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Enhancing Road Safety through Crime Hotspot Detection and Secure Route Planning

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***Abstract:** In the light of increasing criminal activities, it is become important that everyone should concern about individual safety. It has been seen those criminal activities near criminal hot spot happening frequently. Road safety is of paramount significance, as people frequently need to travel often through unfamiliar areas via various modes of transport, such as walking, public transport, private vehicles, auto rickshaws, or cabs. It is observed this incident are more often when victims are likely to be individual. This paper aims to enhance the safety of people. It analyzed criminal records happened recently and aims to take individual feedback regarding certain incident in particular area. This System intended to take geographical locations as input, to identify the safest route between a given source and destination at a particular time. The approach uses optimized A* algorithm to determine optimized route considering crime rate severity and proximity. Open-Source Routing Machine (OSRM) to handle the real-time mapping and routing data. OSRM provides efficient and accurate routing, allowing the system to dynamically calculate the shortest and safest routes based on real-world road networks. The system offers three types of routes-fastest,safest, and optimized using a modified A* algorithm that balances travel efficiency with safety.*

***Keywords:** Safe Routing, Crime Hot Spot Mapping, OSM, A* Algorithm, QGIS.*

I. INTRODUCTION

Traditional navigation systems primarily focus on finding the fastest or shortest route between two points, prioritizing efficiency.

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However, these systems often fail to consider user safety, especially when routes pass through high-crime areas. This oversight can expose travelers to unnecessary risks, particularly in urban settings. To address this gap, our research introduces a Smart Navigation System that integrates crime data into route planning, providing users with safer, more informed choices for their journeys.

At the core of the system is the A* algorithm, which plays a pivotal role in generating three distinct types of routes:

- The fastest route, which follows the conventional logic of prioritizing the shortest and quickest path.
- The safe route, which recalculates the route based on crime severity in the area. By assigning greater weights to road segments near crime hotspots, the system effectively steers users away from dangerous locations.
- The optimized route, which balances safety and travel efficiency. It avoids areas with high crime rates but still ensures a reasonable travel time, combining the best of both worlds.

The system is developed using OSMNX (Open Street Map NetworkX) to map the network of roads in Pune. Crime data is sourced from a CSV file and processed using the Haversine function to calculate distances between points. The result is a dynamic and responsive system that can adapt to changing conditions, whether those are updates in crime data or shifts in user preferences. The data includes crime severity ratings, which are integrated into the routing algorithm to ensure routes are as safe as possible.

For visualization, the system employs Folium, which allows users to interact with the map in real-time. Routes, crime hotspots, and start/end points are all displayed on an easy-to-use interface. The user can switch between the fastest, safest, and optimized routes, making comparisons based on personal needs. This interactive approach gives users the power to choose routes that align with their preferences for either safety, efficiency, or a balance of both.

The main objective of our research is to show that incorporating crime data into route optimization can significantly enhance user safety without compromising efficiency. By considering both the crime rate and the geographical layout, the system offers a more comprehensive solution to urban travel. In future iterations, we plan to integrate real-time crime data, allowing for even more up-to-date recommendations. We also envision the ability for users to customize their risk tolerance, selecting how much safety or efficiency they prefer. Additionally, factoring in traffic conditions will help ensure that routes remain optimal in terms of time and safety, regardless of real-world delays.

With the potential to leverage machine learning techniques, future versions of the system could automatically adapt to individual user behavior, further improving route recommendations. This system not only offers safer navigation options but also has the potential to contribute to overall public safety by assisting law enforcement in identifying and addressing high-crime areas.

II. RELATED WORK

Studies on the A* algorithm determine that this algorithm is widely applied in different domains to find the shortest path in graphs, such as in navigation, robotics, and gaming [1]. It combines Dijkstra's algorithm and the Greedy Best-First Search algorithm to provide cost information and estimate the remaining cost from one node to another. It has been tested in various graph conditions and shows efficiency by minimizing the number of explored nodes while providing the optimal solution. This aligns with the need for efficient pathfinding in smart navigation systems. The study also mentions the importance of using a two-way weighted graph, where each edge has a weight associated with the distance between nodes. This is critical for your project since you not only deal with distances but also modify edge weights based on **crime severity** to prioritize safer routes. The study highlights the role of cost to destination which is calculated by heuristics like Haversine distance.

Heuristic cost in Enhanced A*: It is the euclidean distance between the current and target position of robot. This may be an efficient way to reduce travel distance in controlled settings, it does not take into account external circumstances such as unsafe travel. The output of this project is an extension of the above concept, using severity of crime data in a heuristic function to enable the component to prioritize on relatively safe zones while ensuring that its performance in pathfinding stays optimal. The task of planning a path from the starting point to the destination is termed as path planning and constitutes an essential part in robotics and navigation [6]. The *A algorithm** has long been used in various fields due to its ability to find optimal paths based on heuristic functions, such as Euclidean or Manhattan distances [14]. A* excels in low-dimensional spaces where the cost of traversal is known and can be efficiently computed [15].

The concept of safe route recommendation system has been explored in various research works that utilize geospatial data and crime statistics to predict the safest routes for users [16]. In one such study, accident and crime data from NYC OpenData was used to compute the average risk score for each region through machine learning models like K-Means Clustering and KNN Regressor This approach, while effective for clustering high-risk areas, did not incorporate dynamic route optimization in real-time [17]. Additionally, the Be-Safe Travel system integrated Google APIs with crime data from Surabaya City to recommend safer routes based on a colour-coded ranking of paths [18]. However, this system was constrained to a single city and did not consider real-time crime data or dynamic user attributes. Other systems [19], like SAFEBIKE, which focused on bike-sharing services, accounted for safety levels based on crime statisticsbut the scope was narrow in terms of vehicle types and user preferences [20]. Other studies also utilized decision networks and geospatial data to offer routes optimized for user safety, but they lacked the dynamic edge-weight modifications seen in more advanced pathfinding algorithms like A*[1].

Use of Geographic Information Systems (GIS) and crime mapping has become integral in modern policing and crime prevention [2]. Crime mapping aids law enforcement agencies in identifying high-crime areas, determining crime hotspots, and visualizing geographic crime patterns [3]. The integration of GIS into police work, as discussed in geographic areas, tends to have higher crime rates, which are influenced by environmental and social factors [4]. The relationship between place and crime is central to the analysis of crime patterns. This concept is crucial for your project, where crime hotspot data is used to adjust the weights of paths in the A* algorithm, prioritizing routes that avoid high-crime areas [1]. Hence, the method is crime hotspot identification as widely discussed in the paper gives valuable insight into which suspected locations resources of law enforcement should be deployed [8]. The paper also mentioned the notion of Crime Prevention through Environmental Design (CPTED) which is the application of design and intervention in constructed and natural environments, to prevent crime and reduce fear [9]. A hot spot analysis method used in GIS tools (specifically Getis-Ord Gi) allows crime mapping and spatial analysis to detect whether there exist crime concentration zones significantly more (or less) than what would be expected by chance alone [10].

This method could be highly relevant for your project, as you aim to incorporate crime-aware pathfinding [11]. Understanding crime patterns through hotspot analysis allows you to modify route calculations based on the risk levels of different areas, similar to how the paper maps property crimes, crimes against women, and terrorist acts in the Bishnupur district [12]. paper applies ArcGIS and various spatial statistics tools to analyze the crime patterns [13].

The integration of Geographic Information Systems (GIS) and georeferenced data in route planning has gained considerable attention in recent years [4]. A notable study by Felício et al. (2022) proposes an architecture that leverages OpenStreetMap (OSM) data to calculate and visualize routes while considering various factors such as safety, comfort [5], accessibility, air quality, time, and distance This work outlines a comprehensive methodology involving data collection, development of a georeferenced data model, and the execution of routing algorithms such as Dijkstra and A* for route calculation. It also incorporates a multi-criteria decision-making approach to route planning by adding a new dimension to the OSM data modelWhile they focus on static factors like air quality and comfort, your project advances this concept by integrating real-time crime data into the pathfinding process, which adds a dynamic layer to the decision-making.

The VRP (Vehicle Routing Problems) involves determining optimal routes for vehicles, where factors such as fuel consumption and distance are minimized [6]. The proposed approach integrates geopositioning updates and optimization algorithms like Greedy, Simulated Annealing, and Genetic Algorithms, which improve dynamic routing solutions [7]. This research is highly relevant, as the dynamic updates in VRP mirror the dynamic safety considerations (crime data) in

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your project. Study utilizes hybrid and metaheuristic algorithms such as Greedy, Simulated Annealing, and RandSwap, focusing on improving the route optimization problem by handling dynamic data realistic route planning based on OpenStreetMap (OSM) data. Giraud (2022) presents the "osrm" package, an interface between R and the OSRM API, enabling users to compute routes, trips, isochrones, and travel distance matrices using OSM data(osem2). This package serves a variety of fields, from transport planning to urban analysis, offering functions such as osrmRoute() for shortest path calculations and osrmIsochrone() for identifying areas reachable within a specified time span.

The research **gaps** are identified as follows:

1. Lack of Real-Time Crime Data Integration

Real-time crime data integration is crucial for enhancing the reliability of safety-oriented applications, especially in urban navigation. Without real-time data, systems rely on static or outdated datasets that may not accurately reflect the current safety landscape. This can lead to inefficient routing or even dangerous paths. Incorporating live feeds from law enforcement databases or crowd-sourced platforms, like community alerts or social media, could provide timely updates on crimes happening in specific areas, allowing for better decision-making in routing algorithms. For instance, an app could reroute a user if a new crime incident has just been reported along their current path.

2. Lack of Discussion on Trade-offs Between Safety and Efficiency

An important factor in route optimization, especially in safety-focused navigation, is the balance between safety and efficiency. Safety often comes at the expense of time and distance; safer routes may be longer or slower compared to the fastest routes. The trade-off between these factors needs more explicit discussion, as users may have varying preferences. For instance, someone travelling at night might prioritize safety over speed, while a commuter during the day may value efficiency. Implementing customizable route preferences—where users can choose the degree of safety they desire, even if it means slightly longer routes—would make the navigation system more adaptable to individual needs.

3. Lack of Consideration for Crime Hotspots and Spatial Distribution of Crime

Urban areas typically have specific zones where certain types of crimes are more prevalent, known as crime hotspots. Ignoring these hotspots in route planning overlooks significant risk factors that could lead users into dangerous areas. A more robust system should analyze the spatial distribution of crime and incorporate heatmaps or geospatial crime data to identify risky areas. By avoiding or flagging these hotspots during route planning, the system can significantly reduce potential hazards for users. Additionally, recognizing temporal patterns, such as higher crime rates during specific times of the day, could improve both the safety and reliability of the route suggestions.

4. Dynamic Route Optimization for Safety

Most route optimization systems are built on static models, which do not adapt in real time to evolving safety concerns. Dynamic route optimization, on the other hand, could adjust routes based on live crime updates, road closures, or emergency incidents. By continuously evaluating both the safety and efficiency of possible routes, this system can ensure the user is travelling on the safest available path at any given time. Furthermore, advanced dynamic systems could also consider crowd movement data or local weather conditions, which might impact the safety or viability of certain paths. Implementing such adaptability makes the system much more resilient to real-world changes.

5. Advanced Pathfinding Algorithms

Traditional route planning algorithms like Dijkstra's or A* focus primarily on finding the shortest or fastest path. However, in the context of safety, more advanced algorithms are required to balance multiple factors such as distance, time, and risk. Modified versions of these algorithms can incorporate weights based on the safety of the areas, with higher penalties for routes that pass through known crime hotspots. Additionally, more complex techniques like multi-objective optimization could be employed to allow users to simultaneously optimize for both time and safety, ensuring a personalized navigation experience that adapts to their unique requirements.

6. Dynamic Edge Weight Modification

In traditional pathfinding algorithms, edge weights represent static distances or travel times between points on a graph. However, when considering safety as a factor, edge weights need to be dynamically adjustable based on crime data, traffic incidents, and real-time reports. For example, if a crime is reported in a specific area, the corresponding edges in the graph could be assigned higher weights, making those paths less favourable in the route planning algorithm. Similarly, if a high-crime area has a low incidence of crime during certain hours, the edge weights for that area could be reduced temporarily. This kind of dynamic modification allows for more nuanced and context-sensitive route planning.

III. PROPOSED SOLUTION

Our methodology for enhancing urban navigation systems with safety considerations focuses on integrating geospatial crime data and dynamically modifying road networks to account for crime severity.

We begin by incorporating crime data (latitude, longitude) into the routing system, enabling the identification of crime hotspots along potential routes. Each crime incident is assigned a severity score based on its type, with higher scores indicating more dangerous crimes, such as a 0.8 for severe offenses like armed robbery. These severity scores directly influence the route calculations.

Next, we modify the road network graph by adjusting the weights of road segments. The original weight of a segment, which typically represents travel time or distance, is multiplied by a factor influenced by the severity of nearby crimes. This results in a new weight formula, $w' = w\ (1 + \text{severity})$, where segments near high-severity crimes become less favourable in routing decisions.

To further refine the system, we calculate a radius of influence around crime hotspots. Roads within this radius are penalized more heavily, allowing the routing algorithm to prioritize safer alternatives when planning paths.

We create multiple versions of the road network graph: a base graph (G) that only considers traditional metrics like distance, a crime-aware graph (G_safe) that incorporates crime severity, and an optimized graph (G_optimized) which balances both efficiency and safety.

Finally, we adapt the A* pathfinding algorithm by adjusting its cost function. In this modified version, the cost of travelling between nodes f(u,v) takes into account both the adjusted road segment weight (g'(u, v) (based on crime severity) and the heuristic h(u,v) for the remaining distance. This ensures that the algorithm can provide users with routes that not only minimize travel time but also prioritize safety by avoiding high-risk areas.

By combining these components, our approach offers a dynamic, crime-aware navigation solution that intelligently balances safety and efficiency in real time.

A. Crime Data Processing & Classification

The crime data, which includes coordinates, severity, and types of incidents, is processed to integrate with the routing algorithm. Key steps in this preprocessing include:

- **Geospatial Crime Data Mapping**: Crime incidents are mapped to their respective latitude and longitude in Pune, ensuring precise geolocation for further processing.
- **Severity Score Assignment:** Each incident is assigned a severity score ranging from 0 to 1, representing the impact on route calculation. For instance, a score of 0.8 signifies a severe crime (e.g., armed robbery), while 0.4 signifies a moderate crime (e.g., petty theft).
- **Radius Calculation:** A 500-meter buffer radius around each crime hotspot is used to influence nearby nodes and edges in the road graph. Road segments within this radius are penalized or removed to avoid unsafe areas.

B. Graph Updates for Crime-Aware Routing

Adjusting Weights: In crime-prone areas, the weights of road segments are modified based on the severity score:

$$w' = w \times (1 + \text{severity})$$

Where w' is the adjusted weight, w is the original weight (distance), and the severity score increases the weight to avoid high-crime zones.

Node Removal: For the optimized route, nodes and edges within crime areas with severity scores greater than 0.5 are removed entirely, ensuring dangerous areas are bypassed.

C. Road Network Graph Creation

Using OSMnx, the road network of Pune is modeled as a directed graph, where intersections represent nodes and road segments act as edges. This graph is essential for mapping out different routes through the city. Three variations of this road network are created to serve distinct routing needs:

i. Base Graph (G):

This is the fundamental version of the road network and doesn't take crime data into account. It is used to compute the fastest route, focusing purely on the shortest or quickest path between two points, similar to traditional navigation systems.

ii. Crime-Aware Graph (G_safe):

In this version, the base graph is enhanced by incorporating crime data. The road segments (edges) that pass through crime-affected areas are assigned higher weights based on the severity of the crimes in that area. The formula used is:

$$w' = w \times (1+\text{severity})$$

Here, the weight of each road segment (w) is increased according to the severity of nearby crimes. This adjustment discourages the algorithm from choosing routes that pass through dangerous zones, leading to a safer route that avoids areas with high crime risk.

iii. Optimized Graph (G_optimized):

In this version, the system takes an even more cautious approach. It completely removes the nodes (intersections) and edges (road segments) that fall within areas where the crime severity is higher than 0.5. By doing so, the algorithm is forced to find alternative routes that completely bypass high-crime zones. This graph is ideal for users who prioritize safety over efficiency and wish to avoid dangerous areas altogether, even if it means taking a longer route.

D. Pathfinding Algorithm

The A* algorithm is used for route computation, with modifications to incorporate crime-aware routing:

i. Heuristic Function:

To calculate the geographical distance between two points (used as the heuristic in the A* algorithm), we employ the **Haversine formula**, which gives the straight-line distance between two points on the Earth's surface, considering the curvature of the Earth. This is crucial for accurately estimating the distance between two locations:

$$h(u,v) = 2R \times \arcsin\left(\sqrt{\left(\frac{\Delta\emptyset}{2}\right) + \cos(\emptyset u) \times \cos(\emptyset v) \times \sin^2\left(\frac{\Delta\lambda}{2}\right)}\right)$$

Where:

- **R** is the Earth's radius (approximately 6371 km),
- **Δϕ** is the difference in latitude between the two points,
- **Δλ** is the difference in longitude,
- **ϕ_u** and **ϕ_v** are the latitudes of nodes u and v, respectively.

This formula gives an accurate estimate of the distance between two geographical points, which is essential for determining the most direct route.

ii. Modified A for Crime-Aware Routing:*

To factor in crime severity along the route, we've modified the standard A* algorithm to adjust the weights of the road segments based on nearby crime data. This means that roads near high-crime areas will have higher weights, making the algorithm less likely to choose those routes, favoring safer paths instead.

iii. Cost Function for Safest Route:

In the traditional A* algorithm, the cost function is the sum of the distance traveled from the start (g) and the estimated distance to the goal (h). In our crime-aware approach, we modify the cost (g') to reflect the crime severity along the route:

$$f(u,v) = g'(u,v) + h(u,v)$$

Where:

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g′(u,v) = g(u,v) × (1 + severity) is the adjusted cost incorporating crime severity,

h(u,v) is the Haversine heuristic (geographic distance).

g(u,v) is the accumulated distance from the start to node v.

For the optimized route, the algorithm avoids nodes within high-crime zones (severity > 0.5) entirely. The objective function to minimize is:

$$f(n) = g(n) + h(n) + c(n)$$

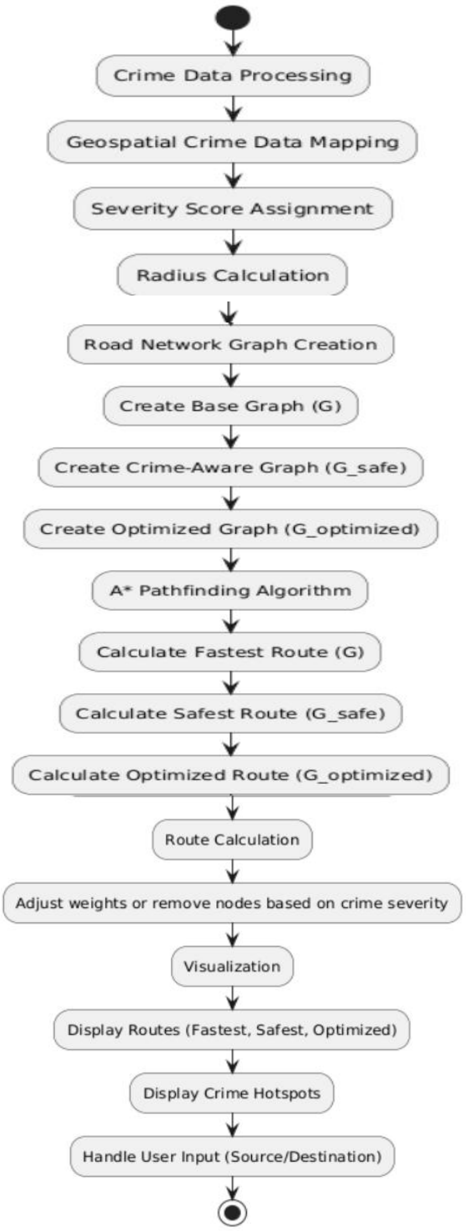
Where:

g(n) is the total distance from the start to the current node,

h(n) is the heuristic (Haversine distance to the destination),

c(n) is the crime penalty for proximity to high-severity crime spots.

E. Flow Chart



[Fig.1: Flow Chart]

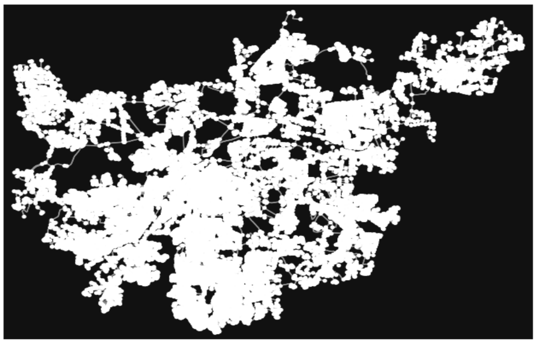
F. Integration & Visualization

i. Road Network Creation

To create an efficient routing system that incorporates safety considerations, we used OSMnx, a powerful tool for downloading and processing road networks. Specifically, we focused on the road network of Pune, creating three key versions of the graph: the base graph, crime-aware graph, and optimized graph.

1. **Base Graph (G)** – This graph represents the standard road network, focusing only on distance or time, and is used for the fastest route calculations without factoring in crime data.
2. **Crime-Aware Graph (G_safe)** – This version integrates crime data, adjusting road weights based on proximity to crime hotspots and the severity of crimes along the route. It prioritizes safety, leading to safer but potentially longer routes.
3. **Optimized Graph (G_optimized)** – The optimized graph balances both efficiency and safety by incorporating both time/distance metrics and crime severity. It avoids high-crime areas while still aiming for reasonable travel times.

Each version of the graph is designed for different routing needs: finding the fastest, safest, or optimized route, depending on user preferences. A diagram of this network creation process illustrates how the road network is transformed at each stage, from the base graph to the crime-aware and optimized versions.



[Fig.2: Diagram of Road Network Creation]

ii. Route Visualization:

To visualize the calculated routes, we used Folium, an interactive mapping library. This allowed us to clearly display the different types of routes by color-coding them for easy comparison:

- **Blue** represents the fastest route, which ignores crime data and focuses purely on time or distance efficiency.
- **Green** marks the safest route, which uses crime data to avoid high-risk areas, providing the most secure path.
- **Yellow** is used for the optimized route, which strikes a balance between safety and efficiency, avoiding areas with the least crime while still considering travel time.

These routes are displayed on a map, allowing users to see exactly how the routing decisions are made and the paths suggested by the system.

G. Real-Time Updates

To make the system dynamic, we integrated OSRM (Open Source Routing Machine), enabling the computation of routes in real time. As crime data is updated, whether from official reports or user-generated alerts, the system adjusts the routes accordingly. This ensures that the safest and fastest paths are always current, reflecting any recent crime incidents.

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For instance, if a user reports an incident in a certain area, that area is immediately flagged, and the weights in the crime-aware graph are adjusted. This real-time adjustment allows for on-the-fly rerouting to ensure users avoid recently affected zones and can navigate with up-to-date safety information.

H. Route Metrics

To offer users a meaningful comparison between routes, several key metrics are calculated for each suggested path:

1. **Route Distance** – This is measured for each route, enabling users to see how much longer the safest or optimized routes are compared to the fastest route.
2. **Safety Score** – Each route is assigned a safety score, based on the severity and frequency of crimes along its path. Routes that pass through high-crime areas will have lower safety scores, helping users make an informed decision if they are willing to trade safety for speed.
3. **Travel Time** – Using the route distance and assuming normal traffic conditions, travel time is calculated for all routes. This metric helps users evaluate how much time they might save by taking the fastest route or how much longer the safer options might take.

By combining these elements—road network graphs, real-time updates, and key metrics—we provide a comprehensive and flexible navigation system that caters to different user priorities, from safety to efficiency.

IV. RESULTS

A. Crime Risk Assessment

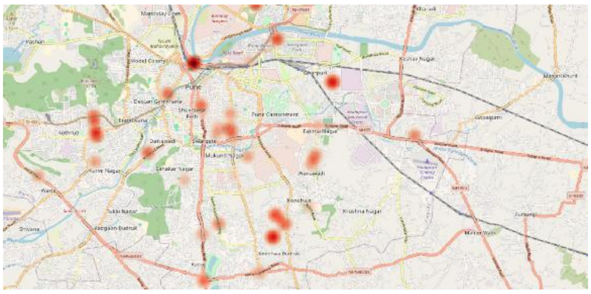
We created raw simulated crime data, which includes detailed records of crime locations and a crime severity rate, and transformed it into a format suitable for geospatial risk mapping. The data was simplified into key elements such as latitude, longitude, and severity scores to assess crime risk across various regions. The crime severity rate is calculated based on the type of crime (e.g., theft, assault, etc.) and its frequency in specific areas. This transformation allows us to generate a heatmap that highlights high-risk areas in the city of Pune, effectively pinpointing crime hotspots.

The severity score ranges from 0 to 1, where a higher value represents a greater risk and a lower value reflects reduced crime exposure. This metric helps categorize regions into different risk levels, enabling users and law enforcement to better understand which areas require attention. For instance, densely populated neighborhoods with frequent crimes will have higher scores, indicating the need for caution. A sample of the transformed data is shown below, which illustrates how various crime spots are represented based on these scores, aiding in the creation of actionable insights for safer route planning.

Below table shows a sample of the transformed data:

Table 1: Crime Risk Assessment

Latitude	Longitude	Severity
18.5204	73.8567	0.6
18.5074	73.8077	0.4
18.5306	73.8476	0.2
18.5583	73.7796	0.6

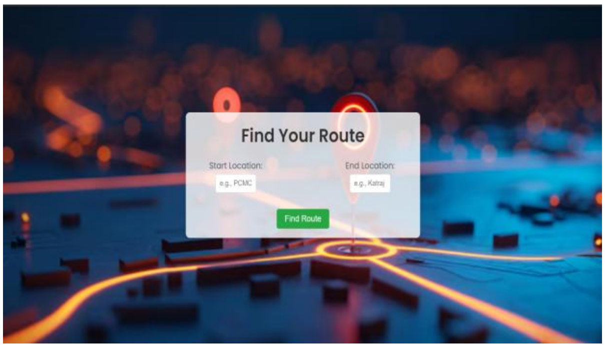


[Fig.3: Pointing Crime Spots on Map using QGIS [11] Tool (Generated using Simulated not on Basis of Real Time Data)]

B. User Input and Dynamic Crime Updates

Our system allows users to input their source and destination points by name (e.g., Swargate, Viman Nagar), making it more user-friendly and intuitive. Utilizing the Open Cage API, these place names are geocoded into coordinates like latitude and longitude, enabling precise routing. The application dynamically updates routes based on live crime data, ensuring that users are always provided with the most current and relevant information. Recent crime incidents are factored in to adjust the route recommendations, offering safer or more optimized alternatives. Additionally, the fastest route is always displayed so users can compare the trade-offs between speed and safety themselves.

The UI enhances the user experience by enabling real-time interaction, allowing users to switch between different route options at any time. This flexibility gives users control to select routes based on their own preferences, whether they prioritize safety, speed, or a balance of both. The seamless interaction between live data and user input ensures a dynamic and responsive navigation experience that adapts to changing conditions.



[Fig.4: Home Page]

C. Route Comparison

The visualization of these routes, overlaid with crime spots, provides users with a detailed view of the trade-offs between safety, time, and distance. By clearly marking high-crime areas along each route, users can make informed decisions based on their personal safety preferences. The fastest route emphasizes efficiency, potentially passing through riskier areas, while the safest route prioritizes avoiding crime hotspots, even if it means a longer travel time. The optimized route seeks a balance between the two, offering a compromise where safety is increased without significantly increasing travel time. This comparison empowers users to choose the

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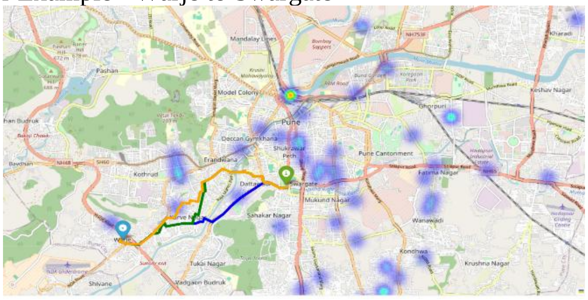
route that best aligns with their priorities, ensuring a safer and more efficient journey.

Table 2: Route Comparison

Route Type	Distance(km)
Fastest Route (Blue)	7.23 km
Safest Route (Green)	8.56 km
Optimised Route (Yellow)	8.31 km

For Example - Warje to Swargate



[Fig.5: Generated Routes from Warje to Swargate]

D. Performance Metrics

To evaluate the performance of the A* algorithm for route planning, we considered several key metrics:

Accuracy: This measures the precision of crime avoidance in the safest and optimized routes. It reflects how well the system steers users away from crime hotspots based on their preferences. Users can define their personal tolerance for crime risk, and the system adjusts routes accordingly. The accuracy is judged by how effectively the chosen route reduces exposure to crime based on these user-defined thresholds.

Execution Time: This refers to the time taken by the system to compute routes, especially when working with large graphs and real-time crime data. Given the complexity of balancing crime avoidance with travel efficiency, ensuring minimal delays in route calculation is crucial for a smooth user experience.

Safety Index: This is a calculated metric that assesses the reduction in crime exposure for users traveling along the safest and most optimized routes. It quantifies how much safer a route is compared to the fastest option by taking into account factors such as the number and severity of crime spots avoided. The higher the safety index, the greater the reduction in crime risk along the chosen route.

Together, these performance metrics ensure that the system not only provides safe and efficient routes but also meets the users' expectations for real-time performance and safety improvements.

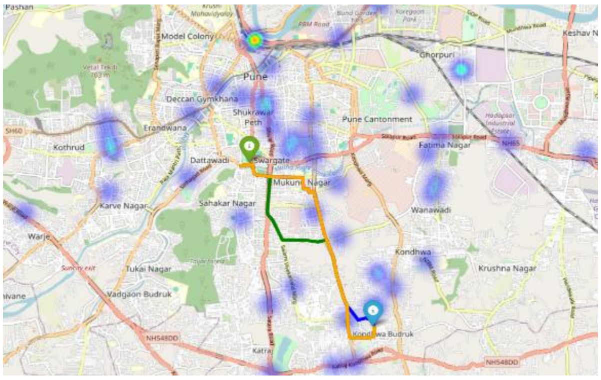
Table 3: Performance Matrics

Metric	Value
Accuracy (Crime Avoidance)	85%
Execution Time	1.5 s
Safety Index	0.85

E. Visualization Evaluation

The visualization tools employed, primarily Folium, provided interactive mapping features that significantly enhanced user engagement. Folium's capabilities, such as heatmaps and dynamic route plotting, allowed users to visually assess the safety and efficiency of different routes. By overlaying crime hotspots along the proposed routes, the system offered a clear representation of high-risk and low-risk areas. This visual distinction between zones of varying crime severity empowered users to make more informed decisions about their travel plans.

The user interface was designed to be intuitive and responsive, allowing users to switch between routes and view detailed information about crime spots. The use of color coding—red for high-risk areas, green for safer routes, and blue for the fastest path—enabled users to quickly assess the safety implications of their chosen route. This real-time visual feedback, combined with interactive features, ensured that users had all the necessary information to select the route that best met their personal safety and efficiency needs.



[Fig.6: Generated Routes from Swargate to VIIT]

V. CONCLUSIONS AND FUTURE SCOPE

This project successfully integrates crime data into urban route planning, providing users with a safer and more informed navigation experience so they can reach their destinations safely and on time. By utilizing real-time crime records and converting this data into severity scores, we generate risk assessments that highlight high-risk areas in the city of Pune (or any other city). The system offers three types of routes—fastest (base route), safest, and optimized—using a modified A* algorithm that balances travel efficiency with safety.

In addition to delivering accurate route recommendations, the platform allows for real-time crime entries, ensuring that users are updated with the latest safety precautions as situations evolve. The crime data is continually updated, and new information is factored into the routing calculations to provide the most current and relevant results. This capability empowers users to avoid areas with increasing crime rates dynamically, improving both personal and public safety.

Multiple simulations and comparisons have shown that the optimal route significantly decreases crime exposure while maintaining reasonable travel times. The integration of real-time crime data with urban navigation also indirectly supports police departments by enabling better resource allocation, as officers can be deployed more effectively in high-crime areas. Ultimately, this project demonstrates the potential to dramatically enhance public safety, providing both immediate benefits to users and long-term positive impacts for law enforcement strategies and community well-being.

In the future, this project can be scaled to include several

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impactful features that enhance safety and law enforcement capabilities:

Enhancing Women's Safety: Future iterations of the system could be specifically designed to address women's safety by focusing on high-risk zones associated with harassment, assault, and sexual violence. By analyzing crime patterns related to these offenses, the system can recommend safe alternative routes, particularly during late hours or through poorly illuminated areas. This would allow women to avoid areas that statistically pose a higher threat, contributing to a safer and more secure travel experience. The system could also include additional features such as real-time alerts for women when they enter high-risk areas or provide a panic button feature linked to emergency services for immediate assistance.

Dynamic Patrol Route Generation: Law enforcement agencies could benefit from this system by utilizing real-time crime data to dynamically generate optimal patrol routes. By visualizing areas with high criminal activity and crime hotspots, the system can help police departments optimize patrol strategies and allocate resources more efficiently. This real-time optimization would not only deter criminal activity but also provide an immediate remedy by ensuring faster law enforcement response in areas with increased risk. Additionally, predictive algorithms could be integrated to forecast potential crime surges, enabling proactive policing that further enhances public safety.

By incorporating these features, the system could evolve into a powerful tool for improving women's safety and optimizing law enforcement efforts, thereby creating a safer urban environment for all citizens.

Personalized Safety Recommendations: The system could be expanded to provide personalized safety recommendations based on the user's preferences, travel history, and demographic factors. For example, users could input their comfort level with certain areas or times of day, and the system would provide tailored route suggestions, factoring in crime data and their personal safety concerns. This would offer a more customized and user-centric approach to safety during travel.

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After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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- **Funding Support:** This article has not been sponsored or funded by any organization or agency. The independence of this research is a crucial factor in affirming its impartiality, as it has been conducted without any external sway.
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