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Optimal location of rescue bases on the Chalous road: a deep learning-based approach

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ABSTRACT

Objective: Road accidents, especially on mountainous roads, pose significant traffic safety challenges that require accurate prediction and optimal management. In Iran, as a disaster-prone country, road accidents rank as the second-highest risk in terms of occurrence frequency, after earthquakes, highlighting the critical importance of road accidents as a significant risk factor. In this study, using data from the Red Crescent mission reports along with road, environmental, and traffic features, a deep learning transformer model was developed to identify accident-prone locations on the Chalous road corridor. This model extracted complex nonlinear patterns with considerable accuracy and predicted high-risk points categorized into three accident severity classes (fatal, injured, treated on site). Subsequently, using the Grey Wolf Optimizer algorithm, the optimal placement of rescue bases was performed to increase road coverage and reduce response time. Results showed that rescue coverage on the Chalous corridor increased from 22.77% to 86.91%, and average response time decreased from approximately 14 minutes 45 seconds to 8 minutes 22 seconds, representing a 64% improvement in coverage and a 43% reduction in reaction time, respectively. This study demonstrated that integrating real-world data, advanced deep learning models, and optimization algorithms provides an effective tool for improving rescue management, enhancing safety on high-traffic and high-risk corridors, and reducing injuries and fatalities. The findings can serve as a basis for designing intelligent crisis management systems and developing preventive programs in other regions of the country.

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Introduction

The increasing number of vehicles has made road accidents a major global safety concern, with costs equivalent to 3% of annual GDP (Zheng et al., 2019). In Iran, road accidents rank second in frequency after earthquakes (Soltani et al., 2021). Machine learning models, particularly transformers, are more effective than traditional methods in identifying complex accident patterns (Zhang, 2019; Astarita et al., 2023).

In recent years, numerous studies have been conducted on predicting road accidents and optimizing rescue base locations. For example, Goli and Malmir reduced the response time of rescue vehicles using a coordination search algorithm and credibility theory optimization. They stated that optimization algorithms are essential for determining the optimal locations of rescue bases in crisis management (Goli & Malmir, 2019). Li et al. presented a combined LSTM and CNN model to predict the risk of accidents on urban roads (Li & Yuan, 2020). Shang et al. used RF-RFE, LSTM networks, and BOA optimization to develop an automated accident-detection system for intelligent transportation (Shang et al., 2020). Guo et al. improved rescue response time in urban search and rescue operations using a transformer and attention-based LSTM (Guo et al., 2021). Yang et al. used reinforcement learning to reduce the response time of rescue vehicles in mountainous regions (Yang et al., 2021). Zhao et al. enhanced the prediction accuracy of the LSTM model by optimizing it with the Grey Wolf Optimization (GWO) algorithm (Zhao et al., 2022). Astarita et al. developed a GWO-ANN hybrid model to predict accident severity and optimize rescue-base locations (Astarita et al., 2023). Wang et al. introduced the Dual-Transformer model to predict spatio-temporal relations of accidents (Wang et al., 2023). Mousavi et al. used the Particle Swarm Optimization (PSO) algorithm to identify 10 optimal sites for developing the emergency response network in Alborz Province (Mousavi et., al 2023). Al-Thani et al. developed a multi-attention transformer model for accident prediction (Al-Thani et al., 2024). Huang et al. used the DGWO-F2OPT algorithm to increase the response speed of emergency vehicles (Huang et al., 2024). Forouzandeh et al. tested six machine-learning models to predict crash severity. Random Forest performed best, while Naïve Bayes had the lowest accuracy. (Foroizandeh et al., 2025). Jiang et al. predicted the severity of injuries in accidents using a transformer model (Jiang et al., 2025). Peng and Yan introduced the TTT-Enhanced Transformer model, which improved road accident prediction performance (Peng & Yan, 2025). Based on these studies, this study uses a transformer model for optimal location of rescue bases in mountainous corridors to compare road coverage and response times in the current and proposed states.

Method

Describe This study focuses on the mountainous Chalous corridor, a key transportation route between Mazandaran and Alborz provinces. Due to its unique geographic location, its role in northern travel routes, and high traffic volume, especially during peak seasons, the corridor is known for its high accident rate and hazardous areas (Mousavi et al., 2023). These factors make it a priority for road rescue and emergency planning. Figure 1 shows the distribution of road accidents on the Chalous corridor from March 2017 to January 2024.

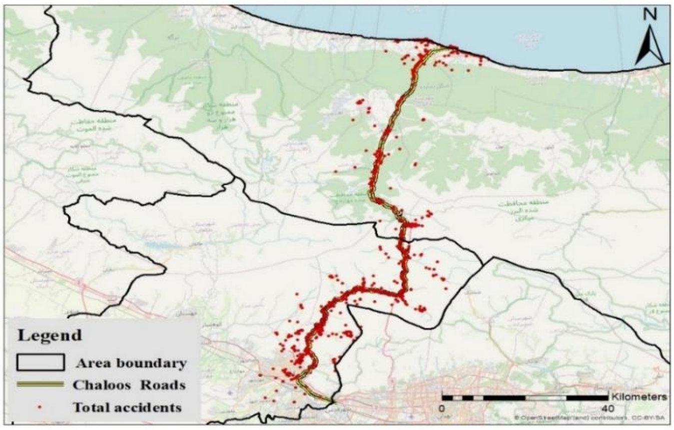

Fig. 1. Distribution of road accidents in the studied corridor

In this study, road accident data, including fatalities, injuries, and on-site treatments, were collected from the Red Crescent Rescue Organization, along with environmental, traffic, and road characteristics from the Road Maintenance and Transportation Organization, for the period from March 2017 to January 2024, to identify accident-prone locations along the studied corridor (Table 1). Finally, to evaluate and compare the coverage percentage of rescue bases and response times in both current and proposed scenarios, the optimal placement of rescue bases was determined using the GWO algorithm.

Table 1. Characteristics and Categorization of Input Features for the Deep Learning Model

Data Provider Organization	Feature Names	Feature Categories
Road Maintenance and Transport Organization	Rainfall, snow and blizzards, landslides and ground subsidence, fog and visibility reduction, slipperiness, floods and waterlogging, dust storms, normal conditions	Environmental Features
Road Maintenance and Transport Organization	Blocked and heavy, flowing and semi-flowing, unclear status	Traffic Features
Road Maintenance and Transport Organization	Night or day conditions, road type (main, secondary, rural, etc.), road surface condition, presence or absence of tunnels, presence or absence of bridges, road slope, altitude above sea level, route type (one-way or two-way), proximity to arterial roads, days of the week, start time, end time, incident time, start date, end date, and other related features	Road Features

The features were input into the model as raster data and numerical codes, which were then divided into two parts: training (70%) and testing (30%). The model output was presented as a raster map in four different classes: fatalities, injuries, on-site treatment, and no accident. Subsequently, to improve emergency response, the optimal placement of Red Crescent bases was carried out using the GWO algorithm, aiming to reduce the response time to road accidents to less than 14 minutes. The inputs to the algorithm included the map of accident-prone locations, the positions of the bases, and their operational radius from accident hotspots. The deep learning model used in this study is the Transformer, which, unlike RNN and LSTM, relies on an attention-based structure, enabling parallel processing and learning long-term dependencies. This makes it suitable for time series analysis and traffic data, outperforming traditional models like LSTM and CNN in detecting accident-prone areas (Vaswani et al., 2017; Wu et al., 2021). Given the significant role of metaheuristic algorithms in solving complex problems, the Grey Wolf Optimization algorithm was used in this study for optimal base placement. Introduced by Mirjalili et al. in 2014, this algorithm is inspired by the social behavior and hunting strategy of grey wolves (Astarita et al., 2023). After predicting accident-prone locations with the Deep Transformer model, the optimal placement of rescue bases was determined to improve road coverage and reduce response time.

Results

In To evaluate the performance of deep learning-based classification models, several models were trained. Among them, satellite_classification_tversky_2 showed the best performance in terms of accuracy and loss on the training, validation, and test datasets. In Figure 2, the accuracy and loss graphs of this model are presented, where the continuous reduction in loss and the maintenance of high accuracy across different data sets indicate successful learning and the model's ability to generalize to new data. The model was able to predict accident-prone locations in three categories: fatalities in red, injuries in green, and on-site treatment in blue, using environmental and traffic features (Figure 3). To evaluate the coverage of Red Crescent bases, the operational radius of the existing rescue bases was first determined based on their geographic locations in the road network. Then, using the Network Analysis tool, the coverage of roads and response times of the existing and proposed bases were compared. This analysis enabled the calculation of the coverage percentage and response times for each base based on access through the road network (Figure 4).

The results of the analysis provide a basis for comparing the current situation with the proposed base locations to quantitatively assess the improvement in road coverage and response time. In this context, the optimal location of rescue bases was determined using the Grey Wolf Optimization algorithm. Figure 5 shows the accident density and the positions of both existing and proposed bases. The algorithm suggested five optimal base locations for the Chalous corridor, which are situated near high-density accident areas, thereby improving access and response time in the mountainous routes.

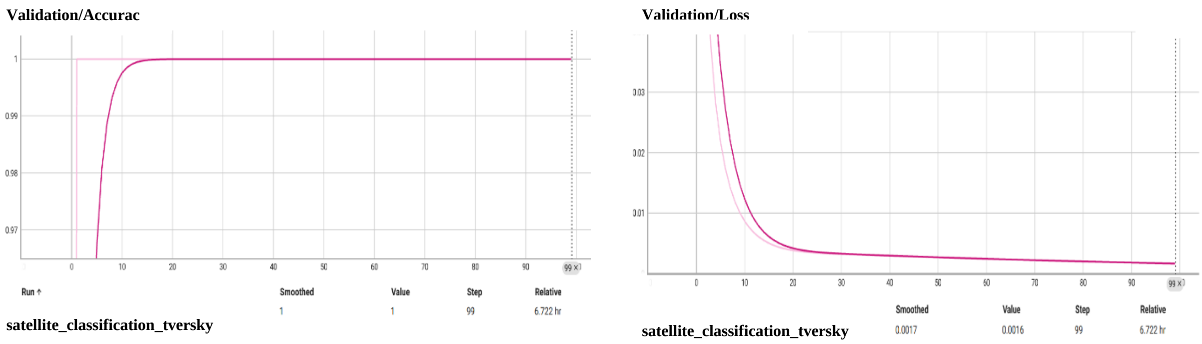

Fig. 2. Accuracy and Loss Graphs of the Model

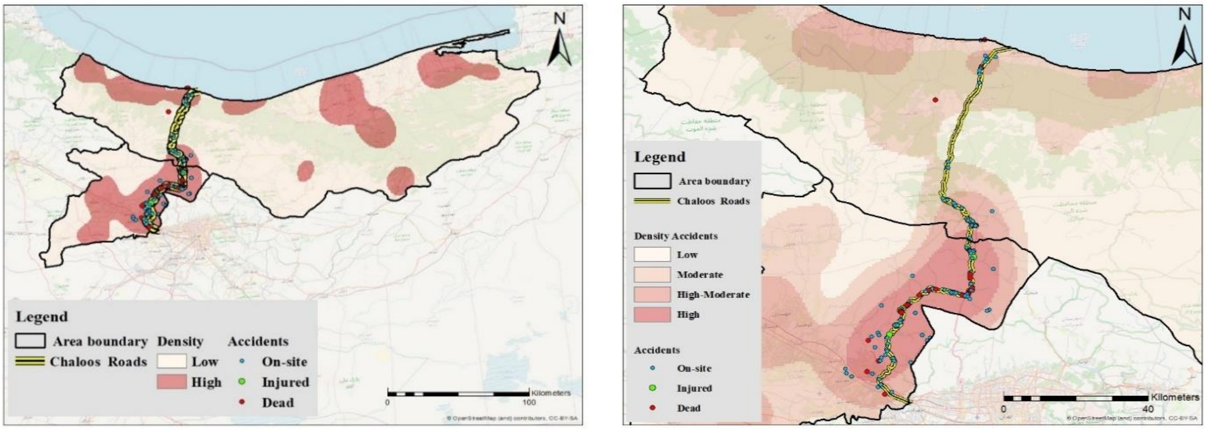

Fig. 3. Predicted Road Accidents by the Deep Learning Transformer Model

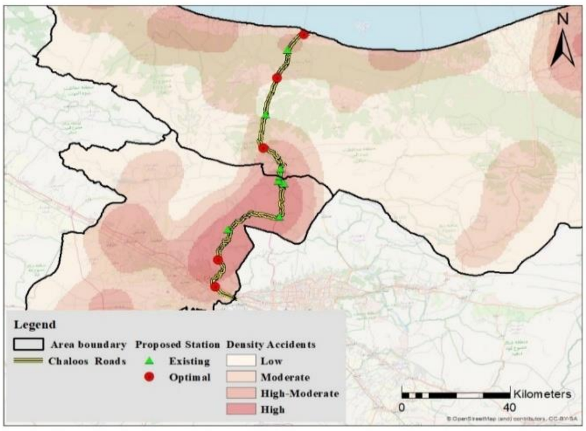

Fig. 5. Optimal Location of Rescue Bases

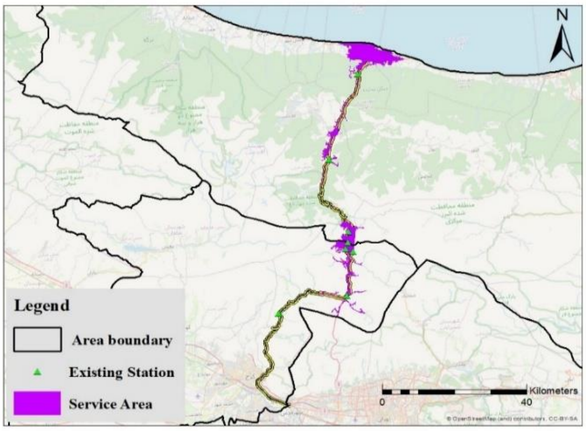

Fig. 4. Operational Radius of Existing Bases

The results of the comparison of response time and rescue coverage on the Chalous corridor showed that the average response time for the identified accident-prone locations was approximately 14 minutes and 45 seconds (884.66 seconds), which is close to the 14-minute standard. In contrast, sections of the corridor without rescue coverage had less impact on the average response time due to a lower number of recorded accident-prone locations. Therefore, while the average response time of the current situation seems satisfactory, it does not fully reflect the coverage and efficiency of the entire corridor. The current rescue coverage on the Chalous corridor is 22.77%, which increased to 86.91% with the proposed optimal location of bases. This represents an absolute increase of about 64% in total coverage. Thus, the proposed coverage is nearly 3.8 times that of the current situation. Furthermore, with the optimal location, the response time decreased from approximately 884.66 seconds to around 501.06 seconds (8 minutes and 22 seconds), showing an improvement of about 43% in the speed of emergency response, as shown in Table 2. This significant reduction could directly impact the reduction of injuries and fatalities and enhance the quality of emergency services.

Table 2. Comparison of Response Time and Coverage of Routes in the Current and Proposed Scenarios

Rescue and Relief Base	Chalous Axis		Length of Covered Main Axes (km)	Total Length of Axes (km)
	Covered Axis %	Average Response Time (seconds)		
Existing Status	22.77%	884.66	6795.68	19349.78
Proposed Status	86.91%	501.055	14673.08	

Conclusions

In this study, accident-prone locations on the Chalous corridor were identified using the Transformer deep learning model and real Red Crescent mission data. Then, the optimal placement of rescue bases was determined using the Grey Wolf Optimization algorithm, resulting in the establishment of five new bases in high-accident areas. These changes led to an increase in rescue coverage from 22.77% to 86.91% and a 43% reduction in response time. Overall, the findings of this study demonstrate significant improvements in the quality and speed of rescue services on the Chalous corridor, which could contribute to reducing fatalities and accident-related injuries.

Author Contributions

Bahare Sadat Mousavi: Conceptualization, Methodology, Software, Formal analysis, Data curation, Visualization, writing – original draft, Writing – review & editing. Meysam Argany: Supervision, Writing – review & editing. Najmeh Neysani Samany: Supervision, Writing – review & editing. Ahmad Soltani: Data curation, Resources. Mohsen Forouzandeh: Methodology, Software, Validation.

Data Availability Statement

The data that support the findings of this study were obtained from the Iranian Red Crescent Society and are not publicly available due to institutional and privacy restrictions.

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Ethical Considerations

The study was conducted using secondary data obtained from the Iranian Red Crescent Society. All data were anonymized to protect individual privacy. The study complied with institutional and national guidelines for ethical research.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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