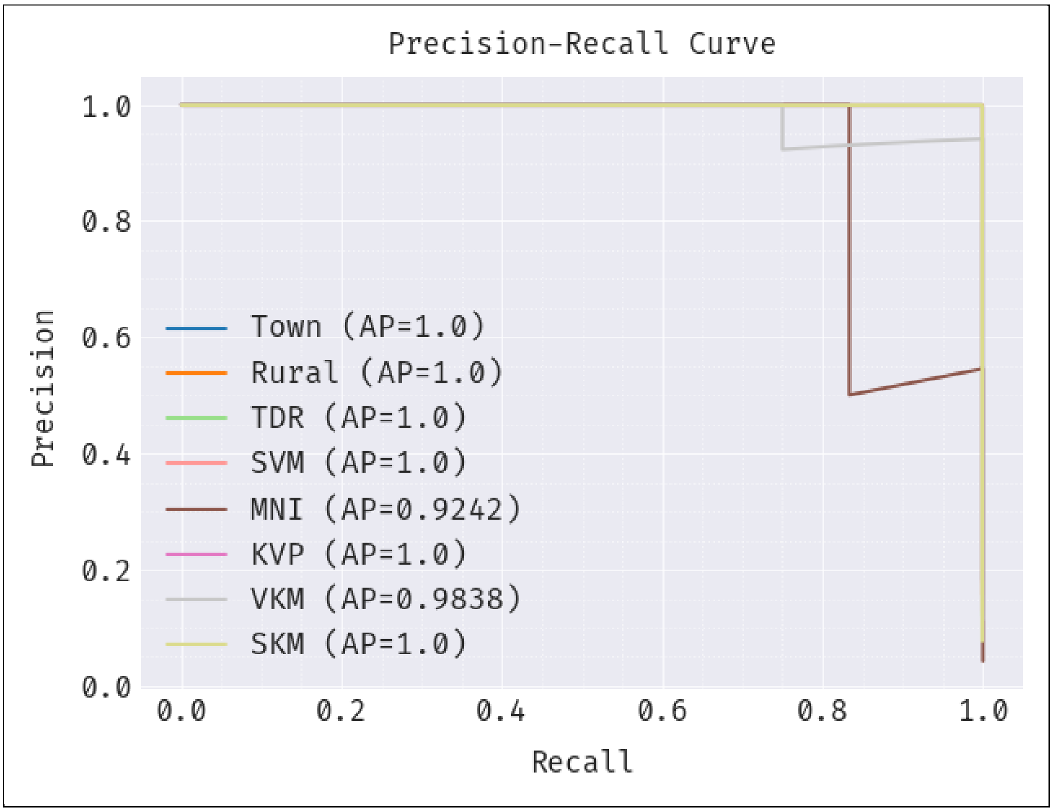

Fig. 5. PR curve of the ABCODL-CP technique

The ROC curves offered by the ABCODL-CP algorithm are represented in Fig. 6, which has the capability the discriminate the classes. The figure indicates valuable insights into the trade-off between the TPR and FPR rates over distinct classification thresholds and varying counts of epochs. It presents the accurate predictive performance of the ABCODL-CP model on the classification of distinct classes.

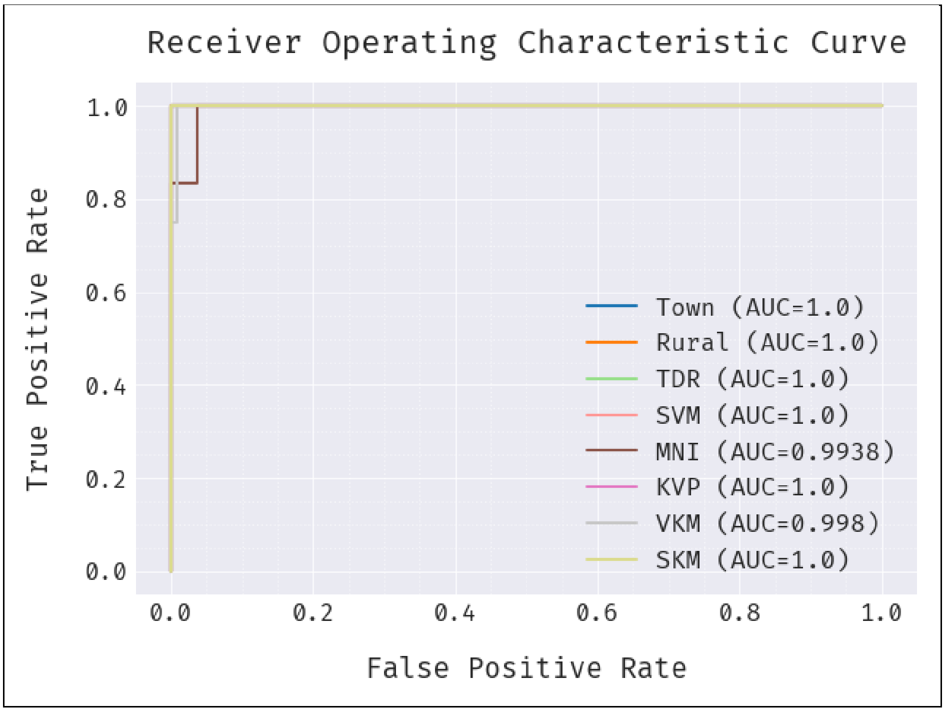

Fig. 6. ROC curve of the ABCODL-CP technique

To estimate the performance of the ABCODL-CP approach on SDO prediction, training (TR) and testing (TS) $accu_y$ curves are defined, as exposed in Fig. 7. The TR and TS $accu_y$ curves define the performance of the ABCODL-CP approach over distinct epochs. The figure offers meaningful details regarding the learning task and generalization capabilities of the ABCODL-CP model. With a higher epoch count, it is perceived that the TR and TS $accu_y$ curves are improved. It is observed that the ABCODL-CP approach obtains improved testing accuracy which can recognize the patterns in the TR and TS data.

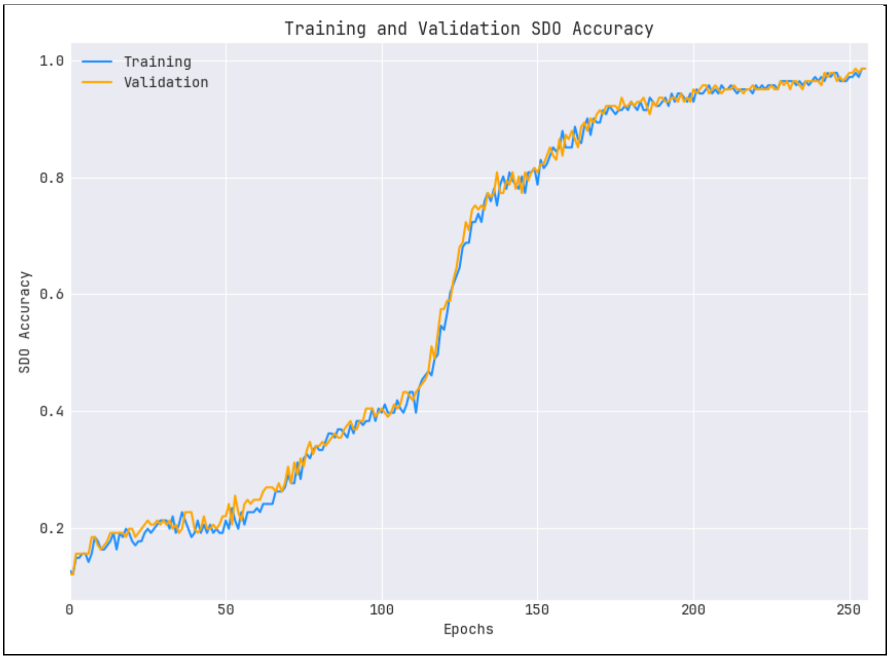

Fig. 7. $Accu_y$ curve of ABCODL-CP technique on SDO prediction

Fig. 8 exhibits the overall TR and TS loss values of the ABCODL-CP approach on SDO prediction over epochs. The TR loss exhibits the model loss is minimal over epochs. Primarily, the loss values are lesser as the model modifies the weight to decrease the prediction error on the TR and TS data. The loss curves exhibit the extent to which the model fits the training data. It is experimental that the TR and TS loss is steadily minimal and portrays that the ABCODL-CP system effectually learns the patterns exhibited in the TR and TS data. It is also observed that the ABCODL-CP algorithm adjusts the parameters to minimize the discrepancy between the prediction and the original training label.

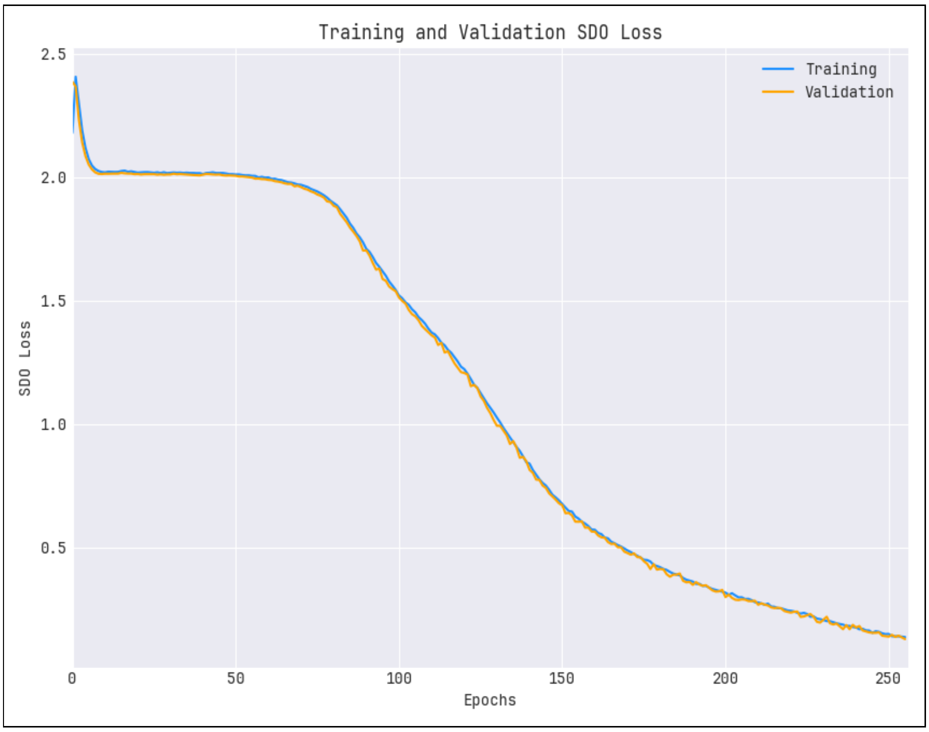

Fig. 8. Loss curve of ABCODL-CP technique on SDO prediction

Table 3 and Fig. 9 represent the SDO prediction accuracy of the ABCODL-CP technique with other ML models [21]. The results highlight that the ABCODL-CP technique gains a higher accuracy of 99.65%. At the same time, the random forest, decision tree, NB, KNN, and GNB models obtained decreased accuracy values of 83.39%, 75.90%, 77.64%, 76.90%, and 64.60% respectively.

Table 3 SDO prediction accuracy of ABCODL-CP approach with other ML techniques

Methods	Accuracy (%)
ABCODL-CP	99.65
Random Forest	83.39
Decision Tree	75.90
Naïve Bayes	77.64
KNN-Model	76.90
Gaussian NB	64.60

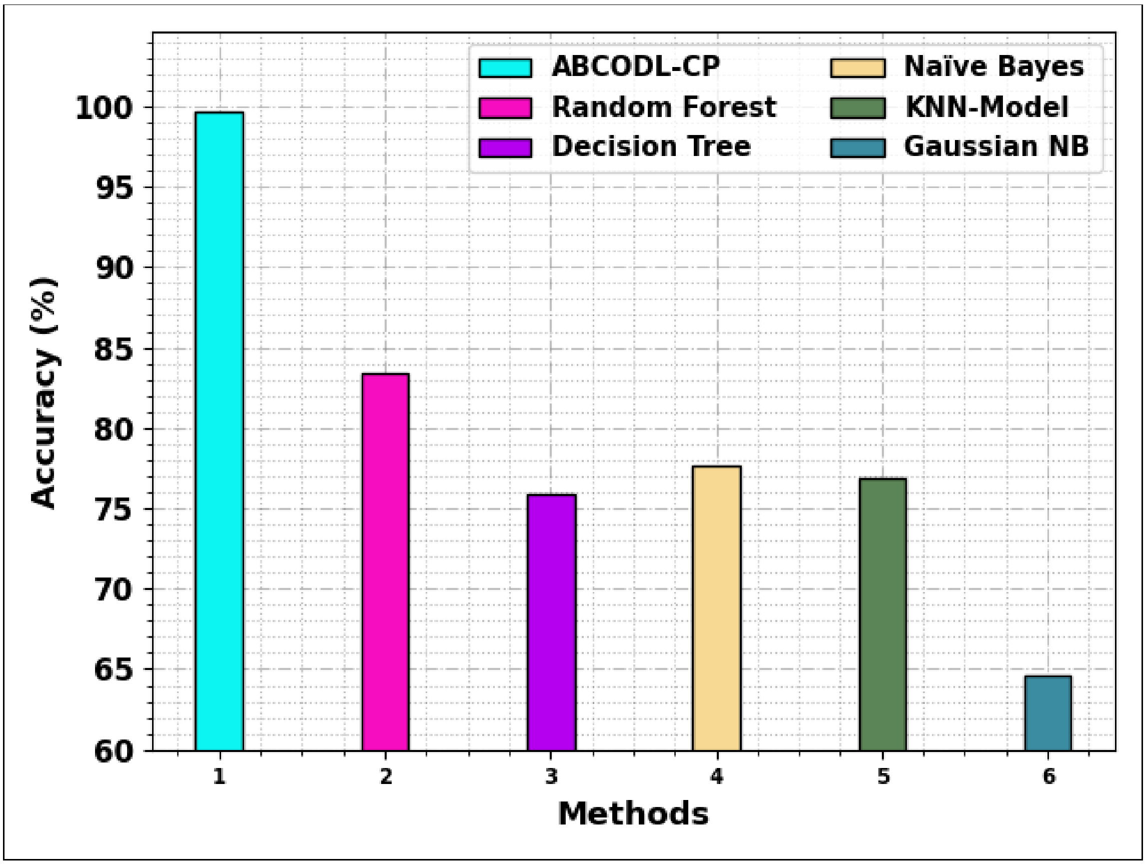

Fig. 9. SDO prediction accuracy of ABCODL-CP approach with other ML techniques

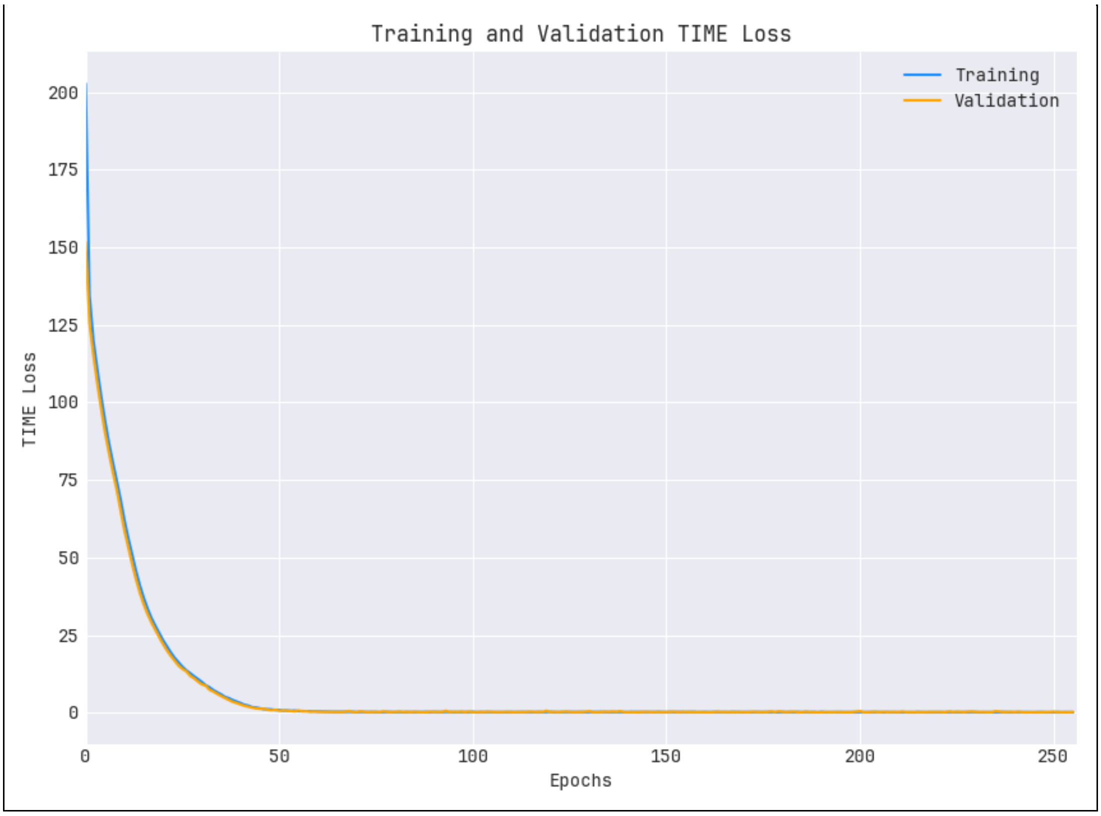

Fig. 10. Loss curve of ABCODL-CP technique on time prediction

Fig. 10 displays the overall TR and TS loss values of the ABCODL-CP algorithm on time prediction over epochs. The TR loss exhibits that the method loss gets lesser over epochs. Primarily, the loss values get reduced as the model modifies the weight to minimize the prediction error on the TR and TS data. The loss curves establish the extent to which the model fits the training data. It is experimental that the TR and TS loss is steadily decreased and portrayed that the ABCODL-CP approach effectively learns the patterns revealed in the TR and TS data. It is also noticed that the ABCODL-CP model adjusts the parameters to decrease the discrepancy between the prediction and the original training label.

Table 4 and Fig. 11 represent the crime time prediction result of the ABCODL-CP technique. The outcomes implied that the ABCODL-CP approach accomplishes effective prediction performance. It is also noticed that the ABCODL-CP technique achieves minimal MSE of 0.1128, MAE of 0.2634, and MAPE of 0.0352.

Table 4 Crime time prediction outcome of ABCODL-CP technique with varying measures

Metrics	Values
MSE	0.1128
MAE	0.2634
MAPE	0.0352

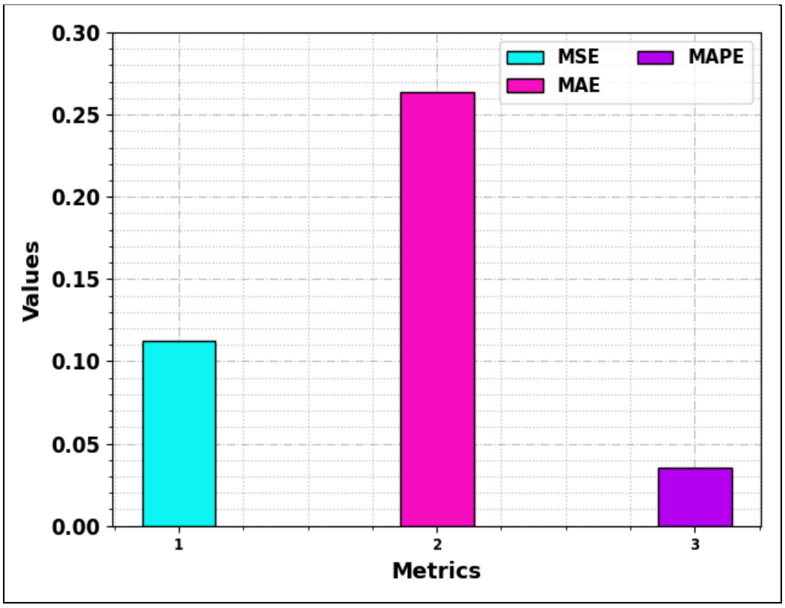

Fig. 11. Crime time prediction outcome of ABCODL-CP technique with varying measures

In Table 5 and Fig. 12, a comparative MSE result of the ABCODL-CP technique with existing approaches is given. The experimental values indicate that the linear regression and redge regression models attain higher MSE values. At the same time, the logistic regression and SVR models offer slightly decreased MSE values. However, the ABCODL-CP technique gains better predictive performance with a minimal MSE of 0.1128.

Table 5 MSE outcome of ABCODL-CP technique with existing approaches

Metrics	Values
ABCODL-CP	0.1128
Logistic Regression	0.1267
SVR Model	0.1453
Linear Regression	0.1675
Redge Regression	0.1780

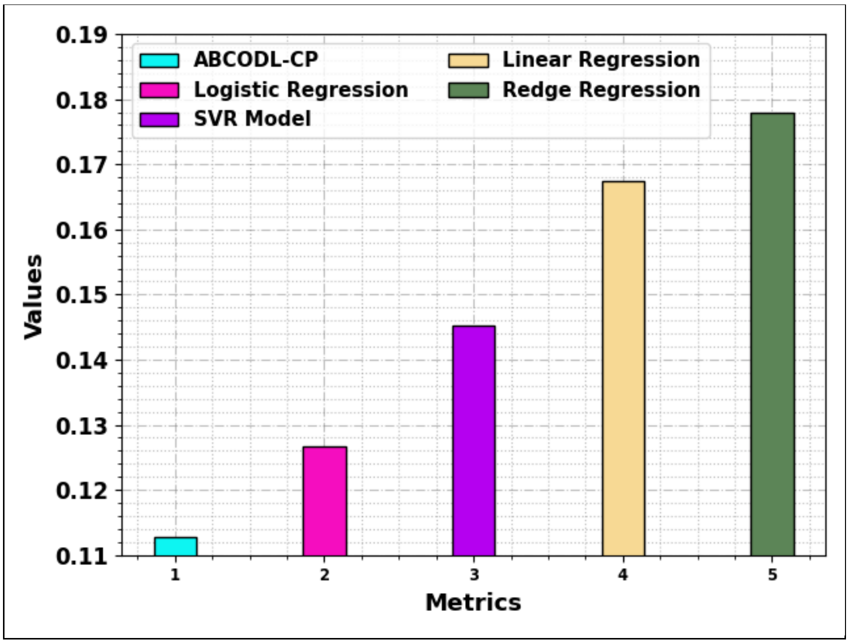

Fig. 12. MSE outcome of ABCODL-CP technique with existing approaches

Fig. 13 demonstrates the sample crime location and time prediction results of the proposed model. The results shown that the proposed model properly predicts the location as KVP and time as 9.44.

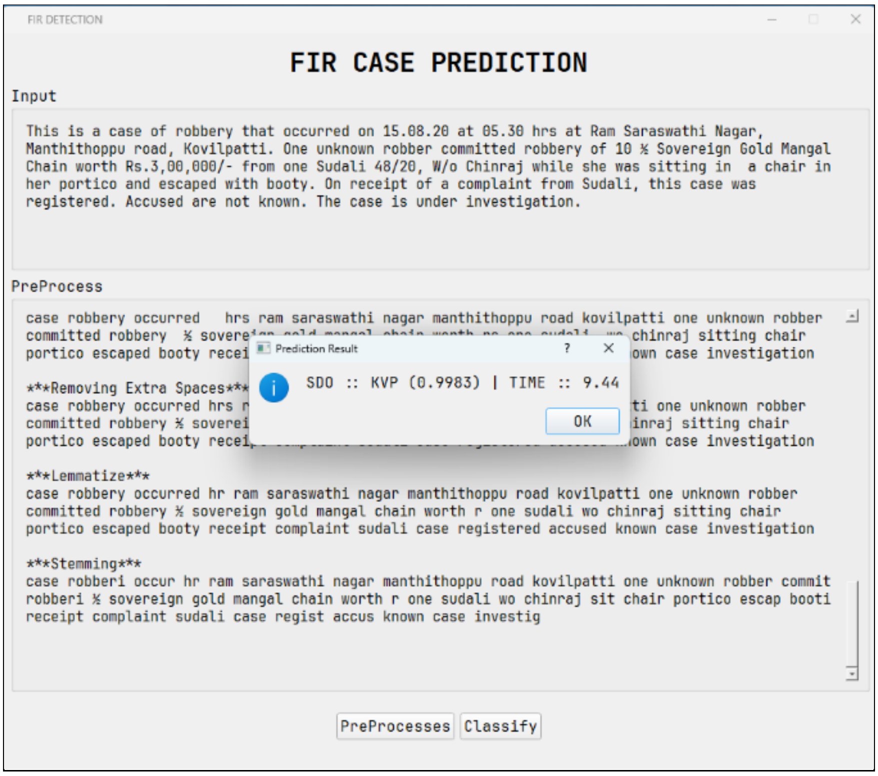

Fig. 13. Sample Crime Location and Time Prediction Results-1

In Fig. 14, the sample crime location and time prediction results of the proposed model is clearly defined. The figure highlighted that the proposed model accomplishes effective prediction of the location as Town and time as 11.21.

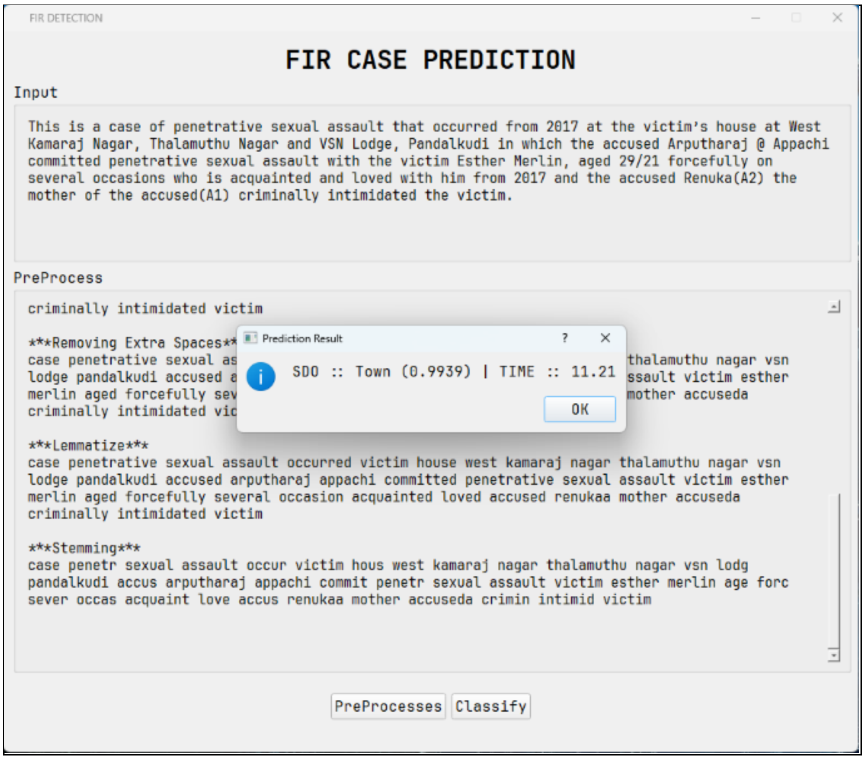

Fig. 14. Sample Crime Location and Time Prediction Results-2

These extensive results ensured the better performance of the ABCODL-CP technique in the crime prediction process.

5. CONCLUSION

In this study, a new ABCODL-CP algorithm was established for the automated crime prediction process. The main objective of the ABCODL-CP technique is to investigate the FIR data to forecast the location and time of the crime events. To accomplish this, the ABCODL-CP technique undergoes four major operations namely pre-processing, TF-IDF feature extractor, AC-BiLSTM-based prediction, and ABC-based parameter tuning. The TF-IDF vectorizer can be used to convert unstructured FIR narratives into structured numerical representations, thereby capturing the importance of terms within the reports. Moreover, the ABCODL-CP technique uses the AC-BiLSTM model for crime location and time prediction. Furthermore, the ABC algorithm is applied for hyperparameter tuning, ensuring the classifier's accuracy and reliability in forecasting crime location and time. The experimental evaluations performed on the real-time FIR dataset underline the effective performance of the ABCODL-CP technique, thereby assisting law enforcement in resource allocation, patrol planning, and proactive intervention..

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