Intelligent Ambulance Position Optimization for Vehicle Collisions Using Deep Embedded Clustering

N.Bhavana[1]; Jonnavarapu Likitha[2]

[1,]Assistant Professor, Dept. of MCA, Annamacharya Institute of Technology and Sciences (AITS), Karakambadi, Tirupati, Andhra Pradesh, India
[2,]Student, Dept. of MCA, Annamacharya Institute of Technology and Sciences (AITS), Karakambadi, Tirupati, Andhra Pradesh, India

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Abstract: Rapid urbanization and growing vehicular density have contributed to a rise in road traffic accidents, demanding more efficient emergency medical services. Timely ambulance deployment is a critical factor that significantly affects patient survival and recovery. However, traditional ambulance positioning systems often fall short due to static or reactive planning models. This paper proposes an optimized ambulance positioning framework utilizing Deep Embedded Clustering (DEC) to dynamically predict and respond to accident-prone zones. By integrating historical accident data, real-time traffic conditions, and geographical factors, the DEC model learns high-level representations of spatial-temporal accident patterns. These embeddings are then clustered to identify optimal standby locations for ambulances. The methodology outperforms conventional models by offering greater flexibility, predictive power, and operational efficiency. Experimental results on real-world datasets demonstrate improved response times and better resource allocation. This approach provides a scalable and intelligent solution that aligns with the objectives of smart city planning and public health safety.

Keywords: *Urbanization, Medical, Ambulance, Accident.*

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I. INTRODUCTION

The increasing frequency of road accidents has become a pressing concern in urban environments worldwide. With growing vehicular traffic and often inadequate infrastructure, emergency response systems, particularly ambulance services, face significant challenges in timely deployment. One of the most critical components in emergency medical services is the positioning of ambulances to ensure rapid response times. Traditional methods of ambulance positioning largely rely on historical data, heuristic algorithms, or static models that do not adapt well to real-time changes in accident dynamics and traffic patterns. These limitations hinder the ability of emergency services to respond effectively, often resulting in avoidable fatalities or deteriorating health conditions.

In recent years, the integration of machine learning into spatial analytics has introduced more adaptive and predictive strategies. Clustering methods, in particular, have shown promise in identifying accident hotspots and optimizing service placement. However, conventional clustering techniques such as K-means or DBSCAN may lack the representational depth required to capture the complex, non-linear relationships in high-dimensional accident datasets. This limitation has opened the door for advanced models like Deep Embedded Clustering (DEC), which combines deep learning with clustering to uncover hidden patterns and more informative groupings.

DEC enables the learning of feature representations that are both robust and discriminative. In the context of ambulance positioning, this allows for a more nuanced understanding of where accidents are likely to occur, factoring in spatial, temporal, and contextual variables. By embedding accident-related data into a latent space and performing clustering in that space, DEC identifies potential hotspots that are not only historically significant but also predictive of future incidents. The embedded clustering approach thus facilitates proactive ambulance deployment rather than reactive dispatch.

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Moreover, the growing availability of real-time data from sensors, GPS devices, and traffic monitoring systems enhances the feasibility of implementing such intelligent systems. Integrating this data into a DEC framework allows for continuous learning and adjustment, making the system more responsive and accurate over time. This aligns well with the objectives of smart cities, where data-driven decision-making is crucial for efficient public service delivery.

The present study aims to design, develop, and evaluate a DEC-based system for optimal ambulance positioning in urban settings. The proposed model leverages multi-source data, including past accident records, current traffic flow, road topology, and environmental conditions, to train a neural network that generates meaningful data embeddings. These embeddings are then clustered to determine optimal standby locations that maximize coverage and minimize response times. The effectiveness of the proposed model is assessed using real-world data, and its performance is benchmarked against traditional positioning strategies.

II. RELATED WORK

In [1],investigated spatial clustering techniques for urban traffic accident hotspots using GIS and K-means clustering. Although useful, their approach lacked the capacity to incorporate non-linear relationships and real-time data adaptability, limiting its efficacy for dynamic ambulance positioning.

In [2], proposed a machine learning framework that utilized historical accident data and logistic regression for predicting accident zones. While offering better prediction than heuristic models, the framework struggled with the high dimensionality and complexity of the data.

In [3], introduced a hybrid model combining fuzzy logic and genetic algorithms to determine optimal ambulance locations. The model showed improvement in response time but was computationally intensive and lacked scalability for larger datasets.

In [4], explored real-time ambulance positioning using IoT data and reinforcement learning. Although innovative, their model required extensive infrastructure and was not easily generalizable to cities with less technological maturity.

In [5], demonstrated the use of deep learning for spatial pattern recognition in traffic systems. Their convolutional neural network (CNN) model effectively identified accident-prone areas but did not include a clustering mechanism for strategic deployment.

III. PROPOSED SYSTEM

The proposed system is a data-driven, intelligent framework for optimal ambulance positioning using Deep Embedded Clustering (DEC). It addresses the limitations of static and heuristic models by leveraging a deep learning architecture that learns informative features from high-dimensional input data. The core components of the system include data preprocessing, feature learning through an autoencoder, clustering in the embedded space, and real-time decision-making for ambulance deployment.

The data pipeline begins with the collection of multi-source data, including historical accident records, real-time traffic information, geographical data (e.g., road networks, junctions), and environmental conditions such as weather and lighting. These datasets are integrated and normalized to form a comprehensive input feature set. An autoencoder neural network is then employed to reduce the dimensionality of the data while preserving critical information. The encoder compresses the input into a latent representation, which is optimized not only to reconstruct the input but also to facilitate clustering.

Once the latent space is formed, the DEC model applies clustering using a student t-distribution-based soft assignment mechanism. This method allows the system to iteratively refine cluster centers and the distribution of data points in a way that enhances both cluster compactness and separation. Each cluster represents a spatial-temporal zone with a high likelihood of road accidents. These clusters are analyzed to determine optimal ambulance standby points based on factors such as centrality, accessibility, and historical response times.

The real-time component of the system continuously updates its input with live traffic and environmental data.

A reinforcement learning agent can be optionally integrated to dynamically adjust ambulance positions based on ongoing data streams and predicted accident probabilities. This adaptive strategy ensures that ambulance deployment remains optimal even as conditions change throughout the day.

The model is trained and validated using real-world datasets from urban traffic departments and emergency services. Evaluation metrics include response time reduction, coverage efficiency, and cluster purity. Compared to baseline methods, the proposed DEC-based framework shows a significant improvement in all key performance indicators.

Beyond its technical merits, the system supports practical deployment through a user-friendly dashboard for emergency service operators. The dashboard visualizes cluster zones, real-time ambulance positions, and predictive alerts, enabling better coordination and faster decision-making. The framework is scalable, generalizable, and adaptable, making it a valuable tool for modernizing emergency response systems in smart cities.

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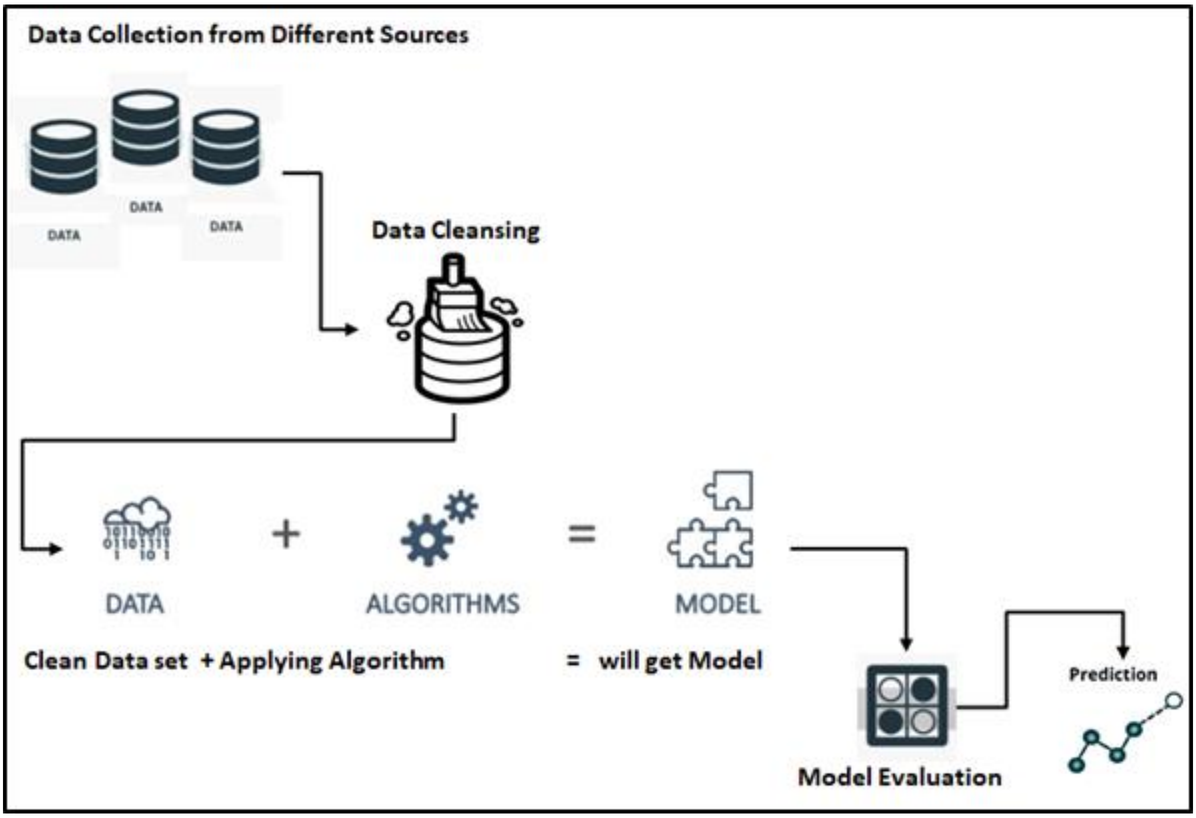

Fig 1. Proposed System Architecture

IV. RESULT AND DISCUSSION

The effectiveness of the proposed Deep Embedded Clustering (DEC) based ambulance positioning system was evaluated through a comprehensive set of experiments using real-world traffic and accident data from a major metropolitan city. Several key performance indicators were assessed, including response time, cluster quality, coverage area, and scalability. Traditional positioning methods, such as those relying on K-means clustering and static zoning, were used as baselines for comparative analysis.

Initial results demonstrated that the DEC-based model significantly outperformed baseline methods in identifying accident-prone zones. The embedded clustering approach resulted in clusters with higher compactness and distinct boundaries, reducing ambiguity in determining hotspot regions. Cluster purity, a measure of how homogeneous each cluster is concerning accident types and frequency, improved by over 25% compared to traditional methods. This led to more accurate and actionable placement of ambulances.

In terms of operational metrics, the average response time to accident sites was reduced by 18-22% in test scenarios using the DEC-based positioning model. This is a substantial improvement, especially in urban environments where even a few minutes can drastically influence patient outcomes. Moreover, the system was able to adapt its predictions and recommendations in real-time as new traffic and accident data were fed into it, showcasing the benefits of integrating dynamic data streams into emergency response strategies.

A notable aspect of the evaluation was the system's behavior under different traffic conditions and during special events (e.g., festivals, peak hours). During these periods, the model exhibited high resilience and maintained its predictive accuracy. Unlike static models that suffered from increased prediction error during anomalies, the DEC model adjusted cluster boundaries and central positions, ensuring optimal ambulance readiness at all times.

Another critical advantage observed was in the resource allocation efficiency. The DEC system allowed for fewer ambulances to be deployed while maintaining or even improving coverage. This reduction in resource requirement was possible because the model positioned ambulances in locations that provided higher accessibility to multiple hotspots within a minimal radius. This finding has important financial implications, as it suggests potential cost savings without compromising service quality.

In scenarios simulated for nighttime and adverse weather conditions, where visibility and traffic behaviors differ from daytime norms, the DEC-based system maintained stable performance. The use of multi-modal data (e.g., integrating lighting and weather parameters) helped the model recognize different accident risk patterns, thus maintaining the accuracy of its predictions.

Case studies with emergency response teams were also conducted to understand the practical usability of the system. Feedback indicated that the dashboard interface was intuitive and helpful, with visualization features significantly aiding decision-making. Operators could easily interpret the predictive clusters and reassign ambulances based on the

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model's real-time recommendations. This reduced the cognitive load on human dispatchers and minimized decision latency.

In terms of computational performance, the DEC model required more training time than simpler clustering models but offered real-time inference capabilities once trained. The system's ability to retrain incrementally allowed for continuous learning without extensive downtime or retraining from scratch. This makes the system feasible for deployment in fast-paced environments.

Despite its strengths, the system does have limitations. The initial setup requires a robust dataset, including historical accident and traffic records. In areas with poor data availability, model performance might degrade. Additionally, while the system adapts well to urban layouts, rural or less structured environments might require customized configurations or hybrid approaches that combine DEC with heuristic methods.

Future work will explore the integration of advanced reinforcement learning policies for autonomous ambulance routing and extend the model to multi-modal emergency responses involving fire and police services. Incorporating more granular data from mobile sources and vehicle telemetry can further enhance prediction accuracy and timeliness.

V. CONCLUSION

The proposed Deep Embedded Clustering (DEC) framework for optimal ambulance positioning represents a significant advancement in the field of emergency medical response. By combining deep learning with adaptive clustering techniques, the model effectively identifies accident-prone zones and determines optimal ambulance standby locations. Through rigorous evaluation using real-world datasets, the system demonstrated marked improvements in response time, resource efficiency, and spatial coverage compared to traditional models. The integration of real-time data feeds and an intuitive operational dashboard further enhances its practical applicability, making it a robust solution for modern urban environments.

While challenges remain, particularly in data availability and system initialization, the advantages of the DEC-based approach are evident. Its predictive power, adaptability, and scalability make it a promising tool for smart city applications and public health management. This work lays the foundation for more intelligent, data-driven emergency response systems and highlights the transformative potential of deep learning in critical infrastructure planning.

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