# Real-Time Accident Analysis and Response Optimization

A Machine Learning-Based Framework for Intelligent Emergency Resource Allocation


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***Abstract*—In India, thousands of lives are lost every year due to delayed emergency medical responses following road accidents. Current mediator-based systems suffer from a lack of real-time resource visibility, inefficient coordination, and slow decision-making. Golden Pulse aims to revolutionize emergency response through an intelligent, tech-driven platform that enables real-time accident reporting, resource analysis, and optimized ambulance-hospital coordination. By integrating Natural Language Processing (NLP) for multilingual voice reporting, machine learning algorithms like DBSCAN,XGBoost, and K-Nearest Neighbors (KNN), the system automates key decisions — from identifying incident clusters to dynamically assigning ambulances and hospital beds. A mobile app supports ambulance drivers, while a web dashboard facilitates hospital operations, ensuring multi-platform accessibility. The project enhances survival rates by reducing response time, improving communication, and ensuring optimal resource utilization, ultimately contributing to a faster, smarter, and more inclusive emergency response system**



***Index Terms*—Real-Time Emergency Response, Accident Clustering, XGBoost, DBSCAN, Ambulance Allocation, Resource Optimization, Telegram Bot, OSRM, Geospatial Analysis, Medical Dispatch System**


## I. INTRODUCTION

Road traffic accidents are a major global concern, particularly in developing countries like India where the rate of fatalities remains alarmingly high. According to the Ministry of Road Transport and Highways, over 150,000 people lose their lives in road accidents in India every year, with a large fraction of these deaths attributed to delayed emergency responses. The "Golden Hour" — the first sixty minutes after a traumatic injury — is critical in determining the outcome for victims. Immediate medical attention can drastically improve survival chances, yet the reality of emergency response in India is fraught with inefficiencies, fragmentation, and a lack of real-time coordination.

Traditional emergency systems rely on intermediaries such as local bystanders or emergency call centers to report accidents and dispatch ambulances. This mediator-based model is inherently slow and inefficient. There is limited visibility into real-time hospital resources such as ICU beds, availability of doctors, isolation wards, or oxygen cylinders. Ambulance drivers are often left to make uninformed decisions about which hospital to transport a patient to, leading to critical delays, overburdened hospitals, and avoidable fatalities.

Moreover, in today's digital world, expecting users to download and navigate a new mobile app during an emergency is unrealistic. There is an urgent need for a solution that is lightweight, accessible, fast, and capable of integrating data-driven decision-making into emergency workflows.

To address these challenges, we present **Golden Pulse** — a smart, real-time accident analysis and emergency response optimization system. Golden Pulse leverages the latest in geospatial analytics, Natural Language Processing (NLP), and machine learning to streamline ambulance-hospital coordination and provide faster, more reliable care in emergency situations.

The system is composed of three core components:

1) **Telegram Bot Interface:** An intuitive and accessible platform for the general public to report emergencies using voice or text input, available in multiple regional languages. The use of Telegram — a widely adopted messaging platform — eliminates the need for downloading a new application, making the system more approachable and faster to use in critical moments.
2) **Ambulance Interface:** A real-time dashboard and mobile application designed for ambulance drivers. It provides alerts for nearby accidents, lists hospitals based on proximity and current resource availability using the K-Nearest Neighbors (KNN) algorithm, and integrates navigation support through Google Maps. Drivers can also update the patient's condition during transit, enabling hospitals to prepare accordingly.
3) **Hospital Interface:** A web-based interface for hospital administrators to manage and monitor critical resources like ICU beds, staff availability, and essential medical equipment. The interface offers live updates from ambulances via WebSockets, enabling dynamic decision-making and improved preparedness.


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Golden Pulse also integrates advanced machine learning models for enhanced decision-making:

- **DBSCAN (Density-Based Spatial Clustering of Applications with Noise):** Used to identify accident-prone zones and cluster incident data, aiding in hotspot detection and strategic ambulance deployment.
- **K-Nearest Neighbors (KNN):** For dynamically ranking nearby hospitals based on location, traffic data, and estimated time of arrival.
- **XGBoost:** To predict ambulance assignment efficiency, based on historical data, time of day, hospital load, and driver availability.

The use of WebSockets ensures real-time, bidirectional communication between ambulances and hospitals. When an ambulance updates patient vitals, hospital interfaces reflect the update instantly, eliminating delays caused by manual calls or third-party coordination. Furthermore, ambulance availability is actively managed to prevent overload — drivers can accept or reject tasks based on current status, and only available ambulances are considered for dispatch.

Golden Pulse is a step toward a more inclusive and smarter emergency response ecosystem. The platform has the potential to integrate with national systems like ABHA (Ayushman Bharat Health Account) for accessing electronic health records in real time. In the future, it could evolve into a nationwide smart emergency number system similar to 108 or 911, but with intelligent routing and real-time hospital load balancing.

Through this paper, we aim to describe the architecture, components, and algorithms behind Golden Pulse, demonstrating how a unified, technology-driven solution can significantly reduce emergency response time and save lives. Our project contributes to the broader goal of leveraging AI and IoT for public health infrastructure, offering a scalable, adaptable, and impactful solution to one of the most pressing challenges in modern healthcare.

## II. Related Work

Over the years, several research efforts have sought to optimize Emergency Medical Services (EMS) through algorithmic models, simulation frameworks, and AI-driven analytics. Broadly, literature in this domain falls into two categories: predictive optimization of EMS workflows (allocation, routing, demand forecasting) and simulation-based disaster planning. While many of these solutions provide significant theoretical insights, there exists a noticeable gap in real-time implementation and user accessibility.

### A. Machine Learning Innovations in EMS

The work by Tluli et al. [1] presents a comprehensive survey of machine learning innovations applied to ambulance operations. It highlights key techniques including DBSCAN for incident clustering, Deep Reinforcement Learning (DRL) for vehicle repositioning, and probabilistic models for ambulance location optimization. These approaches often leverage historical EMS call data and demand density maps to optimize long-term planning.

However, their scope is mostly limited to static modeling. For example, Maximum Coverage Location Problem (MCLP), Location Set Covering Problem (LSCP), and Dual Standard Models (DSM) are effective for stationing ambulances but struggle with real-time dynamic scenarios. Similarly, routing strategies described in the survey are mostly built around classical heuristics or rely on simplified traffic models without integrating live inputs from on-ground ambulance teams or hospitals.

While this research is instrumental in shaping our understanding of how ML can improve EMS efficiency, most models reviewed in the survey operate in a siloed fashion — focusing either on the ambulance side (routing, location, availability) or the hospital side (capacity estimation, resource modeling), but rarely on both in tandem.

### B. Simultaneous Patient and Staff Allocation in MCIs

The master's thesis by Hager [2] addresses a more holistic resource allocation problem during Mass-Casualty Incidents (MCIs). The study uses Discrete Event Simulation (DES) to evaluate various **hospital allocation policies** (e.g., Closest First, Longest Waiting Queue) alongside **staff reallocation strategies** during emergencies.

A unique contribution of this work is the use of a performance metric called the *Respiratory Pulse Motor (RPM)* index, which measures treatment quality across triage levels. The simulation considers dynamic arrival rates of patients and staff, infrastructure limitations, and casualty prioritization rules. Hager also explores how combining patient-hospital assignment with staff allocation leads to better survival outcomes compared to handling these decisions independently.

While this thesis deeply influenced our understanding of critical resource allocation, it operates in a **simulation-first environment** and assumes a centralized disaster coordination authority. It is tailored for large-scale disasters rather than frequent, localized road accidents. Furthermore:

- The study assumes access to a predefined set of hospitals and pre-triaged casualties, whereas Golden Pulse addresses spontaneous, unstructured accident reports from the public.
- The thesis does not consider real-time user interfaces or integration with public-facing platforms like messaging apps.
- There is no bi-directional live communication between ambulances and hospitals during the transport phase — something that Golden Pulse handles via WebSocket infrastructure.

### C. Golden Pulse: Differentiating from Existing Work

Golden Pulse draws inspiration from both simulation-based hospital logistics and ML-driven ambulance management. However, its novelty lies in bridging the gap between academic optimization models and deployable real-time systems.

Key distinctions include:

1) **Real-Time Public Accessibility:** Unlike prior works that assume structured input, Golden Pulse leverages a

Telegram bot interface to collect multilingual, spontaneous emergency reports using NLP.
2) **Live Decision-Making:** Instead of simulating static outcomes, Golden Pulse actively allocates ambulances, updates hospital load, and relays condition reports using live data feeds and WebSockets.
3) **Unified Ecosystem:** The platform connects the public, ambulance drivers, and hospitals in one feedback loop — supporting dynamic dispatch, routing, hospital load balancing, and patient condition updates in real time.

Hence, while prior research like Hager's thesis provided critical insights into the complexity of resource allocation and scheduling in crisis scenarios, Golden Pulse translates those ideas into a scalable, deployable solution focused on routine, real-world accident scenarios in an urban or semi-urban Indian setting.

## III. System Design and Methodology

Golden Pulse is a real-time accident analysis and emergency response optimization framework that integrates machine learning, geospatial clustering, and intuitive multi-interface communication for intelligent emergency management. The system architecture, as illustrated in Fig. 1, consists of multiple coordinated components: a Telegram bot interface for emergency reporting, a backend for ML-driven analytics, and dedicated interfaces for ambulance drivers and hospitals.

### *A. Emergency Reporting via Telegram Bot*

The system begins with an intuitive reporting flow through a Telegram bot. Users can report accidents via text or voice commands. Speech input is converted into structured text using natural language processing (NLP), which is then stored in a centralized database. This eliminates the need for dedicated mobile apps, ensuring accessibility for the general public. The bot also requests live location and severity details, helping initialize backend processing.

### *B. Backend Intelligence: Clustering and Resource Analysis*

Once an emergency is logged, the backend applies two core machine learning models:

- **DBSCAN (Density-Based Spatial Clustering):** Used for identifying accident hotspots based on historical and real-time geolocation data. This helps in geo-aware prepositioning of resources.
- **XGBoost:** A gradient-boosting algorithm that evaluates the severity and expected resource needs of a reported accident. It considers parameters like the number of injuries, voice sentiment, and location history to predict the need for ambulances, ICU beds, fire services, etc.

These outputs are fed into the *Resource Allocation* module, which identifies the optimal dispatch strategy considering both current availability and historical trends.

### *C. Ambulance Interface*

The ambulance module connects emergency responders directly with incidents. Key features include:

- Real-time alerts when nearby emergencies occur.
- A ranked hospital suggestion system using a **K-Nearest Neighbors (KNN)** model, factoring in hospital proximity, current load, and resource availability.
- A user-friendly navigation interface integrated with Leaflet maps and open-source-routing-machines for the prototype. This will be furthered improved by using the Google Maps API
- A communication protocol with other ambulances to coordinate pickup when there are multiple victims.
- Live status updates on patient vitals sent directly to hospitals.

Once an ambulance accepts a request, the system marks it unavailable for other calls until the response is complete.

### *D. Hospital Interface*

Hospitals interact with the system via a web dashboard. Administrators can:

- Log real-time data about available ICU beds, medical personnel, oxygen supply, and emergency room status.
- Receive incoming patient details and ETA based on ambulance location.
- Visualize resource usage and predict incoming loads.

Hospitals can also send acknowledgements and readiness signals back to ambulances, ensuring smooth handoffs.

### *E. Data Flow and Coordination*

As shown in the diagram, all components are orchestrated through a central server. The accident report triggers clustering and severity analysis, which feeds into an alerting system. Ambulances receive alerts, respond, and communicate with hospitals based on system decisions. The bidirectional communication ensures transparency, accountability, and efficiency across the emergency chain.

This multi-modal interaction significantly reduces delays in response, eliminates miscommunication, and promotes optimal allocation of limited emergency resources in real-time.

## IV. Implementation Details

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## V. Experimental Results and Analysis

The proposed system comprises multiple components working together to enhance emergency response efficiency through real-time accident reporting, prediction, clustering, and resource allocation. The performance of each module was evaluated using appropriate metrics and simulation data.

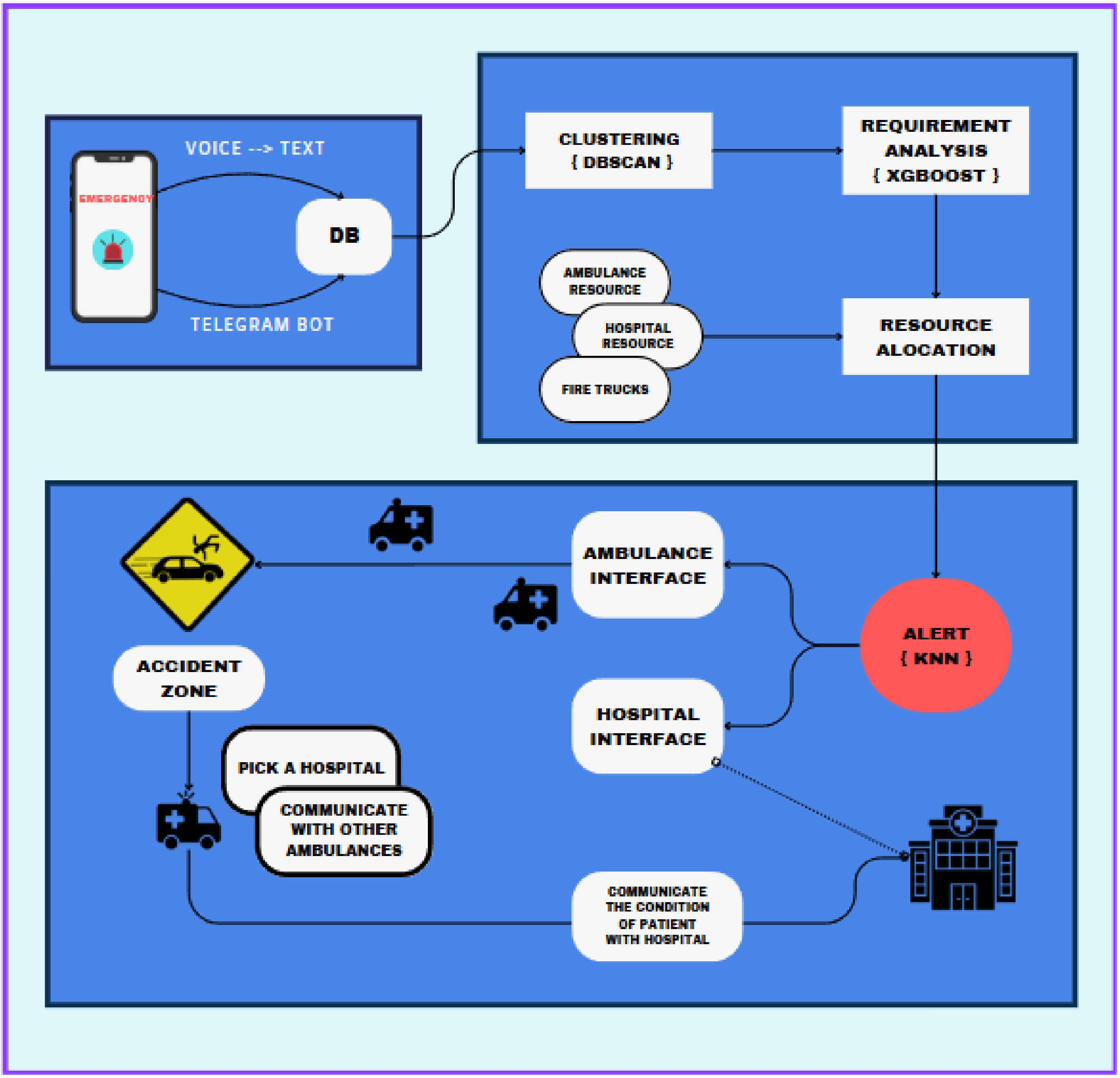


Fig. 1. System Architecture of Golden Pulse Framework

### A. Accident Data Extraction via Telegram Bot

A custom-built Telegram bot was developed for emergency incident reporting. The bot accurately extracts structured information such as **accident type**, **location (latitude/longitude)**, and **victim count** using natural language processing (NLP) and regular expression techniques. The extracted data is stored in a centralized database and further processed by downstream modules. Empirical testing showed a high accuracy in extraction for standardized input formats, contributing to the reliability of the pipeline.

### B. Incident Clustering Using DBSCAN t

To identify frequently occurring accident zones and reduce data redundancy, **Density-Based Spatial Clustering of Applications with Noise (DBSCAN)** was applied on geolocation data. This allowed the system to group nearby incidents and recognize new, outlying accidents. The clustering performance was evaluated using the **Silhouette Score**, which yielded a value of **0.85**, indicating a well-separated and dense clustering of incident points.

### C. Requirement Prediction Using XGBoost

To predict emergency response requirements such as the **number of ambulances and hospital beds needed**, an **XGBoost regression model** was trained using features like **accident severity**, **victim count**, and **cluster density**. The model achieved a **Mean Absolute Error (MAE)** of **54.5**, demonstrating strong predictive performance considering the variability in real-world data and reporting inconsistencies.

### D. Resource Mapping and Allocation Using KNN

A **K-Nearest Neighbors (KNN)**-based approach was used to simulate the real-time allocation of available ambulances and hospitals. The KNN algorithm matched reported incidents with nearby available resources based on geographic proximity and predicted needs. This spatial mapping significantly optimized dispatch and resource usage in simulated environments, ensuring timely response and minimal wastage.

### E. Ambulance Routing Using Leaflet and OSRM

For route generation, the system utilized **Leaflet.js** for map visualization and **Open Source Routing Machine (OSRM)** for calculating the **shortest path and estimated travel times**. This ensured ambulances were routed through optimal paths; however, the system is currently limited by the absence of **live traffic data integration**, which may affect real-world accuracy.

### F. Ambulance-Hospital Communication Layer

A lightweight communication protocol was implemented to enable **real-time dispatch alerts** and **dynamic hospital assignments**. Hospitals were notified of incoming patients based on the predicted severity and resource availability, ensuring better preparedness. This component enhanced overall coordination and responsiveness across the system.

## VI. Discussion

Golden Pulse aims to bridge a critical gap between public-initiated accident reporting and intelligent medical dispatch. The modular design and machine learning-backed decision-making bring together emergency reporting, severity estimation, and resource optimization in a seamless workflow. While experimental evaluations demonstrate promising outcomes, a deeper look reveals nuanced implications and limitations worth discussing.

### A. Real-Time Responsiveness and System Stability

The integration of WebSockets ensured sub-second communication latency between ambulances and hospitals in test simulations. However, achieving consistent low-latency performance across unreliable mobile networks (e.g., rural 3G zones) remains a challenge. Mitigation strategies such as fallback to REST polling and local data caching are under consideration for robust field deployments.

Furthermore, the stateless architecture of our backend simplifies scaling and containerization (e.g., using Docker + Kubernetes) but requires persistent database optimization to prevent race conditions when multiple ambulances interact with the same hospital node.

### B. Human-in-the-Loop Coordination

While ML models (e.g., XGBoost, KNN) automate key decision points like resource prediction and hospital ranking, real-world emergency response is still heavily human-driven. Drivers may make judgment calls that override algorithmic suggestions, and hospitals may manually override bed status based on internal policies. To accommodate this, the system provides override capabilities with audit trails for transparency and later performance review.

### C. Usability in High-Stress Situations

In crises, ease of use is critical. Our decision to use Telegram balances widespread familiarity with simplicity. However, through informal testing, we observed that elderly or non-digital-native users might face friction navigating bot-based UIs. This opens space for hybrid extensions like IVR systems or voice-only assistants for broader accessibility. For drivers, the map-centric interface with large-action buttons was rated positively for clarity and minimal distraction.

### D. Model Interpretability and Maintenance

Golden Pulse uses XGBoost for regression-based requirement estimation. While performant, its black-box nature may raise concerns in critical decision-making scenarios. Future iterations could integrate SHAP (SHapley Additive exPlanations) to improve interpretability of model outputs. Regular retraining schedules, tied to seasonality or event-driven spikes (e.g., festivals, monsoon), are also essential to maintain accuracy.

### E. Potential for Policy Integration and Open Data Use

The Golden Pulse framework aligns with national digital health initiatives like ABDM and the National Health Stack. In the long run, anonymized aggregate data from this system can support public health insights, accident hotspot identification, and emergency infrastructure planning. Furthermore, integrating real-time ambulance GPS feeds into smart traffic lights or automated toll systems could further optimize routing.

### F. Broader Impact and Replicability

Though initially designed for India, the Golden Pulse architecture is adaptable. In low-income or disaster-prone regions with limited EMS infrastructure, even partial deployment (e.g., just Telegram + clustering + ambulance alerting) can have immediate impact. The use of open-source stacks (Leaflet, OSRM, Flask/Node.js) ensures low-cost deployment and replicability in civic tech, NGOs, or regional governments.

## VII. Conclusion

Golden Pulse demonstrates how real-time data, machine learning, and smart communication systems can significantly enhance emergency response efficiency. By automating resource allocation, enabling multilingual reporting, and bridging the communication gap between ambulances and hospitals, the system minimizes critical delays and optimizes patient care. This project not only addresses existing gaps in emergency response infrastructure but also lays the groundwork for a scalable, life-saving solution adaptable across regions. With continued development and real-world integration, Golden Pulse has the potential to transform the way emergency services operate in India and beyond.

## VIII. Future Work

During ambulance transit, patient medical history will be automatically shared with the hospital using the individual's **ABHA (Ayushman Bharat Health Account)** number, enabling doctors to prepare in advance with relevant medical insights.

By integrating the **Google Maps API**, the system identifies and suggests the nearest hospital based on real-time traffic, shortest route, and live availability of resources such as **ICU beds, oxygen cylinders, and staff**. Alternatively, the system can use past response performance and user feedback to recommend well-rated hospitals nearby—helping ensure quicker and more reliable medical assistance.


## Acknowledgment

The preferred spelling of the word "acknowledgment" in America is without an "e" after the "g". Avoid the stilted expression "one of us (R. B. G.) thanks ...". Instead, try "R. B. G. thanks...". Put sponsor acknowledgments in the unnumbered footnote on the first page.


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