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OPTIMIZED FEATURES AND DEEP LEARNING BASED CRIME TRENDS PREDICTION

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Abstract

Crime Prediction is an effort of determining future crime with the intention of diminishing them. Post-analysis of the data from past events, Crime prediction forecasts the future crime on the basis of time and location. In recent decades, the rapidly increasing series of criminal cases make accurate future crime prediction a difficult task. For crime trend prediction, a Prophet Model and Keras stateful LSTM has utilized in a recent study, in which missing value imputation and feature selection has carried out by simple computation as regards the enhancement of dataset quality and crime prediction. Though this method is simple to be applied, yet it has the inadequacy to prove its prediction accuracy. Because the sequence form of the input existed in LSTM maximizes the complexity while estimating the impact of each variable. For confronting these challenges, this study proposes a novel approach explicitly for crime trends prediction. In this model, the missing values have replaced by first Predictive Mean Matching method in the dataset. In addition, an improved bat optimization (IBAT) takes place to extract highly subjective features from the dataset, concerning the performance enhancement of trends forecasting and reduction of time computation. Ultimately, the convolution neural network algorithm has further involved predicting the crimes trends in order to reduce future crime.

Keywords:

Crime Trends Forecasting, Bat Optimization, Analyzing Data And Convolution Neural Network

1. INTRODUCTION

Crime takes place across the society, from when laws have passed for the first time. The term crime refers to an attempt that has committed/omitted by violating laws forbidding/commanding it, for which punishment has imposed, once after conviction. In a classical way, crime has considered being unpredictable, besides it cannot be essentially arbitrary; neither does it occur reliably in location nor time. There necessitates the sound skill in theoretical interpretation for providing feasible solutions to prevent the crime that matches with particular places and times. During the prediction of future crime, the former crime data has analyzed for locations and time of the future crime predictions. The task of crime prediction for future crime identifies the changes in year-to-year crime rate and focuses on that changes in future [1].

In accordance with qualitative and quantitative techniques, crime prediction can be carried out. In qualitative methods, the crime has forecasted as environmental scanning, scenario writing, which play a vital role to identify future factor of criminal activity. In contradiction to that, crime future scope prediction is done using perceptible method. Particularly, crime rate prediction is generalized approach for forecast development which helps in projecting annual crime rate trends established by time series models. Nevertheless, the changes and growth of crime pattern become progressive. The crime data tend to increase in a constant way, which have archived earlier from several sources [2] [3].

Consequently, it becomes the challenging and complicated task for handling and assessing huge data. For resolving these issues in crime trend prediction, a Prophet Model and Keras stateful LSTM has utilized in a recent study, in which the missing value imputation and feature selection has carried out by simple computation, concerning the enhancement of dataset quality and crime prediction. However, these approaches are inadequate to prove its prediction accuracy. The sequence form of the input existed in LSTM maximizes the complexity while estimating the impact of each variable [4] – [6].

To confront these challenges, a novel crime trends prediction system has presented in this study. In this model, the missing values in the dataset have replaced by first Predictive Mean Matching approach. Besides, an improved bat optimization (IBAT) takes place to extract highly subjective features from the dataset as regards the performance enhancement of trends forecasting and reduction of time computation. Ultimately, the convolution neural network algorithm has further included for predicting the crimes trends in an accurate manner in order to reduce future crime.

2. RELATED WORKS

In this segment, various techniques have been conferred for crime trend prediction.

Feng et al. [10] presented the comprehensive data analysis to scrutinize the criminal data from Philadelphia, San Francisco, and Chicago. For that, the data time series has explored initially, besides crime trends in the subsequent years have forecasted. Following that, crime category, time and location are forecasted for resolving the imbalance issue, the various classes have amalgamated into large classes and performed the feature selection task to enhance accuracy. Moreover, many advanced data mining methodologies have executed in this study to carry out crime prediction. Empirical findings demonstrate the capability of the Tree classification methods to efficiently perform during the classification process on K-NN and Naive Bayesian strategies. Besides, for crime trends prediction, Holt-Winters accompanied by multiplicative seasonality proves to be efficient to deliver optimal results. These reliable results can empower law enforcement as well as police department to accelerate the progress of solving unresolved crimes. Besides, facilitate them to trace the criminal activities, predict incidents probability, appropriate resource, utilization besides take timely decision by providing deep insights.

Awal et al. [11] tend to forecast the future crime trends of Bangladesh using a linear regression method. From Bangladesh police official website, the real crime dataset has gathered. On this dataset, the linear regression model has trained. Post-training of the model, the crime forecasting has carried out for different locations of Bangladesh in terms of murder, kidnapping, robbery, dacoity, theft, burglary, women and child repression, etc. This study can be suggested to be utilized by the Police department, as well as Law enforcement agencies of Bangladesh, for forecast, evading and elucidate forthcoming crime in Bangladesh.

Yadav and Sheoran [12] designed a hybrid framework, in which vector autoregressive takes care of the multivariate crime scene, besides fuzzy membership function has employed to perform the crime analysis on the basis of predicted values. This model includes the advantages of both methods by utilizing past multivariate trends-based impending crime event to predict future crime in real circumstances. Through the results, it has demonstrated the efficiency of the proposed model to perform the real-time prediction with accuracy using statistical methods.

Agarwal et al. [13] introduced the statistical methods, namely Weighted Moving Average, Functional Coefficient Regression and Arithmetic-Geometric Progression-based crime prediction in future. From Indian states, the crime data within the span of 2001 to 2013 have taken for this reason. Among that, crime details from 2001 to 2011 have utilized to forecast the crimes for the years of 2012 and 2013. Post-prediction process, the values have compared with the real crime data for the years of 2012 and 2013. Through the variance between real crime records and the forecasted vales, the accuracy of the proposed methods has obtained for both years, which ranges from 85 to 90 percentage.

Shi et al [14] designed a real official data-based large-scale environmental factors data set, besides recommended a random forest algorithm based on genetic algorithm optimization. By this algorithm, a classification method has constructed in accordance with the data belongs to the environmental aspects impacting property-related crime, and estimates the property-related crime trend in that location. Results depict the proficiency of the proposed algorithm to deliver the optimal performance during trend prediction of property-related crime, and enhance the effectiveness to identify the better solution with lesser computational complexity. To forecast the property-related crime, this method includes the robust application prospect, which is able to give alert in advance for the future crime trend.

Das and Das [15] presented the study that focuses on two stage method, which has regarded as an uncomplicated yet effective method to scrutinize crime against women in India. In this approach, the crime reports have gathered by the proposed model from the articles of online newspaper. Post-data collection, as a first phase, an interesting perspective has provided by detecting the named entities, such as person's name , cities, states, etc., from the dataset and top ten entities set belongs to several classes has rated as per their frequency of existence. Through the initial evaluation, a reliable outcome shave derived, subsequently it has associated with crime records brought from National Crime Records Bureau. Nevertheless, recognized entity subtypes are generally overlooked, instead looks over the basic entities that lacks to furnish comprehensive crime trends recognition. Thus, the consideration of subtypes enables providing the requirements of finer distinction in crime data mining domain. In the second phase, named entities sub-type has considered as `Modus Operandi' features (mode of operation) of the crime which can perfectly outline the crime insight done against women in India. Even though there are numerous research have made on crime analysis, the number of research which consider modus operandi features is very low. Throughout study, proposed approach efficiency has depicted, alongside maximum recall as well as precision for recognized named entities.

Morimoto et al [16] introduced an innovative method for crime prediction and made a model with adequate flexibility to get executed in various scenarios. For attaining this objective, an information propagation system has modelled by integrating the information entropy concept. This work empowers the security organizations for addressing/reacting to the occurrence of crime in an effective way. Moreover, enables the local policy makers to avoid or overcome the crime threats, thereby the public safety can be considerably augmented.

3. PROPOSED METHODOLOGY

The proposed crime trends prediction model is elaborated in detailed manner. Predictive Mean Matching method is greatly deployed for missing value imputation. The selection of significant features from the data is performed through improved bat optimization (IBAT). Finally, Convolution Neural Network algorithm is utilized for crime trend prediction. The complete architecture for the proposed crime prediction is shown in Fig.1.

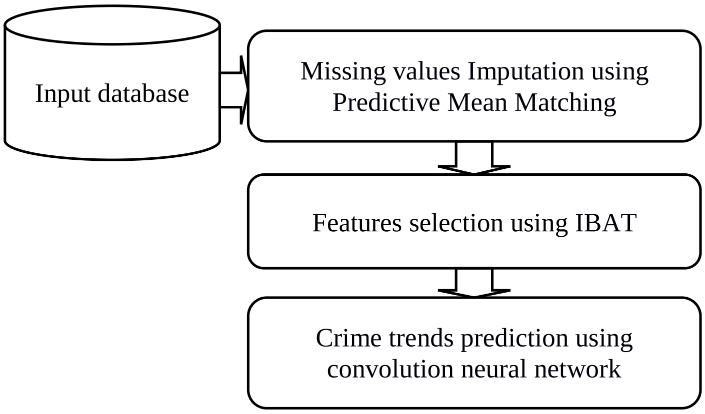

Fig.1. Complete architecture of suggested framework

3.1 MISSING VALUE IMPUTATION USING PREDICTIVE MEAN MATCHING METHOD

Predictive mean matching (*PMM*) is greatly exploited in this research for missing value imputation of input crime dataset and it is regarded as conventional imputation method. This approach imputes missing values $Y_{miss,i}$ of incomplete instance (recipient) Y_i, on the basis of perceived part of that instance $Y_{obs,i}$ for obtaining nearest instance (donor) through distance function which is calculated as missing variables expected values conditioned on the observed covariates, rather than directly on covariates values. The PMM functions as follows [17] [18]:

- *EM* algorithm is utilized for estimating multivariate Gaussian distribution parameters θ over attribute values by means of overall existing data.
- Conditional expected value for the missing part $Y_{miss,i}$ of instance Y_i conditioned on observed part $Y_{obs,i}$ is calculated depending on evaluated factors θ.

$$\hat{\mu}_i = E\left(\frac{Y_{miss,j}}{Y_{obs,i},\theta}\right) \quad (1)$$

- Correspond every recipient Y_i to another instance (possible donor) Y_j=argmin$_j d(i,j)$ which comprises nearest predictive mean pertaining to *Mahalanobis distance,* which has designated through residual covariance matrix from missing items observed ones regression.

$$d(i,j)=\sqrt{\left(\widehat{\mu}_i-\widehat{\mu}_j\right)^T s^{-1}_{Y_{miss,j}\,Y_{obs,i}}\left(\widehat{\mu}_i-\widehat{\mu}_j\right)} \quad (2)$$

in which, empirical covariance matrix has denoted by S

- Impute each missing value in the recipient with same values from its closest donor.

Later, missing value imputation data get transferred to subsequent feature selection process.

3.2 FEATURE SELECTION USING IMPROVED BAT OPTIMIZATION

The input data during this phase are crime instances accompanied by time, place, date, month, and year. Among these, bat optimization selects significant features [19] [20].

3.2.1 Bat Optimization Algorithm:

The animal Bat as well as its echolocation feature with advanced potential are greatly exploited by many researchers. The echolocation mechanism has a prominent role which confers to sound creation and estimation of an object (optimal feature) distance are done using echo signal generated through the bat. Also, it has the ability to differentiate a hurdle (inappropriate attribute) and a prey (optimum attribute) by this echo detection technique permitting them to hunt regardless of complete darkness.

3.2.2 Improved Bat Algorithm:

The capability of the standard bat algorithm is that exploiting the search space, yet it may fall into trap of local optimal features at certain times affecting its performance pertaining to global search. Increasing the search diversity is necessitated for evading trapping into local optimal features in BA. The main objective of the proposed algorithm is augmenting BA by means of an effective operator.

A random based modifications set is mainly involved in this operator for increasing BA, besides permitting for additional mutations in examined results inside BA search. Therefore, jumping out of potential local optima traps takes place. Alternatively, BA's possess the capability for solutions exploitation in the local neighborhood which is assisted with capability for exploring new areas in search space.

The added mutation operator is considered to major difference between IBAT and BA which aids in generation of new solution (optimal features) for each bat and thereby enhancing original BA. The effective optimization algorithm design mainly involves two significant key features namely exploitation and exploration.

As like BA, the definition of every bat (data samples) in IBAT is given, where x_i denotes its position, v_i signifies velocity, r_i denotes emission pulse rate, in addition A represents fixed loudness in a d dimensional search space. At time step t, the new solutions x_i and velocities v_i are specified through Eq.(3), Eq.(4) and Eq.(5).

$$f_i=f_{min}+(f_{max}-f_{min})\beta \quad (3)$$

$$v_i^t=v_i^{t-1}+\left(x_i^t-x^*\right)f_i \quad (4)$$

$$x_i^t=x_i^{t-1}+v_i^t \quad (5)$$

Here, a random vector drawn from a uniform distribution has indicated by $\beta \in [0, 1]$, frequency of each bat has signified via f_i, current global best solution (feature) has signified by x*, which is placed after comparing entire solutions (all features) belongs to entire n bats, at every iteration. A generation of random number is attained through updated bats positioning, if random number is greater than pulse emission rate r_i, a new position will be formed over current best solutions, as expressed through Eq.(6).

$$x_{new} = x_{old} + \varepsilon A^t \quad (6)$$

Here, $x_{old} \in [-1,1]$ represents random number, whereas A^t denotes all bats average loudness at current iteration.

The mutation operation addition for increasing the population diversity which in turn enhances search efficiency along with speeding up convergence to an optimal value is considered to be the main achievement of the proposed algorithm. The recommended algorithm is identical to standard BA on behalf of local search: a new solution is initially derived through local random walk from optimal existing solution (4). This first solution (optimal features) is generated depending on the criteria, i.e. a random real number brought from a uniform distribution must be greater than pulse rate parameter.

A new pair of tuning parameters, value 1 best and value 2 worst is obtained by the new mutation operator in the EBat algorithm. A solution x_v is arbitrarily selected from the NP population in mutation Operator stage, if a random value is smaller than best value 1 which is given as

$$v_r = rand*NP \quad (7)$$

$$X_v = x_{vr} \quad (8)$$

In which, $r \in (1, 2\ldots NP)$; Additional mutation is included into the current solution elements (optimal features) if a random value is lesser than worst value 2, drawing search back to an improved position pertaining to best and worst solutions recorded until now.

Drawing the search back to an optimal position as regards the best and worst solutions recorded up to now. In the instance of BA component get trapped in a local optimum, this mutation proves to be significant, as it is far from the actual global one. Eq.(8) and Eq.(9) express the modification of the mutation operator:

$$x_v=7\times\left(x_{worst}^t-x_v^t\right)\times rand\left[0,1\right) \quad (9)$$

$$x_v=7\times\left(x_v^t-x_{best}^t\right)\times rand\left[0,1\right) \quad (10)$$

Here, a new solution (optimal features) of t^{th} iteration has represented by x_v; random solution chosen by Eq.(9) has indicated by x_v^t, worst and best solutions obtained so far have characterized by variables x_{worst}^t and x_{best}^t, respectively. Or else, the randomization rule aims for adding population diversity, it supports mutation operator for search space exploration proficiently, prominent for maximizing probability of attaining global optimal solution (features) [21].

Improved Bat Algorithm [IBA]

Objective function (accuracy) $f(x)$, $x = (x_1,x_2,\ldots,x_d)^T$

Initialize the bat population (data samples) x_i (i=1,2,….n)and v_i

Designate pulse frequency f_i at x_i

Initialize pulse rates r_i, loudness A_i, Parameter value 1 and parameter value 2.

While (t<Max number of iterations)

Create new solutions (optimal features) by adjusting frequency,

and updating velocities and locations/solutions

if (r and >r_i)

Choose a solution among best solutions

Create a local solution around selected best solution (optimal features)

End if

Create a new solution by flying randomly

Mutation operator

If(*rand*<value 1)then

$v_r = rand*NP$

$X_v = x_{vr}$ where the $V_r \in (1,2,\ldots,NP)$)

If (*rand*<value 2) then

Update worst solution

Else

Update Best solution

End if

Else If Create new mutation solution

Estimate fitness function $f(x)$ for new solution x_v and x_i

Choose best solution from x_v, x_i which includes the Highest Fitness Value.

Create a new solution by flying randomly

If (rand < A_i and $f(x_i) < f(x^*)$)

Take new solutions (optimal features)

Escalate r_i and decrease A_i

End if

Rate bats and identify current best x^*

End while

Post process results and visualization

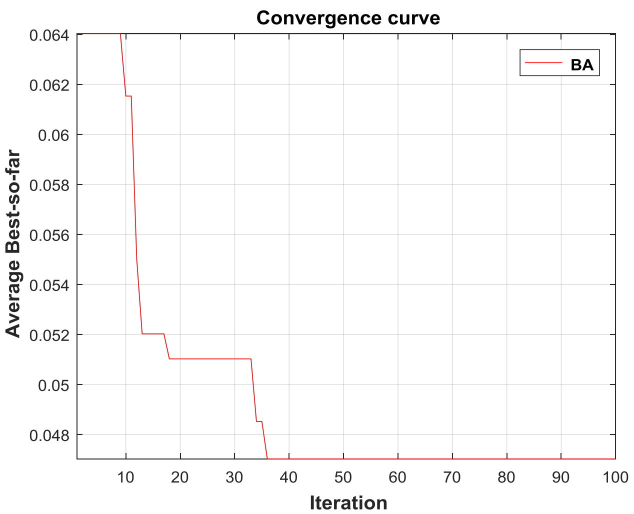

Fig.2. Convergence curve

The selection of Global best features with maximum classification accuracy is performed using improved bat algorithm. The original bat algorithm peculiar features are maintained by mutation which is presented in terms of fast convergence, despite the fact that permitting the algorithm for exploiting further mutation towards an improved diversity.

3.3 CRIME TRENDS PREDICTION USING CONVOLUTION NEURAL NETWORK

ConvNet architecture mainly comprises of three layers namely convolutional, max-pooling and fully-connected layers represented by conv, mp, and fc as presented in Fig.3. The fully connected layer helps in mapping the input features into a feature vector. The joint optimization of all parameters is done through misclassification error minimization across the training set by means of back propagation technique. The feature responses are summarized by ConvNet performing max-pooling operations in every convolutional layer which supports ConvNet for future learning. The classification process is accomplished by fully-connected layers lastly. A softmax layer is greatly utilized as ConvNets last layer for every class probability computation fed as input [22] - [24], since because of mutually exclusive property of underlying crime trends prediction problem.

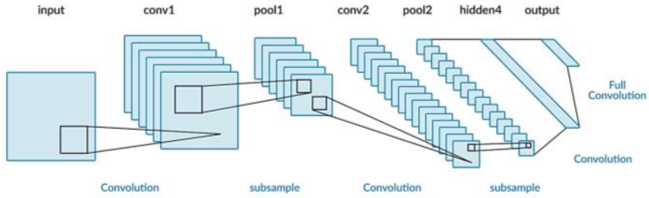

Fig.3. Architecture of the ConvNet

Let a training set $S = \{x^{(i)}, y^{(i)}\}$ comprises m inputs, in which i^{th} input has denoted by $x^{(i)}$ and corresponding class label has notated by $y^{(i)} \in \{0,1\}$. If $y^{(i)} = 1$, then $x^{(i)}$ is a one class patch, else $x^{(i)}$ is an another class patch. Consider $z_j^{(i)}$ as unit j output in last layer for $x^{(i)}$. Subsequently, probability that label $y^{(i)}$ of $x^{(i)}$ is j can be estimated as follows:

$$p\left(y^{(i)} = \frac{j}{z_j^{(i)}}\right) = \frac{e^{z_j^{(i)}}}{\sum_{i=1}^{k} e^{z_j^{(1)}}} \tag{11}$$

4. RESULTS AND DISCUSSION

The empirical findings are elaborated in this section for the proposed methodology. Matlab 2013b simulation environment is greatly exploited for the proposed work. For the three open-access crime datasets, the comparison of the proposed CNN model is done with that of the prevailing NN and LSTM models pertaining to precision, recall, accuracy and f-measure. These datasets encompass 3 cities across United States (such as, San-Francisco, Chicago, and Philadelphia), among which San-Francisco dataset includes a total number of 2,142,685 crime records that occurred within the period of 01/01/2003 and 11/08/2017. The dataset of from Chicago includes 5,541,398 crime incidents, which are obtained from 2017 to 2003. Besides, the Philadelphia dataset comprises 2,371,416 records from 01/01/2006 to 12/31/2017. Word cloud is deployed for crime text representation in the three dataset.

4.1 WORD CLOUDS

The word frequency graphical representations refers to Word clouds or tag clouds in which greater prominence is given to words that appear more repeatedly in a source text. The larger the word in the visual the more common the word was in document(s).

San-Francisco

Philadelphia

Table.1. Performance comparison results

Different methods	Datasets	Metrics			
		Precision	Accuracy	Recall	F - Measure
NN	Chicago	100	84	98.90	99.44
	San-Francisco	25	88.29	60	35.29
	Philadelphia	50	83.33	33.33	40
LSTM	Chicago	99.66	84.28	98.89	99.28
	San-Francisco	21.42	88.94	60	31.57
	Philadelphia	25	80.30	38.88	40
	Chicago	100	87	98.73	99.36
CNN	San-Francisco	95.66	89.19	99.82	97.65
	Philadelphia	100	85.50	98.97	99.48

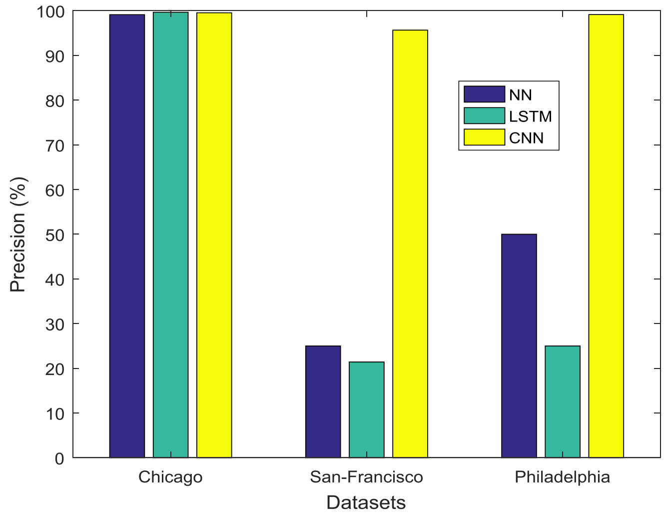

Fig.4. Precision results Comparison of Various Classifiers

The Precision result for various existing classification methods such as NN and LSTM scheme with respect to proposed CNN method are compared for different dataset is illustrated in Fig.4. The X-axis represents different methods while the Y-axis signifies precision values. It is also inferred from the figure, 99.54% precision results are attained for Chicago dataset by the proposed CNN model while existing NN and LSTM method produces merely 99.12% and 99.66% respectively.

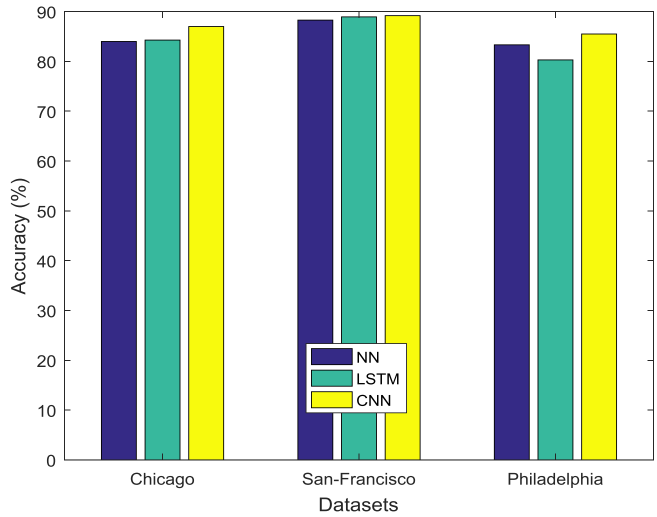

Fig.5. Accuracy results vs. classification methods

The accuracy result for various existing classification methods such as NN and LSTM scheme with respect to proposed CNN method are compared for different dataset is illustrated in Fig.5. The accuracy is greatly improved since fitness function for significant features are utilized by means of Bat algorithm in this research. The x-axis represents different methods while the y-axis signifies accuracy values. It is also inferred from the figure, 87% accuracy are attained for Chicago dataset by the proposed CNN model despite the fact that existing NN and LSTM method produces merely 84% and 84.28% respectively.

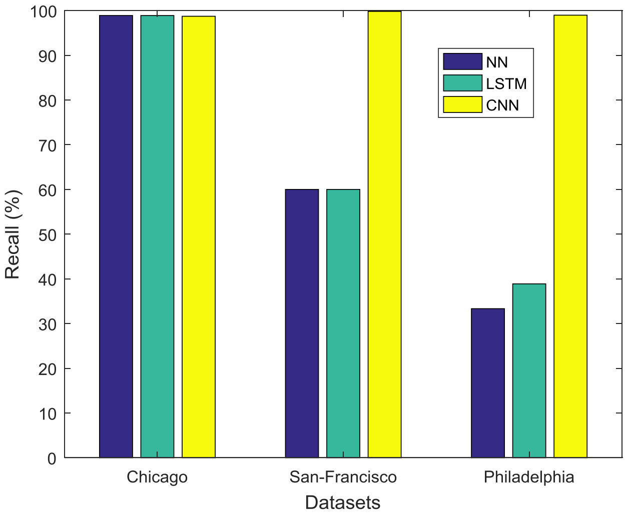

Fig.6. Recall Results vs. Classification Methods

The Recall for various existing classification methods such as NN and LSTM scheme with respect to proposed CNN method are compared for different dataset is illustrated in Fig.6. It is inferred from the figure, 98.73% Recall results are obtained for Chicago dataset by proposed CNN model while existing NN and LSTM method produces merely 98.90% and 98.89% respectively.

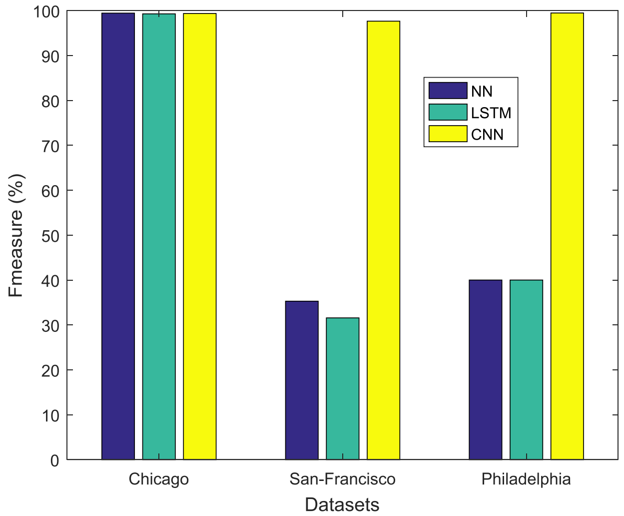

Fig.7. F -Measure Results vs. Classification Methods

The F-measure for various existing classification methods such as NN and LSTM scheme with respect to proposed CNN method are compared for different dataset is illustrated in Fig.7. The f-measure is greatly improved for the suggested technique since convolution function is used for learning features. The Proposed scheme yields F-measure value of 99.36% for Chicago dataset, 99.44% and 99.28% values are obtained for NN and LSTM respectively**.**

5. CONCLUSION AND FUTURE WORK

The crime trends prediction is achieved by providing an enhanced frame work in this research. Predictive Mean Matching technique is greatly involved in missing value replacement in dataset. Improved bat optimization (IBAT) is another technique utilized for choosing influenced features from the dataset and thereby improving trends forecasting performance with minimal time computation. Subsequently, Convolution Neural Network algorithm is exploited for crime trends prediction for obtaining much precise crime trends and thereby evading further crime. The suggested methodology outperforms good results pertaining to precision, recall and f-measure which is validated by the experimental outcomes. In future, other deep learning might be deployed to address the accuracy issues further.

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