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Enhanced Crime Hotspot Prediction and Visualization for Women's Safety Through Deep Learning

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ABSTRACT:
Some parts of a city or region have more criminal incidents than others and these are known as crime hotspots. At such places, women are more likely to face things like sexual harassment, assault, domestic violence, stalking and human trafficking. Finding out these hotspots is important so that law enforcement can work more effectively. The project introduces Safety Locator which uses different types of learning to find and chart locations where women are especially likely to get attacked. It works with a Deep Explainable Decision Tree which uses previous crime data to predict how likely crimes will occur in certain locations. Deep Explainable Decision Trees separate data into crime hotspot groups and display them on Google Maps. Using the number and nature of crimes, the system pinpoints where and when most of the crimes happen which is recorded on a special map. The public will benefit from seeing this map which promotes security and alerts them of risks. Part of data science development is to work on the data, choose features to use, train models, measure their performance, tweak settings and make predictions. The model's behavior is tested by looking at accuracy, precision, recall and F1-score and the parameters are fine-tuned using cross-validation. Safety Locator helps law enforcement agencies keep crime rates down and ensure safety for people by pinpointing those areas most likely to have crimes. Developing safer surroundings for women allows the system to help with gender equality and quality of life improvement.

KEYWORDS: Crime Hotspot Prediction, Women's Safety, Deep Learning, Crime Visualization, Geospatial Crime Analysis, Spatio-Temporal Data, Neural Networks, Safety Prediction Models, Crime Mapping.

1. INTRODUCTION

Today, crime hot spot forecasts are key for law enforcement because they support better use of assets, inform actions before events happen and increase safety for members of the public. Recognizing locations where criminal acts often happen enables law enforcement to act earlier and lower the number as well as the severity of crimes. Decision Trees are preferred for this purpose because their teachable structure, efficiency and reliability help in classifying different crime situations. It depends on historical crime data

and surrounding conditions to specify areas that are more or less at risk (positive or negative). A predictive system for crime typically involves: preparing the data by removing noise, choosing the most useful characteristics, training the algorithm to recognize crime/no crime zones and checking how the system performs. Also, hyperparameters are tuned throughout the process to make the model more accurate at prediction. The xDT model, a kind of binary classifier, is at the heart of the system, deciding which areas are crime hot spots by creating the optimal boundary plane in the space of features. On top of helping group regions, it also reveals the major causes of higher crime in different places. This information is then converted by the xDT model into predictive maps that direct law enforcement on their actions. Forecasting where crime is likely to occur plays a major role in law enforcement for the protection of the community. It is common to use the Decision Tree algorithm in this task, because it is good at differentiating between positive and negative cases. Pre-processing of data, selection of which features to use, training the model, evaluating its performance, tuning the model to improve it and making predictions are all steps in the system. Using a hyperplane, the xDT model splits crime hot spots from non-crime hot spots as two distinctive groups.

2. PROPOSED WORK

The proposal combines the openness of the Explainable Decision Tree (xDT) with the Google Maps API to support women's security.

With the use of the xDT model, predictions are explained so that people can see the core contributing features behind crime in a given location.

Being clear about the reasons supports trust and means people can make informed choices based on the predictions. With Google Maps, the system gives users instant visualization of where crimes are most common in their neighborhood. The layer is useful because it points out risky spots, recent incidents and good ways to travel, making it easier for users to stay safe in the city. If someone presses the emergency button, the system notifies personnel straight away. The emergency contacts specified by the user are notified, along with their position shown on a map and a message is sent to the police helpline nearby. Operating immediately gives responders the ability to prevent or limit harm.

Explainable Predictions: By using the xDT model, those making predictions can see which crime factors influence the results such as the timing, the place and the type of incident which provides transparency and promotes accountability.

Real-time Mapping: By connecting to Google Maps, Crime Overview allows you to see precisely where crimes are happening and decide where to travel safer.

These aspects together form a safe support system that depends on data and practical assistance to prevent problems for women in public.

3. MODULES

1.Crime Hot Spot Finder Web App:

The module must talk to and share data with the back-end system responsible for analyzing the crime data and making predictions.

You can develop APIs or similar data access tools to get the needed data.

HTML, CSS and JavaScript code is written to design and construct the website's user interface.

The back-end part of the website has to manage data processing, intricate machine learning and other important functions. Programmers might work with languages such as Python or PHP and databases including MySQL or MongoDB.

2. End User Module:

2.1. Admin
Login
Build and check the model.

2.2. The term for women in this book is User.
Login
Input Location
Input Route
Check Crime Hot Spot Area on the Map
Take Decision

3. Crime Hot Spot Classification Model:

Data collection: Seek historical crime reports from the location desired and ensure these reports contain the type of crime, the date, time and location.

Data pre-processing: Start by removing duplicate records, records with missing information and unusual extreme numbers. Turn categorical data into numbers and change the data so it can be used by machine learning programs.

Feature selection: Feature selection means choosing the most important features that can show where crime hot spots are

DT model training: Modern DT learning trains a model using the selected characteristics of the training data. Crime hot spots are the positive examples and the negative examples are areas where crime is not common.

4. Crime Hot Spot Predictor System:

User Input: The user specifies a location or a route.

Prediction: Using the DT algorithm, the module will predict areas most likely to experience crime. The regions at risk for crimes are shown on the map.

Crime Hotspot Visualization: Predicted Hotspots on the Map: The crime hotspot visualization part allows you to see where the predictions show crime hotspots on the map. People can check the crime locations, types and how often they occur in every hotspot.

5. Map Visualization:

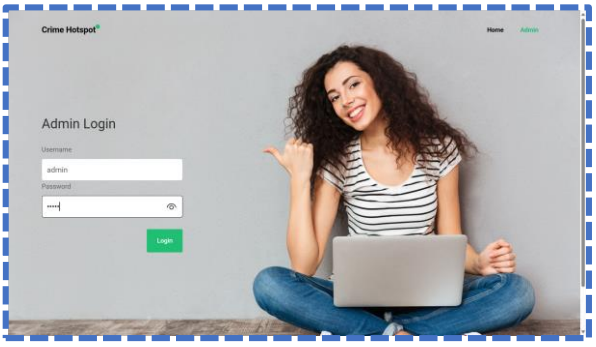
Crime Hot Spot Prediction can be a lot easier when Google Maps provides a clear visual for tracking crime hot spots.

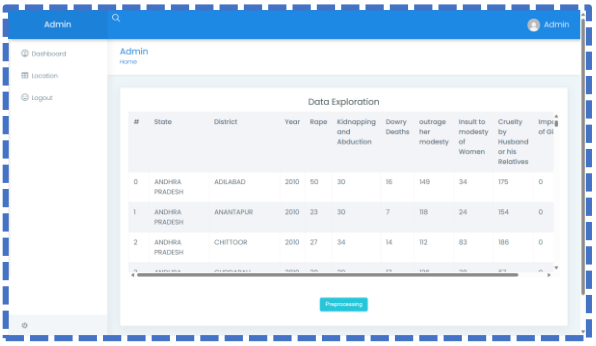
Visualizing the Crime Data: With crime data now joined with Google Maps, the next part is to display it visually on the map.

You can do this by putting heat maps, markers or clusters on the data to show where the most crime is happening.

Because law enforcement can find out about crime trends in certain areas, faster, this integration can help prevent crime and secure the public's safety.

4. RESULTS

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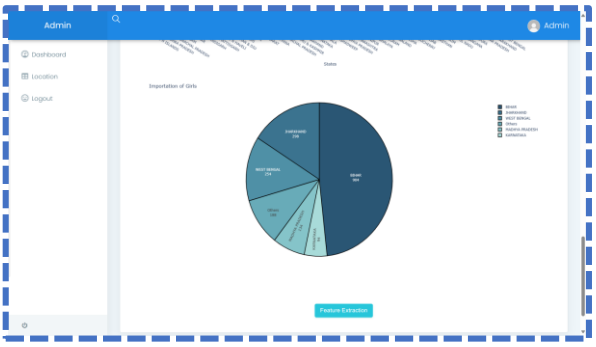
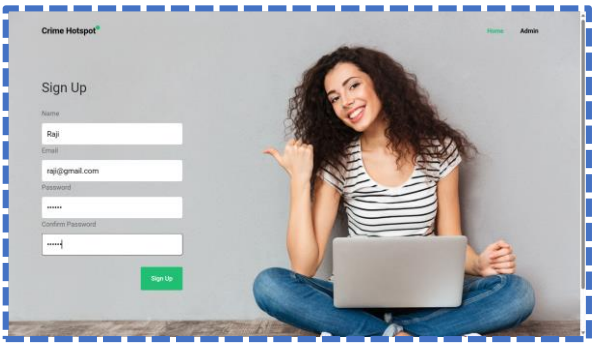
Preprocessing


Admin
Admin
Feature Extraction


Admin
Admin
Classification
Safest States
ID
State
Crime Count
1 A & N ISLANDS 1568.0
3 ARUNACHAL PRADESH 5312.0
6 CHANDIGARH 6052.0
8 D & N HAVELI 566.0
9 DAMAN & DIU 230.0
11 GOA 4124.0
14 HIMACHAL PRADESH 27174.0
19 LAKSHADWEEP 54.0
22 MANIPUR 5586.0
23 MEGHALAYA 5410.0
24 MIZORAM 4306.0


Crime Hotspot
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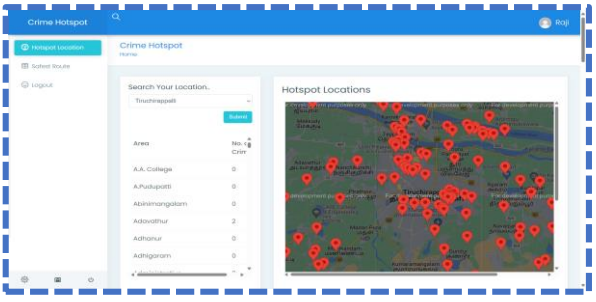
Admin
Sign Up
Name
Raji
Email
raji@gmail.com
Password
Confirm Password
Sign Up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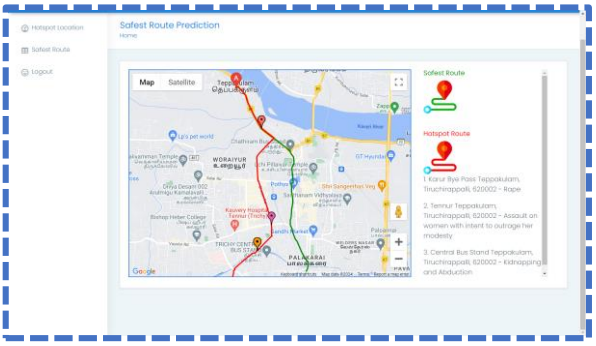
Raji
Crime Hotspot
Search Your Location..
Submit
Area
Hotspot Locations



5. CONCLUSION

Through this project, it was proven that deep learning can effectively help predict and visualize crime hotspots, mainly to protect women in urban areas. Teamwork and combining recent predictive models with geospatial visualization produced a system that helps us pinpoint risky places and present the data understandably and practically. The model can analyze past crime statistics and adjust its approach as threats change which is highly valued by law enforcement agencies, planners and safety groups. To continue, bringing real-time data and social and time-related factors into analysis can strengthen predictions and make cities safer for those who require support, mainly women.

Deep learning suggests where crimes most often take place which can help improve women's safety. Thanks to our system using data from the past, research on locations and advanced technology, it can easily spot places that are most at risk. When users and officials depend on visual tools, they are better ready to look after their assets.

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