Deep Learning-Powered Route Optimization: A GIS-Based Approach using Modified Faster R-CNN

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Abstract

Nowadays vehicles are being used a lot and different types of vehicles come at a time. Many vehicles running at a time leads to collisions and many people are dying in accidents. Pollution and high speed vehicles are running in cities and due to this more than 1.25 million people are dying every year as a result of road traffic accidents globally. Even after that no such technology has been available which gives recommendations in real time to prevent accidents. But my system is providing a good solution to this problem which detects the collision of traffic vehicles and provides collision free route. The aim of my research paper is to solve this challenge by developing an optimal recommendation model on top of a geographic information system in which collision free route is provided using advanced planning techniques. Urban transportation systems face significant challenges due to traffic congestion and accident-prone zones, leading to increased delays, environmental pollution, and safety concerns. Traditional methods often fall short in delivering real-time, congestion-minimized route recommendations and typically do not integrate accident zone detection with traffic management. To overcome these limitations, this study introduces GINSER—a Geographic Information System (GIS)-based optimal route recommendation model powered by advanced deep learning techniques. The main goals of the GINSER framework include identifying accident-prone areas, classifying traffic congestion levels, and recommending efficient travel routes using GIS analysis. CCTV footage is used as the primary input, with image quality enhanced through an Adaptive Gaussian Bilateral Filter (AGBF) for noise reduction. A Faster R-CNN model is employed for object detection and localization within high-risk zones,
while Particle Swarm Optimization (PSO) fine-tunes hyper parameters to boost detection accuracy. To classify traffic congestion into four
categories—low, moderate, high, and congestion-free—a CNN-BiGRU architecture is utilized. GIS further processes spatial and traffic data to suggest the most efficient, congestion-free routes. The model's performance was evaluated using metrics
such as F1 score, accuracy, precision, recall, and specificity, confirming the effectiveness of the proposed GINSER system. The noise-free images using AGBF effectively enhances image quality by reducing noise leading to improved classification accuracy.

PSO is utilized for hyperparameter tuning achieving a high accuracy of 98.24%. The GINSER model achieved a classification accuracy of 99.16%. The GINSER improved overall accuracy by 4.90%, 6.83%, 5.23%, and 0.83% better than TSANet, TCEVis, Ising-traffic, and AID, respectively. Its ability to detect accident prone zones classify congestion levels and recommend optimal routes ensures safer and more efficient mobility.

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Keywords
Urban transportation, Traffic classification, Deep learning, traffic congestion , R-CNN.

1.Introduction

According to the World Health Organization's (WHO) data sheet, traffic accidents claim the lives of about 1.25 million people annually. Nearly 400,000 people under the age of 25 lose their lives on the world's roads every year, with over 1000 deaths occurring every day on average.[1Areas on road networks that have a high number of traffic accidents due to things like bad road conditions, insufficient signs, a high vehicle density, and reckless driving are known as accident-prone zones. [2]Every year, 50 million nonfatal injuries occur around the world [3]. These disturbing statistics illustrate Jason GU was the assistant editor who coordinated the evaluation of this manuscript and approved it for publication. 59134 There is a pressing demand for improved traffic management technologies to promote safety and efficiency in urban transportation networks. The introduction of intelligent transportation systems has resulted in a desire for intelligent transportation systems capable of detecting and tracking diverse items, such as vehicles, motorbikes, and buses [4].Congestion lengthens travel times, increases fuel consumption, and contributes to environmental pollution. Smart traffic control systems make use of technology such as IoT, AI, and machine learning. It improves traffic flow by analyzing patterns and forecasting congestion in real time [5]. Deep learning algorithms are critical for detecting accident-prone zones by analyzing massive volumes of traffic and accident data. By utilizing CNN [6]. To anticipate high-risk zones, RNN and deep learning models use data from past accidents, traffic patterns, weather, and road systems [7]. Deep learning is critical for lowering traffic congestion in addition to accident prediction, and optimization algorithms are compared to contemporary optimization techniques [8].The necessity for real-time data processing, which is necessary to detect trends that result in accidents, limits the effectiveness of the current approaches [9]. Air quality, economic productivity, and urban mobility are all adversely affected by the widespread problem of traffic congestion [10, 11]. In order to manage the unpredictability of traffic flow, traffic congestion systems frequently rely on static solutions like preset routes or fixed traffic signal timings [12]. An intelligent, integrated system that integrates real-time accident detection, congestion classification, and optimal route suggestion is desperately needed, as these gaps demonstrate [13, 14]. The study intends to create the GINSER model using GIS, CNN-BiGRU for congestion classification, and optimized Faster R-CNN for accident-prone zone detection in order to determine the best recommended route. The CNN-BiGRU model was used in the suggested method to classify traffic in real-time into four levels: low, moderate, high, and congestion-free.The most effective and traffic-free routes are produced by GIS route analysis, which examines spatial data and traffic patterns. In places that are prone to accidents, PSO is utilized to hypertune the detection and localization accuracy of objects.

2.Literature Review

Many machine learning and deep learning-based studies have been published in recent years to reduce traffic congestion. This section examines significant advancements in congestion reduction, emphasizing data-driven methodologies and creative control schemes. The following paragraphs provide a list of related studies, with a focus on those that use data from traffic congestion minimization.

Prediction by Abadi et al. (2015) Experts in the field of traffic flow analysis and planning can benefit from traffic

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prediction to better manage traffic congestion by examining the spatial and temporal fluctuations in traffic flow [15]. Both historical flow data and flow uncertainty were taken into account when they created an autoregressive model. This effort was limited, nonetheless, by the lack of data to perform further testing in incident and normal traffic conditions. When forecasting traffic, special attention was paid to the complex temporal and spatial correlations included in traffic data. [16]. Zhang et al. (2021) acknowledged the shortcomings of GCN in capturing the changing spatial correlations within the road network and developed a novel model called the Evolving Temporal Graph Convolutional Network (ETGCN). Within a road network, this model sought to forecast traffic speeds by learning the spatial temporal correlations and their fluctuating states. In 2021, Li and Lasenby. In order to shed light on the XGBoost model and examine how road and environmental elements affect accident severity, Li et al. (2022) created SHAP values. In order to assess the reliability of the elements influencing road travel and plan for future development, Ji et al. (2022) used the SHAP model to calculate the SHAP values of these components. Beyond the capabilities of conventional geographical statistical models, Li (2022) machine learning models can take the role of spatial statistical models, particularly when handling complex geographic and non-spatial aspects. the clustered SHAP approach for assessing a variety of firm capacities, such as profitability and liquidity, among others (Lin and Gao, 2022). A framework was created by Zhang et al. (2023) to explain the landslide sensitivity assessment models using the SHAP-XGBoost algorithm [18]. In 2024 Dong et al. [18] introduced a machine learning-based visual analytics system to study factors influencing traffic congestion. With the multifaceted nature of these components, it is difficult to graphically depict their combined impact. Multi-level investigation of road conditions is made possible by this interactive visual analytics solution.

In 2024, Kumar et al. [19] proposed the traffic conditions to gauge patterns of congestion in situations when there are no lanes. The spatiotemporal distribution of nearby road users, such as cars and motorcycles, defines each traffic state. To record the spatial distribution of nearby road users, we use traffic graphs. The effectiveness of TSANet in accurately predicting traffic conditions across various spatial locations within an intersection is demonstrated by experimental findings on the EoT dataset.

In 2023 Mishra et al. [19] introduced a visual alert of AP features to drivers using dashcam-captured real-time images. On top of several CNN backbones, the proposed module makes use of attention learning via channel, point, and spatial means. The suggested module's categorization accuracy can reach up to 92%. This method has limited scalability for larger traffic networks and requires high computational resources. The experimental result of the suggested module can classify data with an accuracy of up to 92%. In 2024, Kannan [20] introduced to use of GPS and GIS technology to analyze spatial patterns of road accidents, identify high-risk zones, and suggest targeted preventive measures in Thanjavur, Tamil Nadu, India. The analysis of traffic accidents is done by police station, vehicle type, time, road, etc. To take the proper precautions to prevent accidents in high-risk locations, an effort is also designed to identify the zones that are most important. This model relies heavily on the availability of accurate spatial data. In 2024 ElSahly and Abdelfatah [21] introduced the ML-based Traffic Safety for Automatic Incident Detec tion System. A traffic simulation program is used to produce realistic, varied traffic data that takes into account variables that have a big influence on AID performance. 0.89 min

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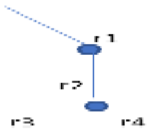
for the (MTTD), 1.01% for the false alarm rate (FAR), and a detection rate (DR) of 95.6% are obtained from the suggested training. This computation ally intensive requires robust simulation environments. In 2024 Kim et al. [22] introduced pilot zones to confirm the safety of autonomous vehicles (AVs) utilizing data for traffic accidents.



The technique uses a CNN + BiGRU model that was trained using DMV dataset data to determine whether traffic accidents were caused by AVs or humans. Accuracy, Recall, accuracy, and F1 score were used to evaluate the model's classification accuracy; the results showed that it achieved 95.03%, 97.8%, 98.9%, and 99.5%, respectively. Table 1 presents a comparative literature review of existing traffic analysis methods highlighting their proposed techniques, advantages, and limitations. In the literature review, these existing techniques have several drawbacks like high false positives and limited training data due to the rarity of traffic congestion. Additionally, these existing routes often fail to provide real time recommendations for minimizing congestion, leaving travelers, and planners with suboptimal solutions. To overcome these challenges, a novel GINSER was introduced for optimal route recommendation using a geographic information system.

3.Proposed Methodology

Several datasets were used in this study; they were cleaned and spatial and data analysis techniques were applied to analyze crash rates, predict likelihood of road accidents, optimize streets, and find the safest and fastest route between a source and destination in a road network.

This study introduces an innovative GINSER model designed for optimal route recommendations utilizing Geographic Information Systems (GIS). The input images undergo enhanced through Adaptive Gaussian Blur Filtering (AGBF) to improve their quality This initial phase guarantees that the subsequent detection and classification models function on high-quality data, thereby reducing false positives and enhancing detection accuracy. The pre-processing of data is essential in preparing data for spatial analysis and machine learning algorithms. According to many re searchers, crash data is the most objective and trustworthy safety data commonly used for road safety analysis, as it is the most reliable indi cator of road safety. The pre-processed images are then analysed using Faster R-CNN, which efficiently detects and localizes objects by integrating region proposals. The Region Proposal Network (RPN) generates bounding boxes around regions of interest (ROI), which are further refined by a bounding box regressed for accurate localization. The hyper parameters of Faster R-CNN are fine-tuned using Particle Swarm Optimization (PSO) to ensure robust detection performance. Additionally, CNN-BiGRU is employed to evaluate the detected regions, merging spatial feature extraction through CNN with temporal dependency analysis. This model categorizes traffic congestion levels into four distinct classes: low, moderate, high, and congestion-free. The outputs from both Faster R-CNN and CNN-BiGRU are subsequently integrated into the GIS module, which synthesizes spatial data and traffic patterns to recommend optimal routes, particularly in areas prone to accidents and varying congestion levels.

3.1 Dataset Used Description

Its Open-source geospatial dataset that provides
global geographic data, such as buildings, roads, landmarks, and natural elements.

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This is used to analyse road networks in Indian cities for identifying traffic congestion hotspots and accident-zones. By spatial data on road infrastructure, traffic density, and historical accident records, the study identifies critical areas where congestion and accidents frequently occur. data offers comprehensive details on traffic f low, intersections, and route layouts and land use, which are analyzed using GIS-based techniques like spatial overlay, heat maps, and network analysis. This approach helps urban plan ners and traffic authorities prioritize interventions, such as road redesign, signal optimization, and infrastructure improvements to lessen traffic congestion and improve road.

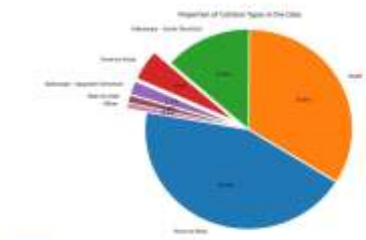


FIGURE 1. Percentage distribution of different types of collision.

the traffic data in the main urban area of Guiyang city are used to study the urban traffic congestion zoning boundary problem. In recent years, the urbanization process of Guiyang city has been promoted and, according to the data, the urbanization rate has reached more than 80%; with the number of motor vehicles reaching more than 5 million, the traffic congestion in Guiyang city has been increasing.

Accidents

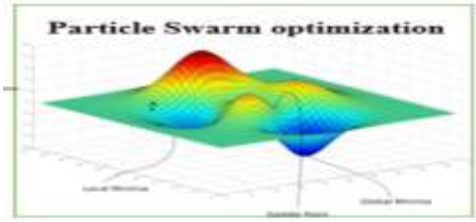
Figure 2. Pre-processed Traffic Image

Input – spatial data (S), Traffic Congestion level (T), Accident-prone zones(A), Real-time traffic images (I) from the user
Output-Recommended optimal routes(R) .
Pre-process the input images using AGBF for noise removal and enhance image quality.

$$P(\text{ Accident }) = \frac{e^{z_1}}{e^{z_1} + e^{z_2}}$$

$$P(\text{ No Accident }) = \frac{e^{z_2}}{e^{z_1} + e^{z_2}}$$

To detect accident- prone zones using Faster R-CNN Extract region proposals with patterns recognize from the images perform bounding box accurate object localization using equation.
To perform optimize Faster R-CNN hyperparameter tuning using particle swarm optimization



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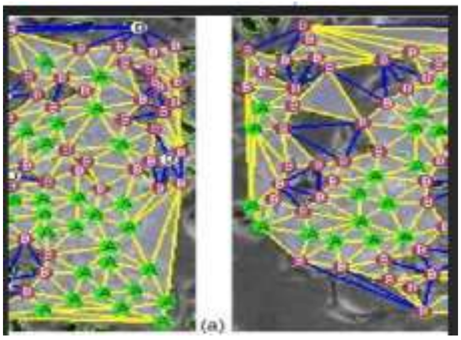
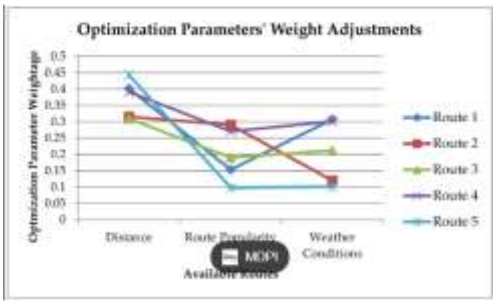


Evaluate fitness to minimize classification and regression losses

Classify the congestion level using CNN-BiGRU To integrate GIS for route analysis and recommendation Use GIS to analyse spatial data and recommend routes based on congestion level accident-prone zones. Recommended the Optimal routes



3.2 Pre-Processing

A bilateral filter is a highly efficient method for denoising digital images while preserving the edges and detail information based on geometric distances and intensity differences between adjacent pixels. Adaptive Gaussian Bilateral Filter (AGBF) is used for pre-processing to improve the image quality and remove noise.

$$G_s(p,q) = \exp\left(-\frac{\|p-q\|^2}{2\sigma_s^2}\right)$$

where (p, q) is the original pixel's coordinate in the image to be processed, ‖p − q‖ spatial distance between pixel p and q and s represent standard deviation controlling spatial influence.

3.3Object Detection Using Faster R-CNN

Now we present a detailed description of proposed method.

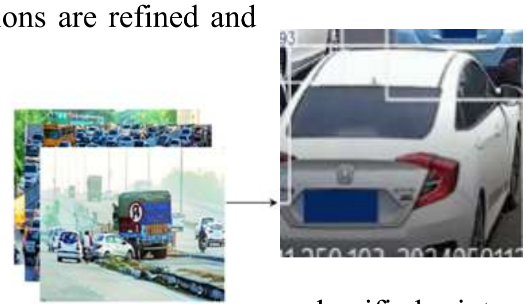
The method is highlighted considering four steps5 viz (a) minimization with adaptive background model (b) Faster R-CNN based subnet operation (c) Faster R-CNN initial refinement and (d) result optimization with extended topological active nets

$$pixel_j(y) = \overline{pixel}_{j-1}(y) + \frac{1}{GP_j\sqrt{2\pi\sigma^2}} \exp\left(\frac{-1}{2}\left(\frac{y-y_j}{\sigma}\right)^2\right)$$

Faster R-CNN is used

to detect and localize objects in accident prone zone areas. It builds upon its p redecessors, R-CNN and Faster R-CNN, by introducing the region proposal network (RPN), which significantly speeds up generating potential object regions.

The ConvNet extracts a rich feature map from the preprocessed image, which is then processed by the RPN to propose regions likely to contain objects. These regions are refined and



Pre-processed Input

classified into specific object categories through a softmax layer after a completely linked layer classification and a bounding box regressor for precise localization.

$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(p_i,p_i^*) + \lambda\frac{1}{N_{reg}}\sum_i p_i^* L_{reg}(t_i,t_i^*)$$

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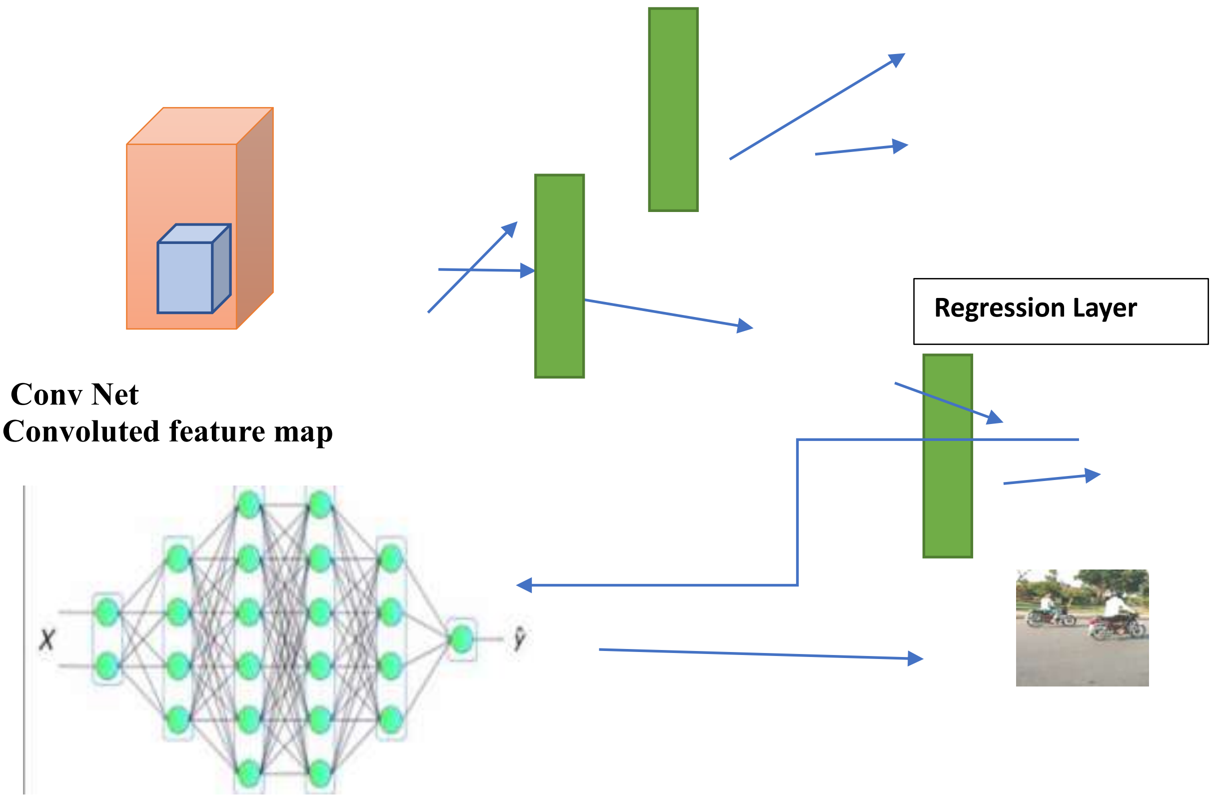

Conv Net
Convoluted feature map

Fully Connected Layer

3.4 Classification Using Cnn – Bigru

CNN is well-known for using convolutional layers to capture spatial hierarchy in data making them highly effective for feature extraction. The CNN-BiGRU model combines the strengths of CNN and bidirectional gated recurrent units (BiGRU) to process and analyze sequential data. BiGRU is a recurrent neural network (RNN) type that is intended to simulate sequential dependencies by processing data in both forward and backward directions. This combination leverages CNN ability to extract local patterns and BiGRU capability to capture temporal dependencies making it particularly suitable for tasks like text classification.

Detected Output

GINSER model struggle with the longest route changes due to evolving traffic conditions highlights the impor tance of incorporating real-time updates

3.5 Geographic Information System

GIS is a solid framework for collecting, managing, analyzing, and visualizing spatial and non-spatial data to understand geographic patterns and relationships. . GIS integrates geographic data, mapping, and spatial analysis algorithms to recommend the most efficient routes

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according on a number of factors, including time, distance, traffic, and environmental constraints. It provides an effective decision-making framework for urban planning, logistics, transportation systems, and emergency services by combining spatial databases, digital maps, and analytical models. Route recommendation in GIS involves solving shortest-path problems, where the goal is to identify the best route between a source and a destination. A network is modeled as a graph G(V, E) , where V is the set of vertices and E represents edges. Each edge eij E has a weight wij , representing cost metrics like distance travel time con sumption. The most commonly used mathematical model for route recommendation is the shortest path problem where the goal is to minimize the total cost.

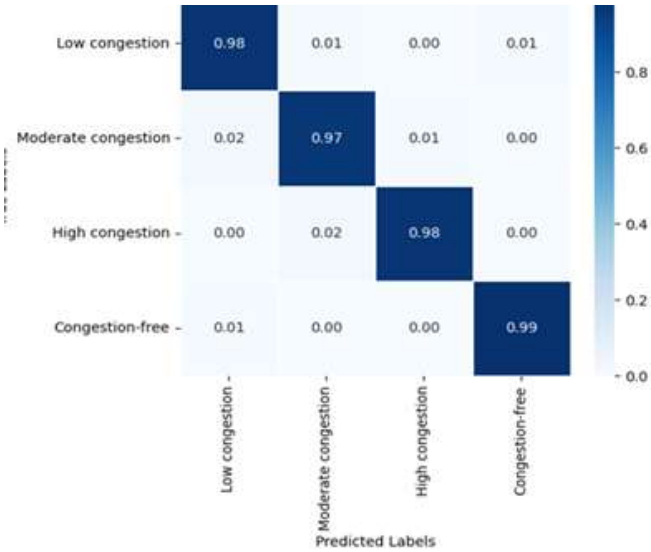
$$C = \sum_{i=1}^{n-1} w_{i,i+1}$$

4 Results

This Section utilizing sevel metrics like recall, specificity, accuracy, precision and F1 score, depending on the images sourced from the OpenStreetMap datasets. The results are critical zones, enabling targeted interventions to enhance road safety and reduce congestion. The user selected three key areas using CCTV cameras: Bhopal, Indore, Ujjain. These areas are analyzed to identify accident-prone zones and traffic congestion hotspots.

4.1.Performance Analysis

The proposed GINSER method was evaluated in this section utilizing several metrics, such as F1 score, recall, speci f icity, accuracy, and precision, on the gathered dataset. Using the mean average precision (mAP), the effectiveness of the proposed Faster R-CNN detection model was assessed.



4.2 Practical Implication

The user selects CCTV images of traffic conditions then processed by the GINSER model to analyze congestion levels. The proposed GINSER determines the best route and provides a congestion-free route recommendation. This technique leverages GIS-integrated features that complement traffic management operations making the model more accessible and applicable to real-world scenarios.

4.3Discussion

The GINSER model's classification accuracy of 99.16% indi cates remarkable dependability in detecting accident-prone zones and assessing traffic congestion levels. The metrics like accuracy, recall, and specificity ensure the system limit false positives and negatives, making it a dependable decision-making resource. For example, the high F1 score throughout congestion levels (99.84% for moderate congestion) demonstrates the model ability to provide fast and accurate recommendations during peak traffic hours or emergencies. Including PSO increases the model's accuracy to 95.24%, demonstrating its efficacy in decreasing computational losses and improving the performance of deep learning approaches such as Faster R-CNN and CNN-BiGRU.

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The GINSER model has essential real-world implications since its GIS-integrated frameworks enable dynamic and precise traffic manage ment. . Expanding the training datasets to include diverse geographic and demographic contexts will improve scalability and ensure broader applicability.

5. **Conclusion**

In this research work smart traffic management of vehicles is studied using Faster R-CNN based deep learning method. It is an intractable problem in computer vision and artificial intelligence domain. Input images are preproc essed using AGBF to remove noise and enhance images. In accident prone zone areas, PSO-based Faster RCNN is used to detect and localize objects. In the proposed model, CNN-BiGRU was used to classify congestion levels as low congestion, moderate congestion, The GINSER enhanced the total accuracy by 3.90%, 6.71%, 4.13%, and 0.70% better than TSANet, TCEVis, Ising-traffic, and AID respectively. In the GINSER model, external data such as IoT sensors or weather updates are not integrated, which limits its ability to adapt the route conditions. Finally, we conducted case studies using real cab trajectory data to demonstrate that the approach presented in this paper offered a more comprehensible explanation of the potential causes of traffic congestion. Considering these limitations, our future work would focus on refining the accident detection systems. This includes implementing advanced algorithms that can better discern between stationary obstacles and genuine accidents, 59146 as well as traffic patterns. These improvements aim to bolster the reliability and precision of traffic accident detection systems in a myriad of real-world scenarios.

6. References

[1] McKnight, A.J., McKnight, A.S., 2003. Young novice drivers: careless or clueless? Accid. Anal. Prev. 35 (6), 921–925. https://doi.org/10.1016/S0001-4575(02)00100-8. Ministry of Energy and Infrastructure (MOEI). 2023, February 16. Ministry Of Energy And Infrastructure Launches Smart Mobility Think Tank To Shape Future Mobility Trends And Inform Policies. MOEI Official Website.

[2] Alkaabi, K.: Identification of hotspot areas for traffic accidents and analyzing drivers' behaviors and road accidents. Transp. Res. Interdiscip. Perspect. 22, 100929 (2023).

[3] V. Adewopo, N. Elsayed, Z. Elsayed, M. Ozer, V. Wangia-Anderson, and A. Abdelgawad, "AI on the road: A comprehensive analysis of traffic accidents and accident detection system in smart cities," 2023, arXiv:2307.12128..

[4] V. Adewopo, N. Elsayed, Z. ElSayed, M. Ozer, A. Abdelgawad, and M. Bayoumi, "Review on action recognition for accident detection in smart city transportation systems," 2022, arXiv:2208.09588..

[5] Mestri, R.A., Rathod, R.R., Garg, R.D.: Identification and removal of accident-prone locations using spatial data mining. In: Applications of geomatics in civil engineering: select proceedings of ICGCE 2018, Springer, Singapore, 383–394 (2020).

[6] Geetha, A., Sobia, M.C., Santhi, D., Ahilan, A.: DEEP GD: deep learning based snapshot ensemble CNN with Efficient Net for glaucoma detection. Biomed. Signal Process. Control 100, 106989 (2025)

[7] Selvarajan, S.: A comprehensive study on modern optimization techniques for engineering applications. Artif. Intell. Rev.. Intell. Rev. 57(8), 194 (2024)

[8] Asha, M.B., Stebi, A.A.: Mass Robot: Predictive Maintenance Using Stacked CNN BI-LSTM for cleaning robots. Int. J. Data Sci. Artif. Intell. 02(05), 155–160 (2024) .

DOI: https://doi.org/10.5281/zenodo.18334656

[9] Dhipa, M., Singh, C.J.C., Michael Priya, E., Shunmugavadivoo, T.: Deep learning-based classification of lichens in Western Ghats using aerial images. Int. J. Comput. Eng. Optim. 02(01), 14–19 (2024)
[10] Arun, R., Muthu, B.K., Ahilan, A.: Deep vein thrombosis detection via combination of neural networks. Biomed. Signal Process. Control 100, 106972 (2025)
[11] Agoylo, J.C.: GIS-based traffic accident hotspot prediction using machine learning. Authorea (2024). https:// doi. org/ 10. 22541/au.173347433.37543456/v1.
[12] Chaudhuri, A.: Smart traffic management of vehicles using faster R-CNN based deep learning method. Sci. Rep. 14(1), 10357 (2024).
[13] Adewopo, V.A., Elsayed, N.: Smart city transportation: deep learning ensemble approach for traffic accident detection. IEEE Access. (2024). https://doi.org/10.1109/ACCESS.2024.3387972
[14] Zhao, X., Hu, L., Wang, X., Wu, J.: Study on identification and prevention of traffic congestion zones considering resilience-vulnerability of urban transportation systems. Sustainability 14(24), 16907 (2022).
[15] Abadi, A., Rajabioun, T., Ioannou, P.A., 2015. Traffic flow prediction for road transportation networks with limited traffic data. IEEE Trans. Intell. Transp. Syst. 16 (2), 653–662.
[16] Li, D., Lasenby, J., 2021. Spatiotemporal attention-based graph convolution network for segment-level traffic prediction. IEEE Trans. Intell. Transp. Syst. 23 (7), 8337–8345.
[17] Li, Z., 2022. Extracting spatial effects from machine learning model using local interpretation method: An example of SHAP and xgboost. Comput. Environ. Urban Syst. 96, 101845.
[18] Zhang, J., Ma, X., Zhang, J., Sun, D., Zhou, X., Mi, C., Wen, H., 2023. In sights into geospatial heterogeneity of landslide susceptibility based on the SHAP-xgboost model. J. Environ. Manag. 332, 117357.
[19] Mishra, S., Rajendran, P.K., Vecchietti, L.F., Har, D.: Sensing accident-prone features in urban scenes for proactive driving and accident prevention. IEEE Trans. Intell. Transp. Syst.Intell. Transp. Syst. 24(9), 9401–9414 (2023)
[20] Kannan, M.M.: Investigation of road accident zone and suggestion for preventive measures by using GPS and Gis Technology in Thanjavur, Tamil Nadu, India. Int. J. Eng. Res. Technol. (2024). https:// doi. org/ 10. 17577/ IJERT CONV1 2IS02034
[21] ElSahly, O., Abdelfatah, A.: Developing a machine-learning-based automatic incident detection system for traffic safety: promises and limitations. Infrastructures 9(10), 170 (2024)
[22] Kim, S., Cho, M., Lee, Y.: Exploration of traffic accident-based pilot zones for autonomous vehicle safety validation. Electronis 13(17), 3390 (2024)