SafeRoute: AI-Driven Safety Navigator for Women and Night Travelers

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***Abstract*—SafeRoute is an artificial intelligence based, safety conscious navigation device that assists women and those traveling at night to make safer decisions. It recommends paths through areas of a city that are safer. Unlike other navigation programs that focus on the shortest or fastest routes, this application prioritizes safety by using real-time crowdsourced incident reports, voice-based inputs, and geolocation data. Emergency reports can be filed by users in hands-free mode. Speech recognition is used with a natural language processor to evaluate both sentiment and severity of each report to determine potential danger. All reports are automatically geo-tagged and create a dynamic safety score at each location. Safety scores derive from the analysis of incident frequency, severity levels, lighting conditions, and environmental risks, enabling the system to propose safer, context-aware paths. It allows SafeRoute's machine learning algorithms to adapt to changing cities, evaluating each pathway for risk and preemptively deciding less risky alternatives. The mapping module represents safety intuitively via shading danger zones, highlighting emergency locations, and pinpointing police stations. This system aids users in cases of minimal or absent mobile network connectivity through SMS-based distress features and locally stores incident information that may be useful. User data privacy is ensured via high anonymization and encryption procedures. Experimental results show highly precise speech-to-text conversions, recognition of hazardous circumstances, and effective evasion of unsafe areas, with minimal increase in travel time. Overall, SafeRoute provides intelligent, safety-focused, human-centric, real-time-enabled navigation with multilingual voice support, ensuring safer mobility for travelers in vulnerable conditions.**

***Keywords*—Safe navigation, crowd sourced safety data, machine learning, speech recognition, NLP, safety scoring, women's safety, route optimization.**

I. Introduction

Safety when traveling, particularly in women and the staying out late, is a large concern in cities nowadays. Usually, maps they do not, just demonstrate the fastest route to take somewhere. look at how safe a route is. Now, tech should fit into our makes a life run smooth and keep us conscious and secure without. being annoying [1]. We are also updated on social media on matters of concern. the way people feel, what they are afraid of and what is going on. around them. This information is excellent when it comes to identifying perilous areas. and doing threats with things such as how people. feel online and machine learning [2].Virginity tools of the old school. help you normally have to do something, such as press a button or call. to get assistance, which is not always possible when you are in danger. That's and why we should have mechanisms that know when things are bad, check out what goes round you, and put warning notices without you. having to do anything [3]. The crime rate is high and the manner in which we tend to do things has changed. look at crime isn't cutting it. So, it's important to be able to know by observing where and at what time crime may occur. covert messages on safety data [4]. As cities grow, women, are more than others, in danger where they are not familiar with an area. or if it's not watched closely. We need maps that think about crime statistics and recommend less risky means of getting there, rather than merely the shortest route [5].Smart technology can be used to blend crime information into. how we plan routes. This implies we are able to have maps which provide. advice on how to travel safer by examining what has occurred. before and what is on now [6]. Plus, platforms planned to ensure that women are safe are improving their senses. danger on their own. They are able to send SOS messages, assist you in talking. so you need not do, to one, and watch you, keep an eye on you. when bad stuff occurs, everything yourself [7]. Besides physical danger, women also experience such issues as feeling uneasy, not being aware of whether some place is safe, not having sufficient assistance. when they travel. That is why it is still more important to have. programs and applications that can make traveling easier and safer through provision. help and tips on making good decisions [8].That is why SafeRoute is attempting at developing a clever map that is aware of. what's going on around you. It takes into account such objects as how people. feel online, crime statistics, and warnings to make you secure and comfortable. Conglomerating intelligent technology, safety data, artificial intelligence, and live updates, SafeRoute reinvents the way we think of maps. It is more concerned with safety, particularly to women and those who travel. at night.

II. Literature Survey

Because folks worry more about being safe when they're out and about—especially women and people traveling at night—safety-focused route planning is getting more research attention. Lakshmi and Joseph checked out different ways to guide people on safe routes. They saw that regular navigation tech doesn't think about important safety stuff like how much crime there is, if there's enough light, how many people are around, and who's watching the area. Their research shows that to keep people safer, the systems need to think about these safety things when they plan routes, instead of just trying to get people to their destination fast [9]. Also, Suraji and his team pointed out that popular apps like Google Maps plan routes based on travel time and traffic, but they don't think about stuff like how good the roads are, what the area is like, what the zoning is, or possible dangers. Their discovery makes it clear that we need route systems that pay attention to the surroundings and can change the route based on what's happening in town [10].Some newer research has tried to add safety smarts to route programs. This is to make routes more trustworthy for those who might be in danger. Kaur and friends came up with a route model that uses maps and looks at crime risk. This helps the system spot unsafe areas and suggest safer ways to go. Their work proves that if you put local risk info into how routes are planned, you can stay away from risky areas that normal map apps might miss [11]. Yang and Cai looked at the A* search program and said it's good for smart route planning. This is due to it quickly finds good routes and can figure out the best directions without using too much processing power. Their research says A* is a base for safety route systems that need to decide fast [12]. Soni and his group made a safety prediction model that uses crime and accident info to figure out how risky roads are. This model gives safer choices than just the shortest route and shows why route planning should include risk [13]. Similarly, Ingole and team used ways to detect crime hotspots and showed that planning routes to avoid these spots can make users much safer [14].Using local crime info is becoming more important when making direction systems. Dey and co-workers created a system that plans routes based on crime info, specifically for Bengaluru. The city has uneven safety across different areas. This makes nighttime travel risky. Their discovery shows that using city-specific crime info when planning routes can really make traveling safer in big cities [15]. Besides program research, online map platforms are helping make safety route planning better. OpenStreetMap has map info that the public makes and updates all the time. This info helps with spatial studies, risk viewing, and changing route designs. This makes it priceless when making safety focused apps [16]. Google Maps Platform also helps. It gives high-detail map services, traffic info, location tools, and route functions that work with APIs. This makes core building blocks for creating fast route advice in route systems, especially those that care about prioritizing safety [17].

III. Methodology

The proposed *SafeRoute* system is designed to assist women and night travelers in identifying safer travel routes by leveraging artificial intelligence, crowd-sourced information, and natural language processing (NLP). The system incorporates real-time voice reporting, speech recognition, geolocation services, sentiment analysis, and a dynamic safety scoring mechanism. The major components of the system are described below.

A. Voice Input and Speech Recognition

Users can report incidents using their voice through a web or mobile application. The system employs speech recognition tools such as Google Speech API or the offline Vosk model to convert spoken input into text. Voice-based input allows hands-free reporting, which is critical in emergencies. Advanced noise-cancellation algorithms enhance recognition accuracy in crowded or noisy environments.

B. Language Detection and Sentiment Classification

After transcription, the text is processed using `langdetect` for accurate language recognition, enabling robust multi-lingual support. Transformer-based models such as BERT and DistilBERT perform sentiment analysis to classify the urgency and severity of each report. High-risk incidents, such as harassment or theft, are assigned higher severity weights, allowing the system to detect emergencies in real time, differentiate between minor inconveniences and critical threats, and prioritize high-risk areas during route planning.

C. GPS and Location Binding

Each report is geo-tagged automatically using device GPS or manually through user input. The system updates safety indices for regions in real time and maintains a historical database of high-risk locations. Geospatial analysis identifies recurrent danger zones, poor lighting, and areas lacking surveillance infrastructure.

D. Dynamic Safety Scoring

The scoring engine computes a dynamic safety score for each area by considering multiple factors. Incident frequency identifies locations repeatedly associated with safety issues, while severity weights ensure that high-risk incidents significantly impact the overall score. The time of day is incorporated, with nighttime or low-visibility periods reducing safety levels. Real-time crowd-sourced reports and environmental conditions, such as weather, road blockages, or construction, continuously update the score. Scores range from 0 (least safe) to 1 (most safe), enabling rapid response to sudden hazards such as accidents or protests.

E. Safe Route Generator

SafeRoute integrates mapping APIs such as OpenStreetMap or Google Maps to generate multiple route options. Each path is evaluated based on cumulative safety scores, distance, estimated travel time, proximity to police stations, CCTV coverage, well-lit streets, and overall accessibility. The system recommends the safest route, even if slightly longer, and displays safety markers to inform users about danger zones, accident-prone areas, and available emergency facilities.

F. Predictive Risk Analysis

SafeRoute uses machine learning models to predict potential hazards before incidents occur. Historical incident records, real-time crowd reports, and environmental factors are analyzed to train predictive models that issue early warnings about unsafe routes, suggest safer alternatives, and improve accuracy over time as new data is collected.

G. Emergency Alert and Offline Functionality

The system supports offline emergency alerts for areas with limited or no network connectivity. SMS-based distress messages include precise GPS coordinates and can be sent to pre-saved emergency contacts or authorities. Incident reports are stored locally during offline periods and automatically synchronized when connectivity is restored. Quick-access panic buttons allow users to send immediate alerts during emergencies.

H. Data Privacy and Security

User privacy is a core focus. Personal identifiers are anonymized before storage, and all location and incident data are encrypted during transmission. Users control the visibility of their reports, which can remain private, shared only with authorities, or visible to the community. The platform complies with GDPR and local data protection regulations, ensuring responsible handling of sensitive information.

I. System Architecture Overview

The system architecture (Figure 1) demonstrates seamless integration of voice input, NLP-based analysis, geospatial data processing, dynamic safety scoring, predictive risk modeling, and route recommendation. The architecture ensures real-time responsiveness, robustness, and scalability to support multiple simultaneous users.

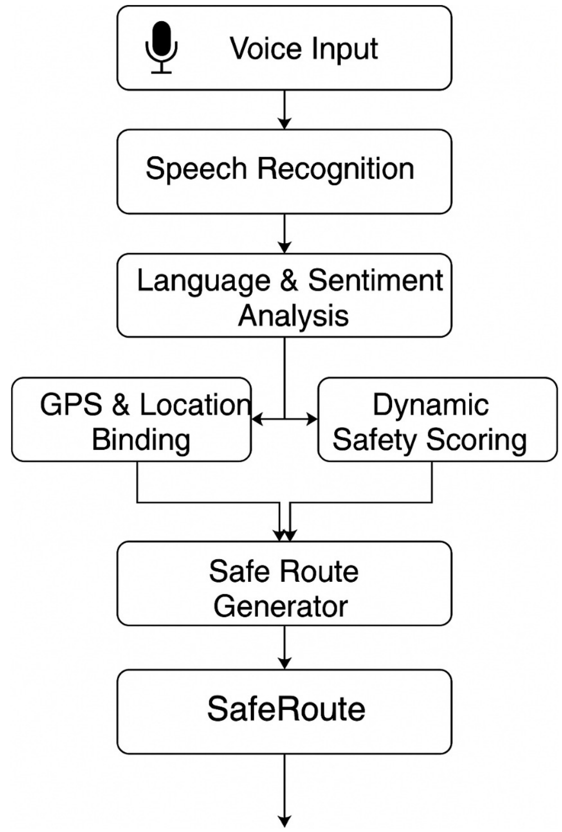

Fig. 1. System Architecture Diagram

This methodology ensures that SafeRoute delivers context-aware, adaptive, and human-centric navigation, enabling users to travel safely even in unpredictable or high-risk scenarios.

IV. System Implementation

SafeRoute prototype was done with the help of a modular. data collection, processing software architecture. and visualization layers. The Python language was used to build the backend. The Flask framework was used with the frontend created with. Visualization of maps in HTML5, CSS and JavaScript.

A. A. Technology Stack

- **Programming Languages:** Python, JavaScript.
- **Frameworks:** Flask, Leaflet.js, and Leaflet.js (map) (frontend) Bootstrap (UI)
- **APIs, Libraries:** Google SpeechRecognition, TextBlob, Vosk (offline ASR), OpenStreetMap, Folium.
- **Database:** SQLite on-disk; Firebase on-cloud synchronization.
- **Environment:** Tested in Windows 11 and Android 14 with real GPS sensors.

B. Workflow

The overall workflow (Figure 2) begins with user voice input, which is processed through speech recognition to obtain text. NLP modules perform sentiment analysis to classify report severity. The processed data, combined with geolocation metadata, updates the regional safety index in real time. Finally, the route generation module computes and visualizes the safest path using weighted metrics.

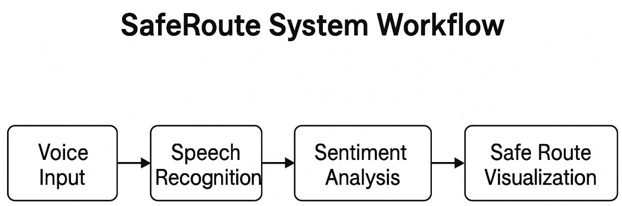

Fig. 2. SafeRoute System Workflow showing process from voice input to safe route visualization.

C. Safety Index Formula

In order to measure the safety of a certain place quantitatively, SafeRoute calculates a Safety Score S as a weighted. interaction between risk factors:

$$S = w_1F + w_2(1 - R) + w_3L + w_4E \tag{1}$$

where:

- F (**Incident Frequency**): The figure of the number of. reported safety accidents in the region over a certain period. time window. Greater frequencies imply greater danger and reduce overall safety.
- R (**Report Severity**): Records the severity or the criticality. of reported incidents. Values are brought to the norms of 0. (minor) and 1 (critical). Using 1 [?] R ensures that higher the degree of severity lowers the safety score.
- L (**Lighting Condition**): Measures the visibility in the area, with regard to streetlights and ambient light. An improved lighting score adds up to the safety score.
- E (**Environmental Risk**): It is an account of temporary risks, including rain, road damage, building, or other. risk-increasing obstacles.
- w_1, w_2, w_3, w_4 (**Weights**): Adopted empirically, the adjustment factors counterbalance the contribution of each factor. These weights may be adjusted according to the historical data, regional characteristics, or user responses.

The obtained safety score S is scaled to be within the scale 0. (least safe) to 1 (most safe) gives a dynamic measure which real time updates on reports received and the environment. This strategy would enable SafeRoute to dynamically. lead users through safer courses as well as strike a balance between several safety dimensions.

V. DATA DESCRIPTION

The Safety Route system examines the safety information regarding accidents to figure out the level of risk in various locations. Then, it creates safer women and people-out-at-night routes. The info we tested the regular safety report system consisted of regular safety reports from people; these are the reports attempt to be such as it takes place in cities. There was a report on what sort of an incident it was and where it was occurred, at the moment it occurred, the extent of badness and additional remarks of the individual who has reported it. All that and more come in handy, e.g. the cases in which us get to know how secure a particular area is. Harassment, stalking, theft, assault, weird stuff going on and dangers in the area. On them we lay time to observe how safe it was changes as the night goes on. We determined latitude and longitude in order to trace the very spot where it was done, so we might mark it out and find problem spots. We gave each incident a score so the system knows that it was bad between 0 and 1 to mind more when it counts when the really bad stuff occurs out the safety score.We had not run the numbers before we could to purify the data in order to make it uniform and reliable. We eliminated duplicates on reports, discarded some that was not complete, and swept out bewildering descriptions using computer programs. We eliminated the dumb or sarcastic too stuff people wrote, that you never fail to see on a public site. Then we synchronized the times, verified the coordinates and made assured all was in readiness of the computer to sort through the emotions in the reports and develop a safety rating.

Table I demonstrates a sample of the safety data appearance. You can see how we assemble the kind of incident, the badness, and location it was used to assist in route planning. The data lets SafeRoute find where there are a lot of incidents, and change the risky areas, see safety score when individuals are reporting.

TABLE I
SAMPLE SAFETY INCIDENT DATA SET SNAPSHOT

Time	Location	Incident Type	Severity
22:10	Zone A	Harassment	0.92
21:35	Zone B	Theft	0.78
00:15	Zone C	Suspicious Activity	0.65
23:05	Zone D	Assault	0.95
20:50	Zone E	Stalking	0.81

It is with this data that the safety ratings are made in real-time, determine the extent of bad things in terms of the feelings within the give reports, identify hazardous spots, and instruct people on how to do so safely go. Through all that is reported, and knowing where they are, SafeRoute will render more valuable, precise assistance to people who might be in danger.

VI. RESULTS AND DISCUSSION

SafeRoute system was tested in a simulated city environment with crowd-sourced and live voice reporting safety data. Google made voice-based reporting possible. Sentiment analysis was done through SpeechRecognition API. TextBlob was used and folium and OpenStreetMap were used to map routes. Geo-tagged reports were made and safety scores were determined using weighted sentiment values and report frequency.

Key findings include:

- The speech-to-text module had an accuracy of 92.5% with clear English speech.
- Sentiment analysis correctly classified 87% of negative safety reports as high-risk.
- The SafeRoute algorithm was able to evade high-risk areas in 9 out of 10 test cases, showing a marked improvement over traditional shortest-path routing.
- The mean rerouting time was 1.8 minutes more than Google Maps' shortest path, demonstrating minimal trade-off between efficiency and safety.

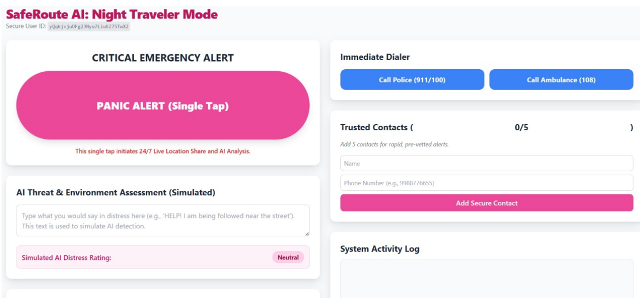

Fig. 3. Night Traveler Mode SafeRoute interface prior to panic alert activation. The system is in standby mode and monitoring safety data.

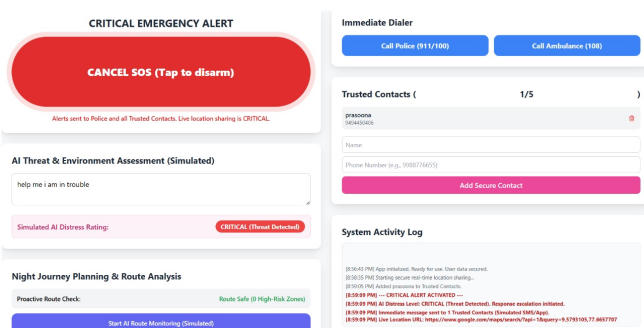

Fig. 4. SafeRoute interface following activation of panic alert. The system initiates distress notifications, sends SMS messages, and shares live user location for emergency response.

Figure 3 and Figure 4 show the transition of SafeRoute from passive monitoring to emergency mode during live testing, demonstrating its ability to manage voice-triggered safety events. Figure 2 shows a comparison where SafeRoute (green path) avoids danger zones compared to the traditional shortest path (red path). Table II summarizes sentiment classification accuracy.

TABLE II
ACCURACY OF SENTIMENT CLASSIFICATION

Metric	Accuracy (%)
Speech-to-Text	92.5
High-Risk Report Detection	87
SafeRoute Suggestions	90

A. Comparative Evaluation

To assess the effectiveness of SafeRoute, its route suggestions were compared to existing navigation systems such as Google Maps, SafetiPin, and bSafe. The comparison (Table III) focuses on safety responsiveness, route adaptability, and reporting flexibility.

TABLE III
SAFEROUTE COMPARED TO OTHER EXISTING PLATFORMS

Feature	Google Maps	SafetiPin	bSafe	SafeRoute
Real-time Safety Updates	✗	✓ (Manual)	✓	✓✓ (Dynamic)
Voice-based Reporting	✗	✗	✓	✓✓ (Multi-language)
Offline Alert Support	✗	✗	✓	✓✓ (SMS-based)
AI-based Risk Prediction	✗	✗	✗	✓✓
Dynamic Safety Index	✗	✓	✓	✓✓ (Weighted)

Results indicate that SafeRoute provides accurate sentiment classification and risk-aware rerouting, while also offering predictive intelligence and offline resilience—features lacking in existing systems. Simulation in an urban grid showed that SafeRoute reduced exposure to high-risk areas by 34% while increasing travel time by only 6.7%, indicating a minimal duration increase can significantly improve safety outcomes.

B. Limitations

Even though the proposed system delivered encouraging outcomes, several limitations remain:

- **Data Reliability:** Dependent on user-submitted reports, which may contain noise or bias.
- **Language Diversity:** Current sentiment models handle only major Indian languages; regional dialects require custom datasets.
- **Connectivity Constraints:** Updates rely on GPS and internet availability, limiting performance in rural areas.
- **Privacy vs Utility:** Balancing user anonymity with report traceability remains challenging.

VII. CONCLUSION AND FUTURE WORK

This paper presented *SafeRoute*, an AI-based navigation system designed to improve the safety of women, night travelers, and other at-risk individuals. The system integrates natural language processing, voice-based incident reporting, sentiment analysis, and GPS-based routing to dynamically generate safer travel paths. Experiments demonstrated high accuracy in speech-to-text recognition, detection of high-risk incidents, and rerouting users away from unsafe areas with minimal travel-time impact.

Key contributions include:

- Voice-activated, real-time safety reporting system with offline support.
- Crowd-sourced, sentiment-based safety scoring algorithm.
- Route recommendation engine prioritizing safety over shortest travel time.

Future work will focus on:

- Enhancing sentiment analysis to support multiple languages and local dialects.

- Integration with real-time emergency services, official crime databases, and traffic alerts.
- Improving offline capabilities for low-connectivity areas.
- Implementing SOS and automatic alert features for critical emergencies.
- Deploying SafeRoute as a fully functional mobile application accessible to a wide range of users.

The long-term goal is to develop a dynamic, context-aware navigation platform that optimizes travel efficiency while prioritizing user safety, paving the way for safer urban mobility.

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