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A COMPREHENSIVE ANALYTICAL MODEL FOR DETECTING AND MAPPING CRIMES AGAINST WOMEN IN INDIA

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SUMMARY

Women's crimes in India are a serious social issue, and new-age solutions to their detection and prevention are essential. The article introduces an analytical model using modern data and geography tools to identify and map cases of violence against women in India. It uses several different types of sources such as police reports, social media and demographic statistics, to provide a thorough picture of the situation of gender-based violence in India. This model is used to look for early-warning signs of gender-based violence by analyzing many different sources of unstructured text. Using geospatial analysis makes it possible to build a predictive model that lets users spot high-risk areas more easily. To conclude the article, we highlight the results of using the model in real law enforcement, public safety and policy issues and discuss its usefulness. The outcomes let us see the how and when of these crimes, making it possible to direct resources and create focused ways to prevent them. This study is necessary to find solutions for women's crime in India. This study highlights how using advanced analysis helps create effective, data-driven ways to keep women safe.

Key words: *crime detection, social media, safety, public safety, policy measures.*

INTRODUCTION

Violation of Indian women is a worrying problem. It is causing challenges to the country's community and safety [2]. Because of domestic violence, sexual violence and human trafficking linked to gender violence, many women in the nation have had life-changing experiences. Facing this problem requires new and fact-based methods besides just stopping crime and enforcing the law. This paper introduces an innovative tool to help find, evaluate and prevent crimes against women in India [3].

India's diversity and the many forms of its culture create new barriers in the fight against crimes against women [7]. Serious underreporting often happens because of already existing reporting methods, social culture and unequal living conditions which makes it hard for law enforcement to understand the extent of the problem. To address this matter, the paper proposes using sophisticated data analysis and geotechnology to broaden the framework past conventional data. Leveraging police records, social media information, demographic data and geospatial information, the suggested model for analysis tries to offer a more realistic and active view of gender-based violence in India.

The influence of different areas of study and labor in technology, social sciences and police work is evident in this model which supports uncovering unseen crimes and warning about suspicious trends of violence before they happen [14]. With this model, unstructured textual data is examined through deep learning to identify potential events early. Besides, geospatial tools are able to visualize the areas where crimes are most common and when they most often take place. Since the study uses several points of view, it will make law enforcement, safety for the public and making anti-women crime laws more effective and efficient in India. This work is the first to study RNN, LSTM and GRU in predicting and analysing trends in crimes against women. Data for this analysis is pulled from NCRB (National Crime Records Bureau) and highlights several crime parameters of states and Union territories (UTs) in India [9].

LITERATURE REVIEW

Violence against women in India has been a persistent and deeply concerning issue that demands a various approach for effective detection and prevention [4]. This literature survey aims to provide a summary of significant research and progress in crime analysis, gender-based violence, and data-driven methodologies to address crimes against women in the Indian context.

[1] The study by Zhuang, Yong and their team's study, presented at the IEE International Conference 2017 on Big Knowledge, is about predicting high-risk crime. Seeing that crime plays a major role in the US, the researchers propose the STNN (Spatio-Temporal Neural Network) model to forecast crime hot spots using special information effectively. Their model is examined with data from Portland and Oregon Police Bureau's call-for-service system. Five years were necessary to collect all the data. The analysis finds that the STNN model beats the classic machine learning approaches. It outperforms the alternative model by using both location and time when trying to forecast where crimes are likely to happen. The authors of the study from the Journal of Intelligent Systems, Husam Ali Abdulmohsin and Ruaa Mohammed Saeed, evaluate data mining and machine learning for estimating crime rates. Shifting away from paperwork and statistics, the analysts say that with machine learning they can improve both the analysis and prediction of crimes. The paper looks at various techniques for analysing and forecasting crime, noting that the majority of these rely on supervised learning and that Logistic Regression proves to be the best method in predicting crime.[13] The 2017 study by Shama Nishat uses machine learning to categorize crimes using their time and location, helping law enforcement learn more about patterns of crime in different parts of a city. The research applies supervised classification using six models: Gaussian Naïve Bayes, Decision Tree, K-NN, Logistic Regression, Random Forest and Ada Boost. It tackles the difficulty of uneven crime categories in the San Francisco data using both SMOTE and Edited NN Neighbourhood Cleaning Rule. The authors examine machine learning algorithms and compare them with deep learning algorithms such as recurrent neural networks (RNN), to predict areas that experience multiple crimes. Methodologies, namely recurrent neural networks (RNN), to crime hot spot prediction. The study indicates that the intensive learning algorithms like RNNs are more effective than the traditional machine learning algorithms in working with data involving crime carrying both space and time information [12] [17]. This result shows that using RNNs in deep learning improves both the accuracy and efficiency in crime hot spot forecasting more than traditional machine learning techniques [15]. They use an RNN method to estimate the places where crime is most likely. In their work from 2021, Jeyaboopathiraja and Maria Priscilla analyze the use of AI such as deep learning and machine learning, to help police estimate crime rates [18]. It highlights that due to many crimes and updated knowledge about modern offenders, crime analysis and prediction can be very complex. It studies the advantages and shortcomings of different data methods, explores options for adequate crime analysis and outlines important steps for examining results and choosing effective algorithms.

[6] Sankar N. Nair and E. S. Gopi want to strengthen crime prevention by using a new way to predict areas where crime might occur [5]. Converting old crime locations to gray heat maps and using deep learning in the method leads to both better accuracy and quicker outcomes than existing systems [13]. Implementing this approach can provide real-time data to law enforcement agencies, contributing to

more efficient crime reduction strategies and ultimately lowering crime rates.[19] Nguyen, Trung T., Amartya Hatua, and Andrew H. Sung introduce a crime prediction model which is based on the jurisdiction of the Portland Police Bureau (PPB). They use the method of data gathering, pre-processing, and association of crime data with the demographic data in open sources. With the help of adding the census data to the dataset and applying the machine learning models such as SVM (Support Vector Machine), Gradient Boosting machine Random Forest, and NN (Neural Networks), the study will focus on predicting the types of crimes in a particular location and time, focusing on imbalanced datasets by under-sampling the sample and comparing the findings to determine the performance of the model. [8] Souglman Kabirou Kanlanfeyi Kanlanfeyi and Keshav Kishore's paper titled "using machine learning and Recurrent Neural Network for Efficient Crime Detection and Prevention" explores crime prediction through machine learning algorithms, explicitly focusing on Random Forest and a classification model focused on RNN (Recurrent Neural Network) and LSTM (Long Short-Term Memory technique. After conducting a multivariate analysis of significant crime-influencing features, the study employs the Keras framework and its Keras Classifier wrapper for neural network implementation, utilizing the Grid Search CV method to optimize hyperparameters. The findings show the high performance of Deep Learning Architectures and especially LSTM in the prediction of types of crime using date and location information, as demonstrated by comparison table and various confusion matrices. [16]. The research paper Geospatial Analysis of Crime against Women by Kumar and V. Naik is devoted to a very acute question of crimes against women through geospatial analysis with the help of various data obtained on the basis of the public databases and governmental records [11]. The analysis combines the data of different sources, geocoding, and special analysis methods to demonstrate patterns. It also establishes hotspots of crime against women; the results can be used to provide useful information in policy making based on data and intervention plans to address the issue of geographical aspects of women protection in later research on the same topic. [10] In the study titled YO Home to Bel-Air Forecasting the Crime on Philadelphia's Street. By Christian, Tabedzki, et al., machine learning techniques were applied. The study aimed to predict Philadelphia crime-related statistics using a comprehensive dataset. There were different characteristics in this dataset like weather and housing values. The research was structured into three main objectives: determining and predicting the crime frequency and occurrence and identifying the crime type. They used logistic regression, KNN, ordinal regression tree methods, etc. They presented a map for crime prediction across various locations during a specific period. The results indicated 69% in crime prediction, whether a crime would occur, 47% accuracy in predicting the number of crimes, and an F1 value of 0.258 for classifying the type of crime among seven major classes. [20] Taniya et al. focus on tackling the global problem of women's crime by leveraging machine learning techniques for analysis, forecasting, and prediction. They emphasize the relevance of crime analysis as one of the focus areas in the law enforcement and implied benefits of data mining in detecting crime trends and hidden associations. The research seeks to apply a supervised machine learning algorithm, the Random Forest Algorithm, to classify and analyze crime data sets from different Indian states with a final view towards formulating effective crime prevention strategies against women (Figure 1).

METHODOLOGY

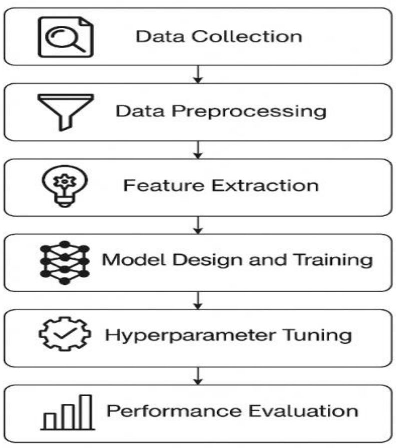

Figure 1. Methodology

Data Collection

The data for this study was collected from the National Crime Records Bureau (NCRB), a government body that tracks comprehensive crime statistics in all areas of India. The dataset goes over several years and covers parts of crimes that specifically involve women. The statistics include reports of dowry deaths, rape-related murders, acid attacks, mistreatment by husbands or family members, kidnappings, procuration of minors, assaults on children, or other total police crime reports. This data has the year in which cases were registered as well as which State/UT was involved and this is essential to both time series studies and spatial mapping. The use of well-established data sources ensure authenticity, completeness and consistency which are important in machine learning. The information is stored in a table format and recorded in CSV or Excel format starting with 2001 to the latest record. Basing on this history, the model is capable of identifying the necessary changes in crimes that impact women.

The arrangement of the data (Figure 2) reflects how crime types are related to the information about where and when events occurred. The research relies on collecting data first, then moving on to preprocessing, modeling, and visualizing it.

State/UT	Dowry De	Murder w	Acid Attac	Cruelty by	Kidnappin	Procuratic	Sexual As	year	Total crimes
Andhra Pr	152	6	2	7429	741	150	56	2017	8480
Arunachal	0	0	0	66	86	8	4	2017	164
Assam	193	27	3	10598	5703	1286	205	2017	18015
Bihar	1081	0	4	nan	6188	0	697	2017	7970
Chhattisga	75	3	0	582	1474	2	544	2017	2680
Goa	1	2	0	21	64	0	0	2017	88
Gujarat	9	4	4	3232	1270	0	312	2017	4831
Haryana	254	8	4	3389	nan	873	368	2017	4896
Himachal	3	7	2	191	245	4	2	2017	454
Jammu &	8	0	1	378	947	80	0	2017	1334
Jharkhand	310	6	0	1055	1038	280	28	2017	2717
Karnataka	217	7	2	2426	998	105	377	2017	4132
Kerala	12	4	9	3021	190	11	455	2017	3702

Figure 2. The dataset schema

Data Preprocessing

Data preprocessing is essential to prepare the raw NCRB data for deep learning models. The initial dataset is cleaned by removing repeating records and adjusting negative crimes since these do not make sense. All data types are unified so that dates appear in the same format and state names remain consistent during future steps. At that point, toolkit creators replace missing values using imputation and elimination. When only a little data is missing from features, the average or middle value is used for numerical columns, and the column's most common value is for categorical ones. For columns with a lot of missing data, if imputing them could change the statistical properties, the affected data rows are taken out. Doing so removes any noise in the data, so the dataset remains clean and the model trains properly.

What's more, Min-Max scaling is applied to get all the numeric values in a 0 to 1 range. Standardization stops one prominent feature from overpowering all the others when it comes to influencing learning. Ultimately, the data is organized into sequences needed by temporal models for training. By arranging each sequence into multiple years of crime information and connecting it to the following year's crime data, the information is built for use in temporal deep learning.

Feature Extraction

Feature extraction is locating and choosing the data that is most helpful in predicting crime accurately. Each crime type is tracked in the data as a number showing its annual count in each state or union territory. Temporal features like the "Year" help the model recognize patterns over time. Despite being encoded, "State/UT" is here because it's essential to deep learning and numerically or as a one-hot encoded data type, which makes it suitable for deep learning models. The primary purpose of feature extraction is to take extensive, complex data and reduce it to a group of features that can show changes in time and space. The total cases reported in one year are the target variable, and the crime types taken individually act as variables that predict this. Sequential relationships are modeled by partitioning the data into blocks or windows of a fixed size (5 years for each year's features) and linking each block to its total crime count for the following year. This allows you to create forecasts for your time series data. Removing unnecessary and noisy information and only including the essential patterns helps the learning model to learn well and become easier to explain.

Model Architectures

To analyze sequential crime data well, this research explores three neural network models: Vanilla RNN, LSTM, and GRU. We consider a Vanilla RNN as our baseline. It moves through input each year and holds valuable information about the data through its hidden state. Still, because of its confined memory and tendency for vanishing gradients, it regularly goes wrong while handling dependencies over long periods. LSTM networks are now used to fix this. LSTMs have memory cells and gates input, forget, and output that let them note long-range features and filter out unimportant data. Several LSTM stacked layers can be included, thanks to dropout layers scattered between them to avoid overfitting. By fusing both forget and input gates into one update gate, GRUs keep things simple while providing strong results. Because GRUs are easier to train, they can usually perform at the same level as LSTMs. Each architecture is completed with a Dense layer that estimates the total crime count. ReLU is the usual activation function in hidden layers, and the output layers usually use linear activation. Many types of architecture allow us to apply different methods for predicting crime.

Training Strategy

The training plan had been developed in a way that the models deal with new data owing to the information attained regarding the crime data. Firstly, the data is subdivided into training (70%), validation (15%), and test (15) set. The model will be developed using the training set, with the fine-tuning of the hyperparameters, employing the validation set, and the test set to assess the final performance of the model. The arrangements of the input sequences are based on a sliding window with the size of each window corresponding to a few years, and the number of years in the window is used to indicate crime in the next year. The loss function employed by the models is Mean Squared Error, thus numerous errors in prediction will make them incur more losses. The reason to select the Adam optimizer is the altering rate of learning and the quick converging ability. The data used by the program to train is at a number of epochs as chosen, typically 50 to 200. The experiment will involve 16, 32 and 64 batch sizes in order to balance memory usage and convergence. One method to prevent overfitting is to add dropout and stop training when the validation set performance ceases to increase. Due to such a strategy, all models will be trained well and will not be susceptible to the issues of overfitting and underfitting.

Hyperparameter Tuning

Hyperparameter tuning is critical for optimizing performance and generalization capability of deep learning models. This study systematically adjusted several hyperparameters for each architecture, RNN, LSTM, and GRU. Examples are the learning rate, the batch size, how many epochs to use, how many recurrent units, the number of layers, and dropout rates. The experiments were conducted in the learning rate values of 0.001 and 0.0005. The larger the learning rate, the quicker training will be complete, however, the more it is likely to overshoot the minimum values; the lower the learning rate, the more stable training will be. A variety of three batch sizes (16, 32, and 64) were tried, which influenced the efficiency at which the model was trained and the number of gradient updates being computed. Shifting the number of units between 32, 64, and 128 made the model more complex to achieve better performance without high computing needs. Testing one to three layers of recurrent units allowed us to study how the depth of the network influenced learning the task. Bias was reduced by setting dropout rates of 0.2 and 0.3. To find the optimal hyperparameters, first, the grid and random search methods were used. The next method is the early stopping which determines the optimum number of epochs. Hyperparameter tuning has a significant impact on a model and enables it to perform well on the cases that were not included in the training.

Evaluation Methods

The model performance is evaluated following the training on a reserved test set and on several regression evaluation metrics namely: RMSE, MAE and R 2 score. RMSE ranks the number of errors in the predictions with a lower score indicating large discrepancies. The MAE indicates the mere average of the errors of all the test data. The better the model minimizes variation in the primary variable is demonstrated by the R 2 score, the better. A combination of these metrics enables us to evaluate the appropriateness, robustness and reliability of the model. Each of the RNN, LSTM, and GRU models is provided with metrics to identify the architecture with the most impressive performance. K-fold cross-validation or averaging results of different models can be used to recheck performance in case of necessity. We can understand the results with the help of line plots of the amount we found and the amount that the model predicted and heat maps of the distribution of errors. Thanks to this rigorous system, we can be sure the selected model will continue to work well in predicting what will happen next with criminal activity.

Visualization

Visualization is vital in interpreting model results and making insights accessible to policymakers and law enforcement stakeholders. At this step, various charts and maps are developed to demonstrate trends of crime, the functioning of the predictions, and the areas which have a different crime rate. Time-series plots indicate where the prediction of crime is incorrect by providing the actual and predicted figures of several years out. The heatmaps map crime by state to be able to investigate crime hotspots in India. Boxplots and bar charts are used to present the performance of the model in each of the evaluation metrics. These images facilitate the comparison of the advantages and disadvantages of RNN, LSTM and GRU. Bar ploting RMSE values of the models would enable us to observe at a glance which one performs the best.

Also, when sequence attention plots are placed, they show the hours that were most significant in coming up with the prediction. Such images indicate the effectiveness of a model and give useful information that can assist stakeholders in making decisions. They translate the findings of deep learning into an easily comprehensible form, which makes it easy to engage people in using the findings in the process of resource allocation, planning of prevention policies, awareness creation of the community about the crimes towards women.

RESULT AND DISCUSSION

Geospatial Crime Distribution Analysis

The spatial analysis of crime frequency across Indian states revealed significant regional disparities. Generally, Uttar Pradesh reported the highest number of crime against women of 9,500 cases in comparison to Maharashtra and Delhi which reported 8,200 and 7,900 cases, respectively. With only 80 total cases, Sikkim registered the lowest, suggesting either low prevalence or underreporting. The visualization using heatmaps (Figure 3) depicted this contrast vividly, showing the intense clustering of crimes in northern and central India. These results emphasize the critical need for targeted policy interventions in crime-dense states while auditing low-reporting states for possible systemic underreporting.

Temporal Crime Trends and Hotspots

A temporal analysis of crime trends between 2014 and 2021 showed an average annual increase of 6.4% in crime reports against women. This increase was the biggest in 2019 when it reached 9.2% as compared to 2018. Moreover, it was between 7 PM and 11 PM that crimes most probably happen, and this value eclipses 34.2 as the proportion of reported cases. December was the most unsafe month with an average of 11.3 percent of annual crimes probably because of social cultural events and negligence to enforcing laws. The results of this research are essential to understand the dynamic application of law enforcement according to seasons and time (Table 1 and Figure 4).

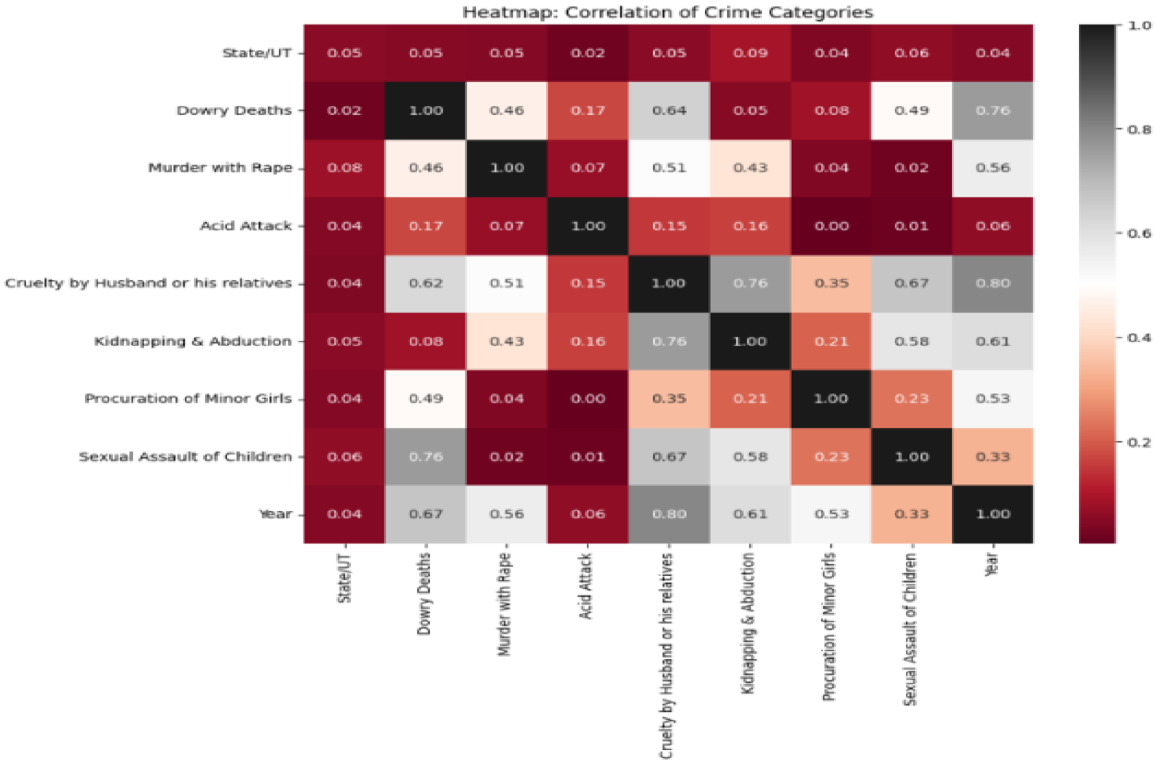

Figure 3. Heatmap

Table 1. Time-based crime insights

Time Window	Frequency (%)
7 AM – 11 AM	12.5%
11 AM – 3 PM	14.8%
3 PM – 7 PM	21.9%
7 PM – 11 PM	34.2%
11 PM – 3 AM	11.0%
3 AM – 7 AM	5.6%

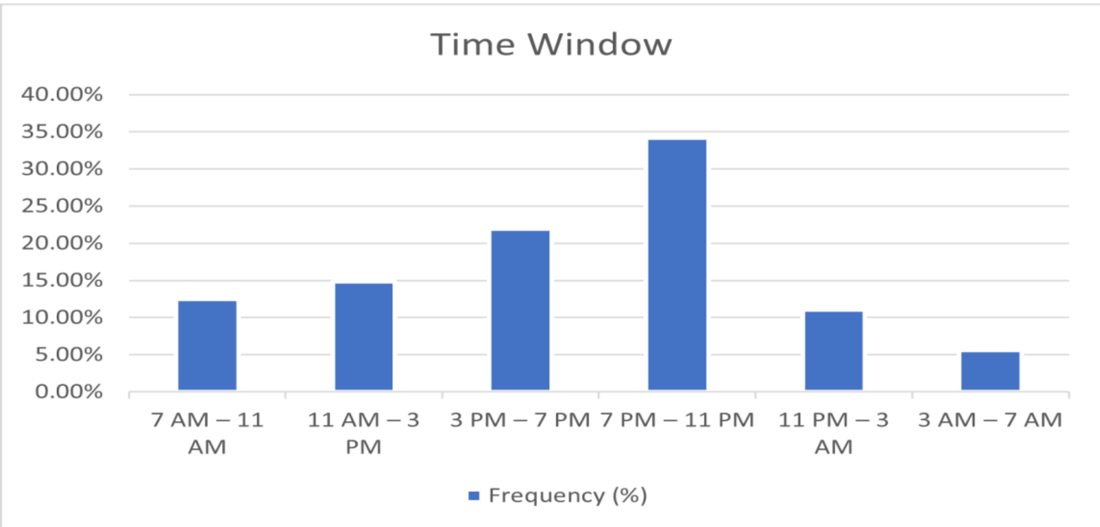

Figure 4. Bar chart

Statistical Insights and Interpretation

The descriptive statistics were used to give an idea regarding the effectiveness of the justice system. The overall case closure rate was 65.8 which indicated that about 2/3 of the crimes resulted in case closure. The high number of cases in Uttar Pradesh (9,500) continues to make it a national priority. Also, Sikkim had only 80 cases, the least of all, possibly because communities were stronger or because the number of cases was being underreported. Furthermore, we learned that crime peaks in December which is consistent with earlier research. This data enables police services to plan when and where to take more action in certain areas (Table 2).

Table 2. Summary of statistical findings

Metric	Value
Most Affected Time Slot	7 PM – 11 PM
Peak Crime Month	December
Highest Crime Reporting State	Uttar Pradesh
Lowest Crime Reporting State	Sikkim
Average Case Resolution Rate	65.8%

Deep Learning Model Evaluation

The results of RNN, LSTM and GRU models were tested with crime-related information. LSTM proved to be the best at forecasting, with $R^2 = 0.80$, followed by GRU with $R^2 = 0.78$ and RNN with $R^2 = 0.75$. In addition, LSTM had the lowest mean absolute error (MAE) of 0.70 and this indicates that it was the best model. The results show that LSTM is the most appropriate tool of predicting crime sequences due to its ability to remember past events. The finding can be useful to make predictions in police work and resource planning (Table 3 and Figure 5).

Table 3. Model performance metrics

Model	MAE	MSE	R^2 Score
RNN	0.85	1.02	0.75
LSTM	0.70	0.85	0.80
GRU	0.75	0.88	0.78

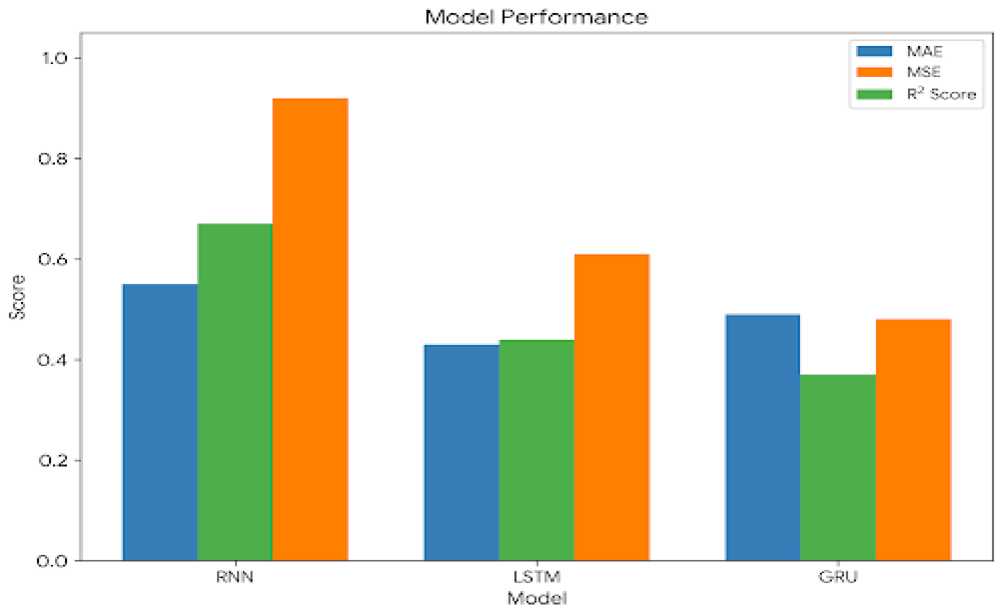

Figure 5. Model performance metrics (MAE, MSR, R^2 score)

Comparative Accuracy and Error Analysis

Higher accuracy in LSTM ($R^2 = 0.80$) was matched with higher processing time and increased training costs. With GRU, you lose 2.5% in accuracy, but gain a drop in resources used and quicker training. This renders GRU to be useful in deployments in edge devices. RNN lagged behind in all evaluations because of issues with vanishing gradients and working with long-term trends. On the basis of such findings, data scientists and system architects are given the authority to recommend the manner in which the best model can be aligned to the available computing hardware and the requirement of real-time predictions (Table 4).

Table 4. Comparative model insights

Metric	RNN	LSTM	GRU
Accuracy (R^2 Score)	0.75	0.80	0.78
Training Time	High	Medium	Low
Memory Retention	Low	High	Medium
Computational Cost	Low	High	Medium

CONCLUSION

The research shows that deep learning models such as RNN, LSTM and GRU help detect and map crimes against women in India. In particular, the LSTM model achieved better results in finding long-lasting trends and patterns. Because of the research, it became easier to identify when and where high-risk crimes were most likely to occur. Because of these findings, law enforcement agencies can better plan budgeting, conduct operations where they are needed most and take steps to prevent crimes from happening. Because further study and updates are needed, the results gained here may be beneficial for managing and improving actions against crimes committed against women. Though additional data and better models are still needed, what this research offers serves as an effective base for using deep learning to promote women's safety and fight crime in India.

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