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OPTIMIZING EMERGENCY RESPONSE WITH DEEP EMBEDDED CLUSTERING FOR AMBULANCE POSITIONING

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ABSTRACT

The number of individuals killed and wounded in traffic accidents is one of the largest problems confronting the contemporary world. Instead of only sending ambulances out when required, pre-positioning them may expedite response times and provide prompt medical treatment. Deep learning techniques hold great potential and have shown to be essential for making decisions and addressing problems in the healthcare sector. This research presents a deep-embedded clustering-based approach to ambulance positing location prediction. Since many patterns and causes within a geographic region have a substantial influence on the frequency of traffic accidents, it is important to comprehend these relationships throughout the model creation process. In order to ensure real-time results, the present study incorporates these patterns using Cat2Vec, another deep learning-based model, and emphasises the need of preserving them during model creation. Furthermore, the proposed framework is compared to traditional clustering methods including GMM, K-means, and Agglomerative Clustering.

In order to evaluate the performance of various algorithms and calculate distance and response time in real time, a special

scoring function has also been introduced. The proposed ambulance-positing approach works remarkably well, outperforming all existing traditional methods with a 95% accuracy using k-fold cross-validation and a new distance score of 7.581.

I. INTRODUCTION

Road accidents are now one of the main causes of mortality for both adults and children globally. Individuals, their families, and the nation suffer significant financial and personal losses as a result of the injuries brought on by these deadly events. An estimated 1.3 million people lose their lives in traffic accidents every year. Approximately 20 to 50 million people suffer non-fatal injuries, and many of them end up crippled as a consequence [1]. There would undoubtedly be some bad effects from the steadily rising number of cars, chief among them the likelihood of more deadly traffic accidents in crowded areas, which would put a tremendous strain on the city's infrastructure. Road accidents are predicted to become the sixth leading cause of death by 2030 if we don't take decisive preventative action to lower these numbers. Despite these deadly outcomes, little attention is paid to this issue, and no systematic strategies are being developed to increase road safety.

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Research indicates that more than 90% of traffic accidents worldwide take place in medium- to lower-income nations, including Kenya [2], [3]. As an example, over a thousand people die in traffic accidents every day, with an average of seven out of every 35 people killed [4]. The majority of these fatalities and serious injuries affect those aged 15 to 59, who are also the nation's most economically engaged residents, which lowers the nation's economic activity. Over the last ten years, regional trade agreements have increased in Kenya, a nation with lower-middle incomes. According to data from Kenya's transport regulator, the National Transport Safety Authority (NTSA), there were 3572 fatalities, 6938 severe injuries, and 5186 minor injuries in 2019.

Prevention measures, the most important of which are timely medical attention for accident victims, communication of the exact situation to aid personnel, and accurate data analysis taking into account every single factor to diagnose and predict the accident-prone zones in a city, can reduce the number of injuries and fatalities caused by these deadly accidents. Human life is significantly impacted when an ambulance is delayed, particularly when responding to an emergency involving a traffic collision [5]. Each second is crucial to human life since more casualties might result if the ambulance doesn't arrive at the collision scene in the crucial hour. Because of the heavy traffic and unique structure of each large city, it is crucial to determine the ideal locations for emergency responders to be stationed throughout the day as they wait to be called. The inexperience with

emergency response system placement makes monitoring and managing these fatal incidents much more challenging. As a result, rapid, automated, and efficient ambulance placement may help physicians and first responders by lowering their workload and allowing for early treatment choices.

These days, technologies like deep learning and machine learning have consistently shown themselves to be a strong and common method to make decisions, particularly when it comes to medical services. Many road safety issues have benefited from the introduction of these technology, and our problem statement also highlights their value. As the ultimate aim of improving Health Care Output (HCO), it is imperative that all patients be healed and that traffic accident casualties be eliminated. Because clustering techniques guarantee ideal positions based on distance metrics and because each centroid's coordinates are the means of the coordinates of the items in the cluster, this work treats the optimum placing of the ambulance (paramedic assistance) as a clustering issue [6]. All types of clustering issues are outside the scope of traditional machine learning techniques like k-means clustering, PAM clustering, agglomerative clustering, etc. [7]. This leads to the development of a unique deep learning-based approach that may be used to improve the performance of this procedure.

In order to solve the issue of the best ambulance placement in a city, we provide a unique clustering-based method in this work that makes use of Deep Embedded Clustering with Auto encoder (DEC-AE). In contrast to conventional clustering

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approaches, the DEC-AE method provides a thorough framework that optimises ambulance location tactics by combining deep learning, clustering, and auto encoder techniques [23]. DEC can efficiently capture the key characteristics and dimensions that influence the clustering process by recreating the input data from the learnt latent representations. Additionally, DEC uses a combined optimisation goal [24] that combines feature learning with clustering assignments. The creation of compact, well-separated clusters in the latent space and the improvement of cluster separate ability are made easier by this simultaneous optimisation. To effectively address clustering issues, DEC-AC integrates adaptive clustering and deep learning [25]. The number of clusters is adaptively determined by the data distribution and uses deep neural networks to develop meaningful feature representations.

DEC is also scalable and capable of managing enormous datasets, which makes it appropriate for real-world applications involving complicated and high-dimensional data. This makes it possible to comprehend the variables affecting the best ambulance placement with more precision and detail. Clustering methods are also included into the DEC-AE methodology, which makes it easier to find groupings of related patterns in the data [25]. This helps with the strategic deployment of ambulances to reduce response times and maximise coverage by enabling the identification of hotspot locations with greater accident probability or particular risk profiles. This approach may also be able to handle a variety of data

sources, such as information on traffic accidents, the features of individual road segments, meteorological conditions, and other pertinent variables. The method may provide a comprehensive perspective of the issue by taking into account several data aspects, improving the accuracy and efficacy of ambulance placement tactics.

The dataset contains facts on Nairobi, Kenya's weather, road segment statistics, and traffic accident data. The study finds potential characteristics and qualities influencing the number of accidents and risk patterns around the city by doing exploratory data analysis on the road survey and meteorological datasets. When converting categorical characteristics during the data pre-processing step, we use a deep learning-based embedding technique called Cat2Vec to maintain these correlations and patterns in the data. A new Distance Scoring Algorithm is used to determine the distance between the collision site and the closest ambulance sites anticipated in order to verify the predicted locations using DEC. Various clustering metrics have been used and contrasted with other conventional clustering algorithms in order to better assess the technique.

The following elements are covered by the methods suggested in this paper:

- The real-time accident dataset is subjected to exploratory data analysis (EDA), which identifies probable characteristics and variables that may lead to accidents and trends across the city.
- Using the Cat2Vec deep learning-based embedding technique, which enables more accurate clustering, a clustering-based method utilising Deep Embedded Clustering

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(DEC) is developed to identify the best ambulance positioning locations throughout Nairobi while maintaining the feature relationships and patterns.

- To verify the DEC model, a new Distance Scoring technique is created that determines the distance between the collision scene and the closest anticipated ambulance location, offering a numerical indicator of efficacy.
- The efficiency of the DEC model is further confirmed by comparing the performance of the suggested framework with and without feature selection strategies and with other clustering methods utilising a variety of clustering metrics.

II. LITERATURE SURVEY

Geneva, Switzerland: World Health Organisation, "Global Status Report on Road Safety."

The World Health Organisation has published the Global Status Report on Road Safety, the first comprehensive evaluation that uses data from a structured survey to characterise the state of road safety in 178 nations. At the international level, the findings may be seen as a "baseline" against which advancements at the regional and global levels can be evaluated. At the national level, the results provide a standard by which nations can evaluate their road safety standing in comparison to other nations. An expert group of road safety practitioners and researchers was consulted in the development of the survey's questions. A self-administered questionnaire was used to gather data; its content was based on the 2004 World Report on Road Traffic Injury Prevention, which was created by the World Bank, WHO, and several other partners. In order to find up to seven more national road

safety experts from various sectors who could fill out the questionnaire, the process used in each country required identifying a National Data Coordinator. Everyone then attended a meeting to reach an agreement.

T. Sivakumar and R. Krishnaraj, "Drinken driving-related traffic incidents in India: obstacles to prevention

Road traffic fatalities are a worldwide health pandemic that has reached crisis proportions, making roads the leading cause of death for youths over the age of 10. Road safety is one of the biggest development concerns in the world, according to the Safe and Sustainable Roads study released by the Campaign for Global Road Safety. It also projects that, if immediate action is not done, the number of persons killed in traffic accidents would increase from 1.3 million to 2 million annually. Currently, 50 million people are wounded annually on the world's roadways, and 3,500 people lose their lives in traffic-related events every day. About 33% of all incidents happen on national highways, and drivers are at fault in more than 78.8% of them, according to the Ministry of Road Transport and Highways. Furthermore, the economies of countries are severely impacted by catastrophic mishaps. A number of factors contribute to India's accident problem, including a preponderance of inadequate safety management strategies, poor placement of traffic control devices, roadside hazards, ribbon development along the highway network, low levels of safety awareness and education, and a weak willingness on the part of road users to change their attitudes. With the cooperation of the National Highways Authority of India, General

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Insurance Council of India, GMR, STPL, and HMRI, the current study aims to investigate and collect the impact and aftereffects of the Pilot Project on road safety on the section of National Highway No. 65 between Hyderabad and Vijayawada in the States of Andhra Pradesh and Telangana that was experiencing a higher number of accidents, particularly fatal ones.

"The significance of a road accident data system and its utilisation," by C. Baguley

This article provides a quick review of the current road accident mortality statistics of developing nations based on TRL's almost three decades of experience and international road safety research program. It covers concerning patterns, underreporting, socioeconomic factors in traffic accidents, and standard procedures for enhancing safety. But because traffic accidents are the primary indicator of safety, its primary emphasis is on the significance of building a trustworthy database and analytic system. Therefore, having access to the information is crucial for pinpointing particular safety issues and assessing how well any new policies are working. The most crucial information for accident reporting is included, along with many analysis system examples.

P. M. Heda, M. Khayesi, and W. Otero, "Kenyan road traffic injuries: extent, causes, and intervention status

The economic and health care systems of Kenya are severely impacted by road accidents. The initiatives in place now are inconsistent, disorganised, and ineffectual. A descriptive study of secondary data gathered from several published and unpublished studies is provided in this

paper. Every year, more than 3,000 people are murdered on Kenyan roadways. Over the last 30 years, the number of traffic deaths has increased fourfold. Young people who are economically productive make up over 75% of road traffic fatalities. Eighty percent of the fatalities are pedestrians and passengers, making them the most susceptible. The two vehicles most often involved in deadly collisions are buses and matatus. Crash characteristics differ significantly between urban and rural settings: most fatalities occur on intercity routes that cross rural regions, whereas pedestrians are more likely to be killed in urban areas. Interventions in road safety have had no discernible effect in lowering the frequency, severity, or repercussions of traffic accidents. Kenya has seen a sharp rise in traffic accidents, but not much has been done to create and apply efficient solutions. The prevention and management of traffic injuries are hampered by poor coordination, a lack of funding and skilled workers, and a restricted ability to carry out and oversee initiatives. To assist identify traffic injuries as a priority public health issue, educate policymakers on current, efficient countermeasures, and mobilise resources for implementation, it is necessary to enhance the collection and accessibility of correct data. To solve the issue, it would be ideal to create a strong lead agency and build coalitions of interested parties.

III. SYSTEM ANALYSIS AND DESIGN

EXISTING SYSTEM

Gaussian Mixture models and SVM were used by Assi et al. [8] and Xiong et al. [27] to propose machine learning models for

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predicting accident vs. non-accident patterns at collision sites. By grouping the accidents using fuzzy c-means, feed forward neural networks, and SVM, they were also able to predict the severity of the crash injuries. To find the attributes from the accident locations that would serve as inputs for the machine learning models, data analysis was done. Precision, sensitivity, and accuracy were used to assess the models. When comparing the models, the fuzzy c-means method outperformed the SVM and conventional k-means clustering models in terms of accuracy.

In order to determine the risk variables that lead to fatal traffic accidents, Ghandour et al. [9] and Tiwari et al. [10] created a machine learning hybrid ensemble classifier that is derived from decision trees and the MSO method. They made use of 8482 incidents and the deaths that resulted from them from the Lebanese Road Accident Platform (LARP) dataset. They conducted sensitivity analysis of the characteristics to assess the influence of the causes causing casualties in a traffic collision. Seven out of nine factors that were chosen had a significant correlation with casualties. The F1 score, precision, AUC-PR curve, and Cohen's Kappa were the metrics used to assess the model's performance. Using a multivariate regression model, Granberg et al. [11] created a simulation-based prediction model to estimate the demand for emergency ambulances in a region.

The information utilised in their genetic regression technique came from a 2005 census survey that included 2076 local regions. Using R-statistics software, a distance matrix was created for each site and

fed into a genetic algorithm to find 35 likely ambulance spots. A substantial R^2 value of 0.71 with numerous coefficients was preferred by the suggested model. When compared to models that used conventional forecasting methodologies, this specific distance matrix-based approach produced superior outcomes. In machine learning, clustering has been investigated in relation to distance functions, cluster validations, and feature selection algorithms [12], [13], and [14].

K-means and Gaussian mixture models are derivatives of the widely used clustering techniques. Although the distance function technique was created earlier, large dimensionality and dataset size restrict its use and popularity. Methods based on batch clustering, fuzzy c-means clustering, and K-means clustering with a FNMF matrix for clustering displaying the correlation patterns of the original data points were suggested by Cao et al. [16] and Moriya et al. [17]. In both methods, the correlation between the crash sites is determined, and then the crash sites are clustered according to the reasons that caused the incidents.

Alkheder et al. [18] suggested a method that uses Naïve Bayes, MLP, and decision tree classifiers to determine the important characteristics that affect the estimation of a traffic accident's severity. It was determined that the decision tree classifier had a higher classification accuracy of 0.08218 after evaluating several models. The characteristics that were more important in determining the severity of the accident were the year of the accident, age, gender, country, and kind of accident.

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Decision trees and genetic algorithms were used by Hashmienejad et al. [19] to create a prediction model for estimating the severity of traffic accidents. Using the test dataset, the set of rules generated by the genetic algorithm technique were also supplied as input to the CART, C4.5, and ID3 decision tree models. The utilised approach outperformed the alternative methods, ANN, SVM, KNN, and Naïve Bayes, with accuracy of 0.8820, recall of 0.889, f-measure of 0.887, and precision of 0.885.

Bayesian networks (BN) techniques were used by Ghosh et al. [20] and Sasaki et al. [21] to create models based on the connection of the characteristics, which were represented as probability distributions. Both determining the causes of traffic accidents and forecasting their severity are accomplished using Bayesian networks. These studies assessed the performance of BSVR by evaluating the models' sensitivity and specificity in addition to MAE and RMSE. To forecast the severity of traffic accidents, Taamneh et al. [22] used Artificial Neural Networks (ANN) in conjunction with K-means. The accuracy of the suggested ANN model was also compared to other machine learning models, and it was found that the proposed model had a superior accuracy of 0.746.

Auto-encoders were employed by Dizaji et al. [23] and Tian et al. [24] to lower the dimensionality in order to acquire the characteristics that had the greatest influence on clustering. Kmeans is used to cluster the features into groups after dimensionality reduction. The method uses auto encoders to get a representational structure of the locations, then adds the Kmeans layer on top

of the encoder layer to get the final model, ignoring the decoder section to get a smooth model. Prior to feature selection and cluster creation, this method maps the data points in feature space using a deep neural network; nevertheless, the objectives of these two distinct processes are not optimised in tandem.

DISADVANTAGES

- **Data complexity:** In order to identify ambulance positioning, the majority of machine learning models currently in use need to be able to properly comprehend huge and complicated information.
- **Data availability:** In order to provide precise predictions, the majority of machine learning models need a lot of data. The accuracy of the model may degrade if data is not accessible in large enough amounts.
- **Inaccurate labelling:** The accuracy of the machine learning models that are now in use depends on how well the input dataset was used for training. Inaccurate labelling of the data prevents the model from producing reliable predictions.

PROPOSED SYSTEM

The dataset contains facts on Nairobi, Kenya's weather, road segment statistics, and traffic accident data. The study finds potential characteristics and qualities influencing the number of accidents and risk patterns around the city by doing exploratory data analysis on the road survey and meteorological datasets. When converting categorical characteristics during the data pre-processing step, we use a deep learning-based embedding technique called Cat2Vec to maintain these correlations and patterns in the data. A new Distance Scoring Algorithm is used to determine the

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distance between the collision site and the closest ambulance sites anticipated in order to verify the predicted locations using DEC. Various clustering metrics have been used and contrasted with other conventional clustering algorithms in order to better assess the technique.

- The real-time accident dataset is subjected to exploratory data analysis (EDA), which identifies probable characteristics and variables that may lead to accidents and trends across the city.

- Using the Cat2Vec deep learning-based embedding methodology, which enables more accurate clustering, a clustering-based method using Deep Embedded Clustering (DEC) is created to discover the best ambulance placing sites around Nairobi while maintaining the feature correlations and patterns.

- To verify the DEC model, a new Distance Scoring technique is created that determines the distance between the collision scene and the closest anticipated ambulance location, offering a numerical indicator of efficacy.

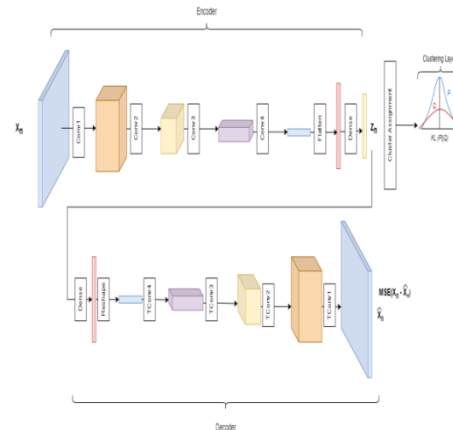
- The efficiency of the DEC model is further confirmed by comparing the performance of the suggested framework with and without feature selection strategies and with other clustering methods utilising a variety of clustering metrics.

ADVANTAGES

The suggested method uses Deep Embedded Clustering (DEC) to automatically arrange paramedic assistance utilising an appropriate ambulance location framework. This study uses Cat2vec, a deep learning-based model, to represent high cardinality categorical variables using low-dimension embedding while maintaining the relationships and

patterns found through exploratory data analysis between each of the categories. This improves the classification accuracy. K-fold cross-validation is used in this research to separate the dataset into training and test sets.

IV. SYSTEM ARCHITECTURE



V. SYSTEM IMPLEMENTATION

Modules

Service Provider

The Service Provider must use a working user name and password to log in to this module. He may do many tasks after successfully logging in, including Train & Test Data Sets, See the Accuracy of Trained and Tested Datasets in a Bar Chart View Accuracy Results for Trained and Tested Datasets, Download Predicted Data Sets, View Cyber Attack Prediction Status Ratio, and View Cyber Attack Prediction Status. See the results of the Cyber Attack Prediction Status Ratio. See Every Remote User.

View and Authorize Users

The administrator may see a list of all registered users in this module. Here, the administrator may see the user's information, like name, email, and address, and they can also grant the user permissions.

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Remote User

A total of n users are present in this module. Before beginning any actions, the user needs register. Following registration, the user's information will be entered into the database. Following a successful registration, he must use his password and authorised user name to log in. Following a successful login, the user may do tasks including registering and logging in, predicting the status of cyberattacks, and seeing their profile.

VI. SCREEN SHOTS



View All Ambulance Positioning Prediction Type II

Accident Type	Accident Severity	Accident Location	Accident Time	Accident Date	Accident Status	Accident Type	Accident Severity	Accident Location	Accident Time	Accident Date	Accident Status
Other	No distancing	Slight injury	Yes	Yes	41.20041015	-23.42040392	No	Position			
Big straight	Getting off the vehicle improperly	Slight injury	No	No	41.073752	-23.51092087	Not In	Position			
U-Turn	No priority to vehicle	Slight injury	No	No	41.20019005	-23.25250000	Not In	Position			



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VII. CONCLUSION

Over the last 20 years, methods for identifying accident hotspots and determining the optimal paramedic placements have evolved and are now essential to the successful implementation of traffic safety management programs. This research aimed to develop and assess algorithms for predicting the optimal locations for ambulance placement in Nairobi using the 2018–2019 Nairobi accidents dataset. The final model used the Cat2Vec model to convert categorical data into numerical data in the form of embeddings for relevant categorical attributes. The optimum ambulance sites were found in the centroids of five clusters that were identified using a clustering-based approach after feature selection and data pretreatment. Common machine learning techniques including K-Means clustering, GMM, and agglomerative clustering were combined with Deep Embedded Clustering to achieve this. The clustering algorithms were evaluated using performance metrics such as the Davies Bouldin Score, Calinski-Harbasz score, V-measure, and Silhouette score. The distance between the centroid and the expected ambulance locations was measured using a brand-new scoring method called Distance Score. Of all the models that were built, the DEC-AE model with Cat2Vec embeddings achieved the highest accuracy of 95% in k-fold cross validation.

There is minimal difference between possible accident locations and ambulance placements, according to the DEC-AE model's distance score of 7.581, which is higher than that of traditional machine learning approaches. The analysis of the various clustering metrics previously addressed indicates that the proposed DEC-AE model consistently outperforms other models in terms of clustering performance. This result shows how well and consistently the DEC-AE model groups the data and finds underlying trends. The study will advise decision-makers on where to spend or implement security measures.

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