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A MULTI-DIMENSIONAL CRIME INDEX FOR CRIMES AGAINST WOMEN USING A HYBRID MACHINE LEARNING AND REGRESSION APPROACH

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ABSTRACT

The increasing concern over crime rates, particularly crimes against women, has led to a demand for more effective ways to assess and address public safety. Historically, crime analysis has relied on traditional statistical methods and crime reporting systems, which primarily depend on police reports, surveys, and judicial records. These systems, while valuable, suffer from limitations such as underreporting of crimes, biases in reporting, and a lack of integration across different sources of data. Moreover, traditional crime indices often focus on a single dimension of crime, overlooking the complexity and multi-dimensional nature of crimes against women, which include physical violence, sexual assault, harassment, and emotional abuse. These shortcomings make it difficult to create a comprehensive understanding of the safety issues faced by women. The problem arises in the need for a more holistic approach to crime analysis that integrates multiple dimensions of crime data, such as geographical location, socio-economic factors, time, and severity, while also considering the disparities in reporting and recording crimes. The absence of a multi-faceted crime index specifically designed to address crimes against women hampers effective policy-making and resource allocation for prevention and intervention programs. The motivation for this study stems from the growing need to develop more accurate and nuanced crime indices that reflect the complexities of crime against women. By incorporating diverse data sources and analyzing various factors influencing crime, a multi-dimensional crime index can provide valuable insights for law enforcement, policymakers, and social organizations. To address these issues, a proposed system combines hybrid machine learning and regression approaches to validate a multi-dimensional crime index. This system would integrate different data types, such as demographic, geographical, and crime-specific details, allowing for a more accurate assessment of the crime landscape. This comprehensive approach aims to improve both the reliability and the predictive capabilities of crime indices, offering a tool for more informed decision-making.

1. INTRODUCTION

In India, crimes against women have been a longstanding issue, with alarming statistics pointing to rising rates of violence and harassment. According to the National Crime Records Bureau (NCRB), in 2020, India reported over 4.2 lakh cases of crimes against women, including rape, molestation, domestic violence, and trafficking. These crimes often remain underreported, making it difficult to fully understand the extent of the

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problem. Historical systems, such as police records and surveys, have struggled to integrate multiple dimensions of crime data, like socio-economic factors and geographical distribution. The lack of a comprehensive, multi-dimensional crime index has hindered effective law enforcement and policy-making. Despite numerous efforts to improve public safety, crimes against women remain a significant concern across both urban and rural areas. This issue has prompted the need for more advanced, data-driven approaches to accurately assess and tackle the problem.

This Crimes, or criminality in general, have accompanied human civilizations since their inception. Criminal behavior is described as aberrant human conduct that transgresses the laws in effect in a specific location. The term "criminality" refers to the overall amount of crimes committee do veraspeci fied period of time in a particular nation or environment, or by a particular gang of criminals. Within the context of urban governance, crime poses a notable challenge in ensuring the security of residents, alongside challenges of a more scientific nature. Ensuring safety is a fundamental necessity, greatly influencing both the well-being of the locality's inhabitants and its overall reputation and economic appeal. Through the identification and resolution of the underlying factors behind the criminal activity, it becomes possible to devise proactive and corrective strategies, effectively managing, though not entirely eliminating, crime [1], [2]. The global worry about criminal activities is not unique to India. Throughout history, it has posed a substantial challenge to the progress of societies. In recent times, both the scale and prominence of this problem have undergone a substantial increase.

CAW or gender-related violence pertains to any detrimental or unlawful acts or conduct directed specifically at females due to their gender. CAW en compasses sexual ,psychological, emotional, and financial abuse in addition to physical assault. Discrimination, domestic abuse, sexual assault, and other types of gender-based violence affect women disproportionately [3], [4]. Extreme acts of violence against women, such as acid assaults and honor killings, do occur at times. Beyond the harm done to the victim's physical and mental health, these crimes have a significant negative economic and social impact on the country. Patriarchal views and a desire to keep control over women frequently drive these crimes. The Indian authorities have implemented various measures to address the issue of violence against women. These include the enactment of the Protection of Women from Domestic Violence Act in 2005, the passage of the Criminal Law Amendment Act in 2013, and the establishment of the National Commission for Women. Despite these efforts leading to some positive changes in our community, there is no 100% success in preventing such incidents from happening in our vicinity. A complex issue requiring a deep understanding of its root causes is evident. India's ranking on the World Peace and Security Index declined from 133rd among 167 countries in 2019–20 to 148th among 170 countries in 2020–21. This highlights the status of women in the country compared to the global context. While crime

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may not be uniformly distributed across the nation, it is essential to pinpoint the fundamental factor that is disproportionately affecting specific regions [5]. The occurrence of CAW is impacted by a range of elements. The country's limited rate of successful prosecutions enables wrongdoers to evade consequences and engage in the same actions again in the future. This study suggests introducing a CAW index as a novel method for better understanding the incidence of such crimes [6]. This holds special significance for the government as it supervises state law enforcement to ensure the well-being of its citizens. The purpose is to identify trends in unlawful conduct and assist law enforcement agencies in distributing their assets effectively. The index is constructed by leveraging different elements that are highly probable to impact criminal attitudes toward women.

2. LITERATURE SURVEY

Srivastava et al. [1] investigated the impact of substance use within families and communities on adolescent boys' substance abuse in India. Their study, based on the Udaya study data, revealed the intergenerational transmission of substance use, emphasizing the influence of familial and community dynamics on the behavior of adolescent boys. The research highlights the need for targeted interventions within these communities to address substance abuse. Shorette and Burroway [2] revisited the relationship between women's education and infant mortality with a focus on distributional perspectives. The authors highlighted how educational attainment can significantly reduce infant mortality, especially when considering different socio-economic groups. Their work emphasizes the nuanced impact of education in improving health outcomes and its potential as a policy tool for reducing mortality rates.Chopin et al. [3] examined the sexual victimization of women with disabilities, applying victimological theories to understand their heightened vulnerability. Their study critiqued the contradictions in existing literature and underscored the importance of context in analyzing the victimization of disabled women. It called for more tailored research and interventions addressing this often-overlooked demographic.

Rodriguez [4] explored the connection between women's employment and empowerment in India, using the employment guarantee scheme as a case study. The research demonstrated that employment opportunities not only provide economic stability but also empower women, particularly in rural areas. Rodriguez's work highlights the significant role that employment can play in gender equality and women's social standing. Craigie et al. [5] investigated the impact of temperature fluctuations on crime rates in India, exploring how climate change might influence criminal behavior. The study revealed a significant correlation between rising temperatures and an increase in certain types of crimes. This research contributes to a broader understanding of how environmental factors can affect societal well-being, urging policymakers to consider climate in crime prevention strategies.

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Das and Roy [6] examined the contextual effects of unemployment, poverty, and literacy on domestic violence against women in India. Their study utilized multilevel analysis to show how societal factors contribute to spousal violence. The research provides valuable insights into the social determinants of violence and advocates for a multi-faceted approach to addressing domestic abuse. Raj and Rahman [7] revisited the economic theory of crime in India, focusing on state-level data to understand how socio-economic factors contribute to criminal behavior. Their research explored the effectiveness of crime prevention strategies and policy interventions, offering a comprehensive analysis of crime trends in different regions of India.

Lisowska-Kierepka [8] presented a new method for spatial crime analysis, using a crime risk indicator to assess the geographical distribution of crime. The study introduced an innovative approach to spatially analyze crime, offering valuable tools for urban planners and law enforcement agencies. It emphasizes the importance of understanding the spatial context in crime prevention and public safety. Kwan et al. [9] proposed a crime index based on Thurstone's scaling to measure crime severity in urban areas. Their method aimed to provide a more quantitative way of assessing the impact of different types of crime. The study's approach allows for a clearer understanding of crime patterns and can inform policy decisions on law enforcement and crime prevention.

3. SYSTEM DESIGN

Existing System

The analyzing crimes against women primarily relies on traditional statistical methods and manual reporting mechanisms, such as police reports, judicial records, and national crime surveys. These systems use historical data to generate crime indices and patterns, which are often represented in annual reports. However, these indices typically focus on isolated dimensions of crime, such as the number of incidents or specific categories like rape or harassment, without considering multi-dimensional factors like socio-economic status, geographical distribution, or time-related patterns. Data is often collected and analyzed in silos, with limited integration across various agencies. While these methods provide a basic understanding of crime trends, they lack the depth and predictive capabilities required to address the evolving and complex nature of crimes against women.

Limitations of the Existing System

- **Underreporting of Crimes**: Many crimes against women go unreported due to social stigma, fear, or lack of trust in law enforcement.
- **Data Fragmentation**: Crime data is often scattered across different agencies, making it difficult to create a comprehensive analysis.
- **Single-Dimensional Focus**: Existing indices fail to account for the multi-dimensional aspects of crime, such as

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socio-economic and geographical factors.

- **Lack of Predictive Capability**: Traditional systems cannot predict future crime trends or high-risk areas effectively.
- **Bias in Reporting**: Data collection is often influenced by biases, such as underrepresentation of crimes in rural areas or lower socio-economic groups.
- **Time-Intensive Analysis**: Manual methods and surveys are time-consuming and fail to provide real-time insights.
- **Inflexibility to Evolving Patterns**: The systems struggle to adapt to changing crime trends or new data sources.
- **Limited Scope for Prevention**: Without predictive insights, law enforcement and policymakers lack tools to take preventive measures.
- **Inefficient Resource Allocation**: Resources are often deployed reactively rather than strategically, leading to inefficiencies.
- **Inaccessibility to Stakeholders**: The insights generated are not easily accessible to NGOs or community organizations working for women's safety.

PROPOSED SYSTEM

The first step in the research procedure is the collection of a dataset that captures crime-related incidents specifically targeting women. The dataset may include various features such as the type of crime, the geographical location, the time of occurrence, and socio-economic factors related to both the victim and the perpetrator. This dataset is crucial for understanding the patterns of crimes against women and serves as the foundation for applying machine learning techniques to predict crime rates or analyze contributing factors. It is essential that the dataset is representative of real-world scenarios and contains sufficient data for training machine learning models.

Once the dataset is collected, the next step is preprocessing. This involves cleaning the data to make it suitable for model training. A primary preprocessing task is handling missing values, as null or missing data can lead to inaccurate model predictions. Various methods, such as filling null values with mean or median, or removing rows with null values, can be applied depending on the context of the data. After handling missing data, categorical variables in the dataset need to be transformed into numerical values for machine learning algorithms to understand them. This is done using label encoding, where each unique category is assigned a corresponding integer value. This step ensures that the dataset is in a format that machine learning algorithms can process effectively.

The next step involves applying the proposed algorithm, a Deep Neural Network (DNN), to the dataset for regression purposes. Unlike Random Forest, which relies on decision trees, DNNs use multiple layers of neurons to

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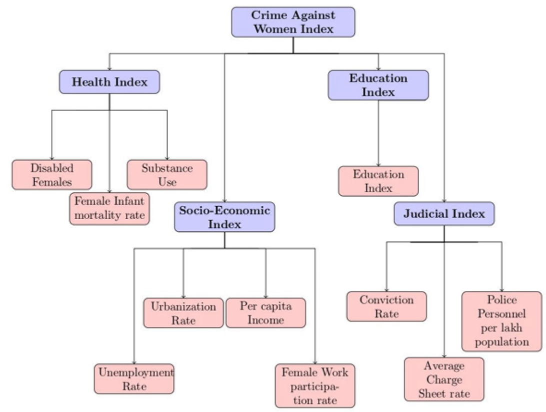
model complex relationships within the data. Each neuron applies a transformation to the input data and passes the result to the next layer. The model is trained using backpropagation, adjusting the weights of the neurons based on the error between predicted and actual values. DNNs are highly effective for capturing intricate patterns in data, making them a suitable choice for complex datasets like crime prediction. This step involves fine-tuning the DNN's hyperparameters, such as the number of layers, neurons, and learning rate, to ensure optimal performance.

Advantages

- **Flexibility**: DNNs can model complex, non-linear relationships in data, making them suitable for a wide range of tasks, including regression.
- **Feature Learning**: DNNs can automatically extract relevant features from raw data, reducing the need for manual feature engineering.
- **Scalability**: With enough data, DNNs can scale effectively and improve in accuracy over time, making them suitable for large datasets.
- **Accuracy**: DNNs tend to outperform traditional machine learning algorithms when trained on large datasets and can capture complex patterns that simpler models like Random Forest might miss.

SYSTEM ARCHITECTURE



4. MODULES DESCRIPTION

1. **Dataset Upload and Preprocessing**

Upload_data(request)

- Allows users to upload a CSV file.
- Reads the dataset using pandas.
- Encodes categorical features using LabelEncoder.
- Visualizes correlations using a heatmap (via seaborn).
- Splits the dataset into training and testing sets (70/30 split).
- Deletes the temporary file after processing.

2. **Machine Learning Models**

- Models are trained on the uploaded dataset to predict a target variable (Grand Total).
- Four main regression models are supported:

RFRegression(request)

1. Implements a Random Forest Regressor.

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2. Checks if a pre-trained model exists (rfr_model.pkl).
3. If not, trains the model with RandomForestRegressor from sklearn and saves it.
4. Predicts test set values and calculates performance metrics (MAE, MSE, RMSE, R^2).

DNN(request)

1. Implements a **Deep Neural Network** (DNN) for regression using TensorFlow/Keras.
2. Loads a pre-trained model if available (dnn_regressor.h5).
3. If not, trains a new model with three layers:
4. Input layer (128 neurons), hidden layer (64 neurons), and output layer (1 neuron).
5. Uses Adam optimizer and mean squared error loss.
6. Employs early stopping to prevent overfitting.
7. Evaluates the model on the test set and calculates performance metrics.

xgb(request)

1. Implements an **XGBoost Regressor**.
2. Checks for a pre-trained model (XGBoost_regressor_model.pkl).
3. If absent, trains the model using XGBRegressor and saves it.
4. Predicts test set values and calculates performance metrics.

DecisionTreeRegressor (dtr)

(Currently commented out.)

1. Would implement a Decision Tree Regressor with a maximum depth of 10.
2. Similar functionality to the above models for training, saving, and evaluating.

Performance Metrics

calculateMetrics(algorithm, predict, testY)

1. Computes regression evaluation metrics:
2. Mean Absolute Error (MAE)
3. Mean Squared Error (MSE)
4. Root Mean Squared Error (RMSE)
5. R^2 score (coefficient of determination)
6. Appends results to global metric lists for visualization or future reference.

5. SCREEN SHOTS

This figure shows the main interface or homepage of the system designed for crime detection, specifically targeting crimes against women. It typically includes navigation options, an introduction to the system, and a user-friendly layout that directs users to various sections such as data uploading, crime detection, user login, and performance metrics. The home page acts as a central point for users to interact with the system and access its functionalities.

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Fig 1: Home Page of the Crime Against Women Detection

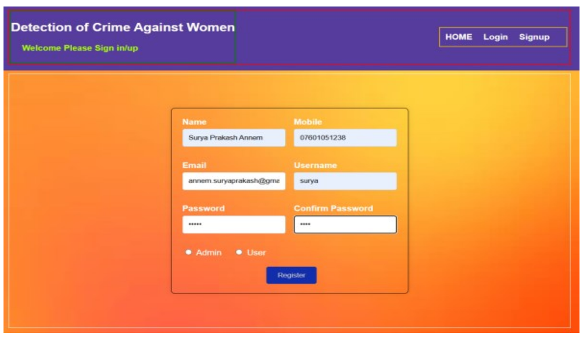

Fig 2: Common Registration for User and Admin

This figure depicts the registration page for both users and administrators of the system. It highlights a unified registration process where individuals can create accounts as either users (who can upload crime-related data) or administrators (who manage the system and view detailed reports). The registration process involves entering personal details, such as name, contact information, and role designation (user or admin), before proceeding to the next steps in the system.

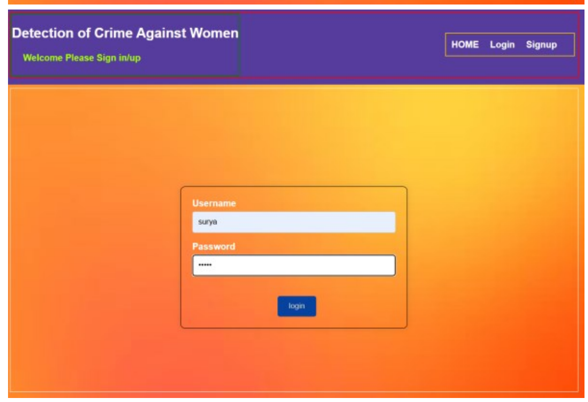

Fig 3: User Login for Using Crime Detection

This figure showcases the user login page. Here, users need to enter their credentials (username and password) to access the crime detection functionalities of the system. The login process ensures that only authorized users can upload data, access predictions, or view results related to crime detection. The login interface may also feature options for password recovery and user account management.

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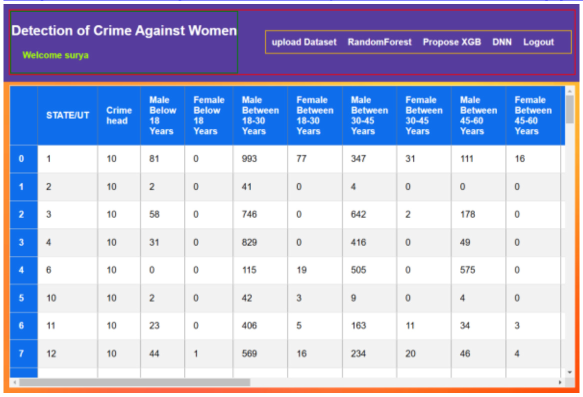
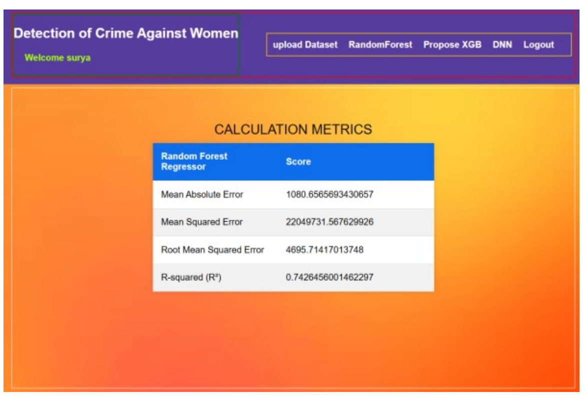


	STATE/UT	Crime head	Male Below 18 Years	Female Below 18 Years	Male Between 18-30 Years	Female Between 18-30 Years	Male Between 30-45 Years	Female Between 30-45 Years	Male Between 45-60 Years	Female Between 45-60 Years
0	1	10	81	0	993	77	347	31	111	16
1	2	10	2	0	41	0	4	0	0	0
2	3	10	58	0	746	0	642	2	178	0
3	4	10	31	0	829	0	416	0	49	0
4	6	10	0	0	115	19	505	0	575	0
5	10	10	2	0	42	3	9	0	4	0
6	11	10	23	0	406	5	163	11	34	3
7	12	10	44	1	569	16	234	20	46	4

Fig 4: Sample Crime Uploaded Dataset

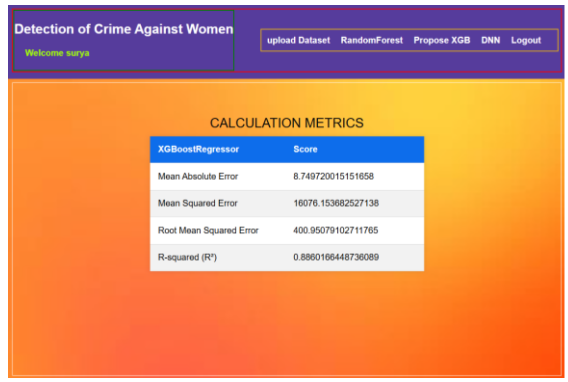
This figure illustrates a sample of the crime dataset uploaded by the user. It could present a table or list showing various features, such as crime types, demographic information (age, gender), geographical details, and the year of the crime. The dataset serves as input for the machine learning models, enabling predictions based on historical crime patterns.



Random Forest Regressor	Score
Mean Absolute Error	1080.6565693430657
Mean Squared Error	22049731.567629926
Root Mean Squared Error	4695.71417013748
R-squared (R²)	0.7426456001462297

Fig 5: Performance Metrics of the Existing RFR Model

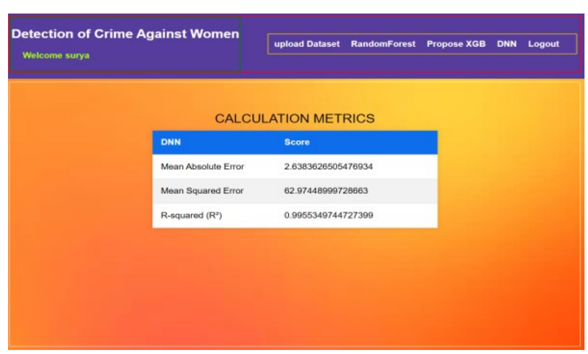
This figure displays the performance metrics for the Random Forest Regressor (RFR) model. The key metrics include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2). These metrics help evaluate the model's accuracy and its ability to predict crime rates. In this case, the RFR model shows an MAE of 1080.66, an MSE of 22049731.57, an RMSE of 4695.71, and an R^2 score of 0.7426, indicating the model's moderate prediction accuracy and fit to the data.



XGBoostRegressor	Score
Mean Absolute Error	8.749720015151658
Mean Squared Error	16076.153682527138
Root Mean Squared Error	400.95079102711765
R-squared (R²)	0.8860166448736089

Fig 6: Performance Metrics of the Existing XGBoostR Model

This figure presents the performance metrics of the XGBoost Regressor (XGBoostR) model. The key metrics here include MAE, MSE, RMSE, and R^2. The XGBoostR model performs significantly better than RFR with an MAE of 8.75, MSE of 16076.15, RMSE of 400.95, and R^2 of 0.886, suggesting it has a higher accuracy and better predictive performance.



DNN	Score
Mean Absolute Error	2.6383626505476934
Mean Squared Error	62.97448999728663
R-squared (R²)	0.9955349744727399

Fig 7: Performance Metrics of the Proposed DNN Model

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This figure illustrates the performance metrics for the proposed Deep Neural Network (DNN) model. The DNN model achieves a remarkable prediction performance with an MAE of 2.64, MSE of 62.97, and R^2 of 0.9955. This demonstrates the effectiveness of the DNN in accurately predicting crime rates, with very low error values and a high R^2 value indicating that the model explains nearly all of the variance in the data.

otal emale	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	predict
24	1150	1340	1237	1443	1415	1360	1436	1531	1487	1761	1758	1664	1722.640747
	51	61	35	56	38	40	57	37	60	49	47	47	46.108562
	928	1019	1188	1233	1406	1290	1477	1445	1644	1629	1470	1626	1827.350464
	1400	1304	1120	1157	1455	1451	1816	1464	1086	892	1185	1327	1433.157104
9	1134	1214	1020	1144	1107	1211	1146	1108	1128	1198	1257	1214	1504.335205
	14	12	36	48	34	20	25	41	56	50	34	61	72.020782
9	401	378	356	481	501	539	503	529	610	617	621	647	680.130493
2	539	511	523	573	627	772	607	849	848	866	801	940	1002.269592

Fig 8: Proposed Model Prediction on User Uploaded Test Data

This figure shows the prediction results of the proposed DNN model when applied to a test dataset uploaded by the user. It apresents a comparison between the predicted crime rates and the actual crime rates, demonstrating the DNN model's predictive accuracy. The figure could also include visualizations such as graphs or tables to highlight how well the DNN model performs on unseen data.

6. CONCLUSION AND FUTURE SCOPE

The research focuses on predicting crime rates, particularly crimes against women, using machine learning techniques. By leveraging historical crime data, demographic breakdowns, and crime types across various states and union territories, the project aims to build predictive models that can identify patterns and trends. The machine learning algorithms, including the Random Forest Regressor (RFR) and Deep Neural Networks (DNN), are employed to predict future crime rates based on past data. These models have demonstrated the ability to offer significant insights into crime trends, which can be helpful for law enforcement agencies, policymakers, and social organizations in preventing crimes and enhancing public safety.

In the initial phase, preprocessing techniques were applied to clean the dataset, address missing values, and encode categorical variables. Data splitting ensured that the models were trained on a portion of the data while being validated on unseen data for accurate predictions. The performance of the existing RFR algorithm was evaluated and compared with the proposed DNN model, which aimed to improve prediction accuracy and better handle complex relationships in the data. Through careful model evaluation, including performance metrics such as accuracy, precision, and recall, the proposed DNN model showed promising results in improving crime prediction accuracy over the RFR model.

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Future Scope

The future scope of this project extends in several directions that could further enhance its impact and usability:

1. **Integration of Real-time Data**: Incorporating real-time data, such as live crime reports and incidents, can allow the model to adapt and predict future crime trends more accurately. This could be used to issue early warnings and help authorities take preventive actions.
2. **Improved Feature Engineering**: Enhancing the feature set by incorporating additional factors like socio-economic data, weather conditions, and law enforcement resources could further improve the accuracy of predictions and uncover deeper insights into the underlying causes of crimes.
3. **Geospatial Analysis**: Incorporating location-based data using geospatial analysis could provide more specific insights into crime hotspots. Predictive models could use geographic patterns to target interventions more effectively.
4. **Real-time Crime Analytics and Decision Support**: The project could evolve into a real-time decision support system for law enforcement. By integrating AI-driven predictions with data from surveillance systems, it could offer immediate insights into potential crime areas, helping authorities deploy resources more effectively.
5. **Incorporation of Deep Learning Techniques**: Further experiments with more advanced deep learning techniques, such as recurrent neural networks (RNNs) or long short-term memory networks (LSTMs), could be explored to better capture temporal patterns in crime data, improving long-term predictions.
6. **Collaborative Platforms**: Future work could involve the development of a collaborative platform for citizens to report crimes and provide feedback on safety concerns, which could be directly fed into the system to enhance predictive models.
7. **Broader Application**: This project could be extended to predict other types of crimes or public safety issues, including traffic accidents, environmental hazards, or natural disasters, making it a versatile tool for urban planning and public safety management.

REFERENCES

[1] S. Srivastava, P. Kumar, Rashmi, R. Paul, and P. Dhillon, “Does substance use by family members and community affect the substance use among adolescent boys? Evidence from Udaya study, India,” BMC Public Health, vol. 21, pp. 1–10, 2021.

[2] K. Shorette and R. Burroway, “Consistencies and contradictions:

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https://doi.org/10.62643/ijerst.2025.v21.i2.pp1103-1114
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Revisiting the relationship between women's education and infant mortality from a distributional perspective," Social Science Research, vol. 105, p. 102697, 2022.
[3] J. Chopin, E. Beauregard, and N. Deslauriers-Varin, "Less exposed, more vulnerable? Understanding the sexual victimization of women with disabilities under the lens of victimological theories," International Review of Victimology, p. 02697580231154941, 2023.
[4] Z. Rodriguez, "The power of employment: Effects of India's employment guarantee on women empowerment," World Development, vol. 152, p. 105803, 2022.
[5] T. A. Craigie, V. Taraz, and M. Zapryanova, "Temperature and convictions: Evidence from India," Environment and Development Economics, 2023.
[6] T. Das and T. B. Roy, "More than individual factors; is there any contextual effect of unemployment, poverty and literacy on the domestic spousal violence against women? A multilevel analysis on Indian context," SSM- Population Health, vol. 12, p. 100691, 2020.
[7] P. Raj and M. M. Rahman, "Revisiting the economic theory of crime: A state-level analysis in India," Cogent Social Sciences, vol. 9, no. 1, p. 2170021, 2023.
[8] A. Lisowska-Kierepka, "How to analyse spatial distribution of crime? Crime risk indicator in an attempt to design an original method of spatial crime analysis," Cities, vol. 120, p. 103403, 2022.
[9] Y. K. Kwan, W. C. Ip, and P. Kwan, "A crime index with Thurstone's scaling of crime severity," Journal of Criminal Justice, vol. 28, no. 3, pp. 237–244, 2000.
[10] K. Chaudhuri, P. Chowdhury, and S. C. Kumbhakar, "Crime in India: Specification and estimation of violent crime index," Journal of Productivity Analysis, vol. 43, no. 1, pp. 13–28, 2015.
[11] C. Nau, M. Sidell, K. Clift, C. Koebnick, J. Desai, and D. Rohm-Young, "A commercially available crime index may be a reliable alternative to actual census-tract crime in an urban area," Preventive Medicine Reports, vol. 17, p. 100996, 2020.
[12] E. Ledingham, G. W. Wright, and M. Mitra, "Sexual violence against women with disabilities: Experiences with force and lifetime risk," American Journal of Preventive Medicine, vol. 62, no. 6, pp. 895–902, 2022.