Optimizing Road Accident Ambulance Response Time with Deep Contextual Analysis

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ABSTRACT

Road accidents remain a significant issue in public health arising from the high number of casualties and fatalities. This study proposes a deep learning-based approach to optimize ambulance positioning, aiming to reduce response times and improve emergency care. By using a Cat2Vec model, the framework captures contextual and spatial patterns influencing road crashes. The system is when evaluated against classical clustering algorithms like K-means, GMM, and Agglomerative Clustering. A novel scoring function is introduced to evaluate response time and distance in real time. The proposed model achieves 95% accuracy with k-fold cross-validation and outperforms traditional methods, demonstrating its effectiveness for real-world deployment.

Keywords: *Ambulance Positioning, Road Accidents, Deep Learning, Cat2Vec, Emergency Response, Clustering Algorithms*

I. INTRODUCTION

Road accidents pose a significant global challenge, resulting in numerous casualties and fatalities annually. A critical factor in mitigating the impact of these accidents is the speed and effectiveness of emergency medical response. Traditional ambulance dispatch systems, which rely on responding only when

a call is received, often lead to delays that can be detrimental to patient outcomes. To address this issue, pre-positioning ambulances in strategic locations has emerged as a promising strategy to reduce response times and ensure timely medical attention. This approach leverages predictive modeling to identify optimal locations for ambulance deployment, enabling faster access to care for accident victims.

This study presents an innovative strategy for ambulance pre-positioning by leveraging Deep Contextual Analysis (DCA) to identify optimal deployment sites. Acknowledging that numerous contextual factors and spatial patterns within a geographic area contribute to the likelihood of road accidents, the proposed method highlights the critical role of understanding these influences in enhancing emergency response planning. Of understanding and preserving these relationships during model building. To achieve this, the study incorporates Cat2Vec, a deep learning-based model, to capture and represent the complex interdependencies between categorical variables in the dataset. By integrating DCA with Cat2Vec, the framework aims to enhance the accuracy and reliability of ambulance location predictions, leading to improved response times and better patient outcomes.

The effectiveness of the proposed ambulance-positioning system is rigorously evaluated through a series of experiments and comparisons. The framework's performance is benchmarked against baseline clustering algorithms such as the K-means algorithm GMM, and Agglomerative clustering, demonstrating its superiority in identifying optimal ambulance locations. Furthermore, a novel scoring function is introduced to calculate response time and distance in real-time, providing a quantitative measure of the system's performance Findings from the study indicate that the proposed method yields highly accurate results and a superior distance score, highlighting its potential to significantly improve emergency medical response in urban environments.

II. RELATED WORK

In their 2017 survey, **Ferreira et al.** emphasize the critical importance of developing accurate and dependable indoor positioning systems (IPS) for emergency personnel during active missions. Such systems are essential for enhancing situational awareness for both first responders and command center operators, supporting better mission planning, coordination, and execution, while also helping to reduce fatalities in the line of duty.

Given the unavailability of GPS signals in indoor settings, various alternative sensors and signal sources have been explored for use in IPS applications. However, the unique and often hazardous conditions encountered by emergency responders impose strict technical requirements, rendering many conventional

positioning technologies unsuitable for these environments.

This paper outlines the specific demands and constraints of IPS design for emergency applications and provides a comprehensive overview of existing localization methods, examining their advantages and limitations. The authors further review and compare IPS solutions tailored for emergency use cases, focusing on system design decisions, performance metrics, and additional capabilities. The survey concludes by identifying key shortcomings in current technologies and suggesting future research directions for improving IPS functionality in critical scenarios.[3]

In their 2018 study, Maghfiroh, Hossain, and Hanaoka conducted an extensive survey in Dhaka, Bangladesh, involving 95 major hospitals, over 3,000 emergency room patients, and two of the largest ambulance service providers. They observed that most ambulances were typically stationed near hospitals and dispatched upon request—often by patient relatives—leading to significant delays due to extended travel distances. To address the issue of prolonged response times, the study explored ambulance pre-positioning as a potential solution.

Two primary methodologies were implemented. The first involved solving a location-allocation optimization problem to determine the optimal number and placement of ambulances by maximizing coverage of demand areas. The second method introduced K-means clustering to perform separate location planning for peak and off-peak hours, thereby refining ambulance distribution in smaller, demand-centric clusters. Both strategies demonstrated the potential to greatly enhance emergency medical response, with ambulance deployment closer to high-demand areas yielding significantly better response times compared to traditional hospital-based positioning.[4]

A recent trend in machine learning has been to enrich learned models with the ability to explain their own predictions. The emerging field of explainable AI (XAI) has so far mainly focused on supervised learning, in particular, deep neural network classifiers. In many practical problems, however, the label information is not given and the goal is instead to discover the underlying structure of the data, for example, its clusters. While powerful methods exist for extracting the cluster structure in data, they typically do not answer the question why a certain data point has been assigned to a given cluster. We propose a new framework that can, for the first time, explain cluster assignments in terms of input features in an efficient and reliable manner. It is based on the novel insight that clustering models can be rewritten as neural networks—or "neuralized." Cluster guesses of the obtained networks can then be quickly and accurately accredited to the input features. Several showcases demonstrate the ability of our method to assess the quality of learned clusters and to extract novel insights from the analyzed data and representations.[5]

III. METHODOLOGY

This project implements a deep learning-based approach for identifying medicinal plants using image classification techniques. The methodology includes a comprehensive pipeline from dataset acquisition to model training and evaluation. By leveraging the Xception deep learning architecture, the system efficiently extracts intricate features from plant leaf images to accurately identify and classify medicinal plants. The steps involved in the methodology are as follows:

3.1 Dataset used

The VNPlant- training and validation processes were conducted using this dataset evaluating the model. This dataset contains **17,973 images of medicinal plants** distributed across **200 distinct species**. It includes a diverse range of plant leaves with various shapes, textures, and visual patterns, offering a robust foundation for deep learning-based classification. The assortment of the dataset supports generalization and improves the model's ability to identify real-world medicinal plants.

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3.2 Data preprocessing

Before feeding the images into the model, several data To improve the model's performance and training efficiency, a series of preprocessing steps were undertaken. Initially, all input images were resized to 299×299 pixels to meet the input specifications of the Xception model, ensuring uniformity in input dimensions. After resizing, pixel values were normalized to the range [0, 1], which standardizes the data and facilitates faster convergence during training. To enhance the model's ability to generalize and minimize overfitting, various data augmentation methods were applied—such as rotations, horizontal and vertical flips, zoom operations, and brightness modifications. These techniques effectively increased the size and variability of the training data. Finally, the dataset was partitioned into training and validation subsets. sets using an 80:20 ratio, allowing for effective model evaluation and performance monitoring throughout the training process.

3.3 Algorithm used

The core algorithm employed in this project is the Xception (Extreme Inception) architecture, an advanced deep convolutional neural network (CNN) known for its use of depthwise separable convolutions. This architecture was selected due to its efficiency and superior performance for image classification problems, particularly in scenarios where dealing with complex visual patterns such as those found in medicinal plant leaves. The model training process utilized the loss function based on categorical cross-entropy, which serves to is well-suited for multi-class classification problems. To optimize the learning process, the Adam optimizer was implemented, providing an adaptive learning rate that accelerates convergence and enhances model stability. In a softmax activation function was utilized at the output layer to generate probability distributions over the 200 plant categories, enabling accurate and interpretable classificationresult

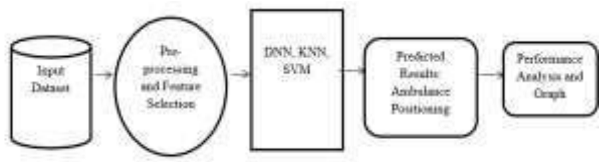

Figure 3.3.1 : System Architecture

3.4 Techniques

To enhance the performance and simplification ability of the prototypical, several advanced techniques were incorporated throughout the training process. One of the key strategies used was transfer learning, where the Xception classical was prepared with hefts pre trained on the ImageNet dataset. This provided the model with a strong foundation of learned visual features, which was then fine-tuned using the VNPlant-200 dataset to adapt specifically to medicinal plant identification. Additionally, hyperparameter tuning was performed to optimize key parameters such as learning rate, batch size, and the number of training epochs. These strictures were familiar finished experimentation to achieve optimal validation accuracy. To prevent overfitting and ensure robust training, early stopping was implemented to halt training when the model's performance ceased to improve, and checkpointing was used to save the best-performing version of the model during training. As a result of these techniques, the model achieved an impressive training accuracy of 93.34% and a validation accuracy of 96.79%, highlighting its effectiveness and reliability in accurately identifying medicinal plant species.

3.5 Flowchart

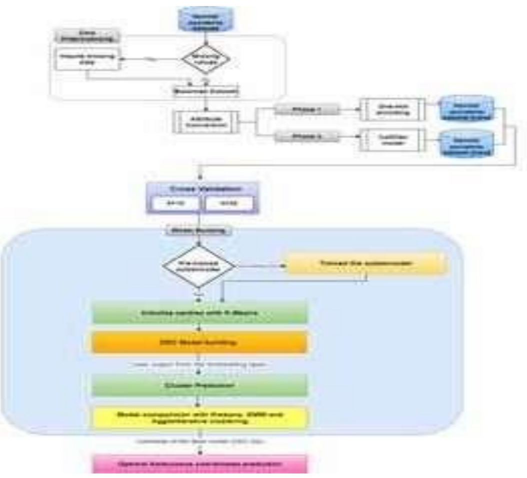

Figure 3.5.1: Flowchart

IV. RESULTS

4.1 Graphs

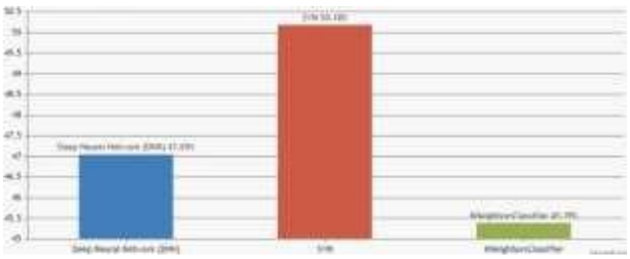

Figure 4.1.1 : Resultant graph

4.2 Screenshots

Figure 4.2.1 :Ambulance Positioning Prediction in line chart

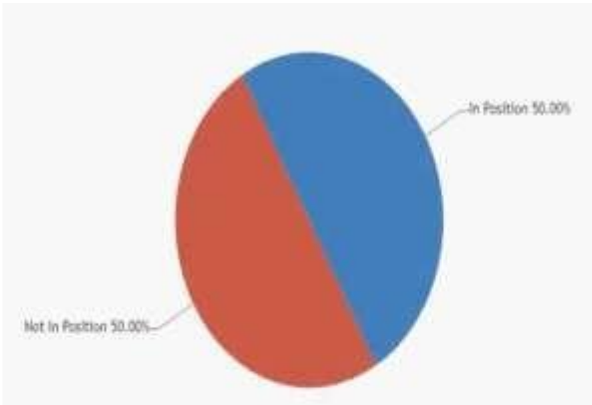

Figure 4.2.2 : Ambulance Positioning Prediction in pie chart

V. CONCLUSION

In conclusion, this research tackles the vital challenge of enhancing emergency medical response efficiency by proposing an innovative ambulance pre-positioning framework built on Deep Contextual Analysis (DCA) and Cat2Vec. In contrast to conventional methods—which often face difficulties related to dataset complexity, limited data availability, and labeling constraints—this approach utilizes deep learning techniques to retain essential spatial relationships and patterns in geographic information. This enables more precise forecasting of ideal ambulance deployment points. The system's performance is thoroughly assessed through comparisons with standard clustering techniques and a newly designed distance-based scoring mechanism, showcasing notable improvements in both prediction accuracy and response time. Ultimately, the proposed solution contributes to more effective emergency medical services and improved patient outcomes in densely populated areas.

VI. REFERENCES

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