AI-Based Analysis of Road Congestion Causes Using Real-Time Traffic Camera Data

Nehala Noushad
Department of Computer Science
Amal Jyothi College of Engineering
Kanjirappally,Kottayam
nehalanoushad2026@cs.ajce.in

Nikhitha Thomas
Department of Computer Science
Amal Jyothi College of Engineering
Kanjirappally,Kottayam
nikhithathomas2026@cs.ajce.in

Reema Maria Suresh
Department of Computer Science
Amal Jyothi College of Engineering
Kanjirappally,Kottayam
reemamariasuresh2026@cs.ajce.in

Rehan T Raj
Department of Computer Science
Amal Jyothi College of Engineering
Kanjirappally,Kottayam
rehantraj2026@cs.ajce.in

Resmipriya M G
Department of Computer Science
Amal Jyothi College of Engineering
Kanjirappally,Kottayam
mgresmipriya@amaljyothi.ac.in

***Abstract*—This study uses real-time data from traffic cameras and artificial intelligence (AI) algorithms to analyse the reasons for traffic congestion in a novel way. By recognising particular sources of congestion, such as accidents, processions, road construction, or general traffic accumulation, the proposed system seeks to supplement current navigation tools. The system makes very accurate predictions about the reasons for congestion by utilising a convolutional neural network (CNN) model that has been trained on a variety of datasets. The methodology, dataset preparation, model architecture, and interaction with a map-based user interface are all covered in detail in this work. The system's ability to give drivers and city planners useful insights is demonstrated by the results.**

***Keywords*—Traffic congestion, artificial intelligence, real-time traffic analysis, convolutional neural network (CNN), deep learning, traffic camera data, road construction, accident detection, processions, traffic management, navigation systems, urban planning, machine learning, data augmentation, web-based platform, intelligent transportation systems.**

I. INTRODUCTION

In metropolitan settings, traffic congestion is still a major problem that increases travel time, fuel consumption, and pollution of the environment. Even though current navigation tools like Google Maps show traffic conditions in real time, they frequently don't offer comprehensive insights into the reasons behind congestion. Both individual drivers and urban planners can make better decisions if they have a better understanding of these issues. This paper suggests a method that employs real-time traffic camera data and artificial intelligence (AI) to analyse the reasons of traffic congestion. To bridge the gap between real-time navigation and actionable insights, the system identifies specific congestion sources like accidents, processions, road construction, or general traffic accumulation.[1]

II. Methodology

A. AI Model

The core of the system is built around a convolutional neural network (CNN), which is specifically trained to classify traffic camera images into predefined categories: accidents, processions, road construction, and no congestion. The architecture of the CNN is designed to efficiently process and analyze visual data. It includes multiple convolutional layers, which apply filters to the input images to detect spatial features such as edges, shapes, and patterns relevant to traffic conditions. These layers are followed by pooling layers, which reduce the spatial dimensions of the data, retaining the most important features while improving computational efficiency and reducing the risk of overfitting. Finally, the output is passed through dense layers, where the extracted features are combined and classified into one of the predefined categories. This architecture allows the CNN to effectively generalize and accurately predict the cause of congestion from diverse and complex traffic images.[5]

B. Dataset Preparation

The dataset used for training the system was prepared from a combination of publicly available traffic camera feeds and manually selected datasets to ensure a diverse and representative collection of traffic scenarios. The data was organized into four distinct categories: accidents, processions, road construction, and no congestion, each representing specific traffic conditions the system is designed to classify. To improve the model's ability to generalize and handle variations in real-world data, data augmentation techniques were applied. These techniques included rotation, to simulate different angles of camera views; flipping, to account for mirrored traffic patterns; and brightness adjustment, to handle variations in lighting conditions such as daylight, nighttime, or overcast weather. By enhancing the diversity of the dataset through augmentation, the system was better equipped to classify complex traffic scenarios and adapt to real-world conditions effectively..

DOI:10.5281/zenodo.15543132

C. Model Training

The model was trained using TensorFlow and Keras, two widely used frameworks for building and deploying deep learning models. These frameworks provided the necessary tools to construct the convolutional neural network (CNN). During the training process, multiple evaluation metrics were employed, including accuracy, precision, recall, and the F1-score, to comprehensively assess the model's performance. Accuracy measured the overall correctness of predictions, while precision and recall ensured the model minimized false positives and false negatives, respectively. The F1-score provided a balanced metric to evaluate the trade-off between precision and recall. To enhance the efficiency and stability of the training process, advanced training parameters were utilized, such as a learning rate scheduler, which dynamically adjusted the learning rate to improve convergence, and early stopping, which terminated training when the validation performance changed, thereby preventing overfitting. These techniques collectively ensured a robust and reliable model capable of accurately classifying traffic conditions[1,4,5].

III. System Design and Implementation

A. Web-Based Platform

The system is implemented as a web-based application that integrates real-time traffic camera feeds with a trained AI model to provide users with actionable insights into traffic conditions. The platform allows users to input their current location and destination, enabling the application to analyze traffic along the route and generate a detailed route analysis. This analysis goes beyond traditional navigation systems by identifying specific causes of congestion, such as accidents, processions, or road construction, in addition to highlighting traffic slowdowns. By combining real-time data with AI-powered predictions, the web-based platform empowers users to make informed travel decisions, offering alternative routes to avoid congestion and reduce delays. The system is designed to enhance user convenience and improve overall travel efficiency through its dynamic interface.

B. Workflow

The workflow of the system begins with fetching real-time images from traffic cameras, which are accessed through publicly available APIs or dedicated traffic surveillance networks. These images are continuously retrieved to ensure that the system operates with up-to-date traffic data. Once the images are captured, they undergo a series of preprocessing steps to prepare them for analysis by the AI model. Preprocessing includes resizing the images to match the input dimensions required by the trained convolutional neural network (CNN), normalizing pixel values to a range of 0 to 1, and adding a batch dimension to ensure compatibility with the model's input format. After preprocessing, the images are fed into the trained CNN, which analyzes them and classifies the traffic conditions into predefined categories, such as accidents, processions, road construction, or no congestion. Finally, the results are visually presented on a map-based user interface, where affected routes are highlighted, and the identified causes of congestion are clearly displayed. This interface enables users to make informed decisions by providing actionable insights, such as the location and severity of congestion, thereby improving travel efficiency and planning

C. Map-Based User Interface

The map-based user interface serves as the central component for presenting the system's insights in a natural manner. It highlights affected routes, allowing users to quickly identify areas of congestion. Alongside the highlighted routes, the interface provides detailed information about the causes of congestion, such as accidents, processions, or road construction, along with the location and severity of the issue. To ensure users have access to the latest traffic information, the interface includes real-time updates, which refresh periodically to reflect changes in traffic conditions. Additionally, congestion severity indicators are incorporated to give users a clearer understanding of the intensity of the congestion, enabling them to make informed decisions about route adjustments or travel plans. This user-friendly interface bridges the gap between raw traffic data and actionable insights, enhancing the overall experience for both drivers and planners.

IV. Results and Discussion

A. Model Performance

The performance of the trained convolutional neural network (CNN) was evaluated on a test dataset, achieving an accuracy of 75%. While the model demonstrated strong overall performance, there were slight variations across different categories.However, the model showed moderate recall for processions, which can be attributed to the limited availability of procession-related data in the training dataset. This highlights the need for additional data collection and augmentation to improve the model's ability to generalize across minimal categories. Despite these variations, the results underscore the system's potential for accurately classifying traffic conditions and providing actionable insights based on real-time data.[6,2]

B. Case Studies

To evaluate the system's practical applicability, two case studies were conducted, showcasing its ability to identify specific causes of traffic congestion. In Scenario 1, the system successfully detected a traffic jam caused by road construction, accurately identifying construction equipment and barriers from traffic camera images. This information was effectively displayed on the map-based interface, allowing users to visualize the affected routes and avoid delays. In Scenario 2, the system demonstrated its capability to identify a procession event disrupting traffic, recognizing the presence of large crowds and associated vehicles in the images. This classification enabled the system to provide timely alerts.These case studies highlight the efficiency of the trained model in analyzing real-time traffic conditions and its practical utility in improving travel efficiency and situational awareness for users.

C. Challenges

The development and implementation of the system faced several challenges that influenced its performance and accuracy. One major issue was the dataset limitations for certain categories, such as processions, which had fewer training examples compared to other categories like accidents and road construction. This imbalance in the dataset impacted the model's ability to generalize effectively, leading to moderate recall for minimal categories. Additionally, the system encountered difficulties due to the variability in image quality, which was influenced by external factors such as weather conditions (e.g., rain, fog, or snow) and lighting variations (e.g., nighttime, shadows, or glare). These factors introduced noise and inconsistencies in the images, making it challenging for the model to extract meaningful features. Addressing these challenges requires expanding the dataset to include more diverse and balanced examples, as well as employing advanced preprocessing techniques and robust AI models that can handle a wider range of environmental conditions effectively

V. Conclusion

This study demonstrates how artificial intelligence (AI) can be used to efficiently analyze traffic congestion sources using real-time data from traffic cameras. The suggested solution, which goes beyond traditional navigation tools by identifying specific causes of traffic slowdowns, such as accidents, processions, and road construction, uses a trained convolutional neural network (CNN) to give insightful information for drivers and urban planners. By facilitating better decision-making, these insights enhance traffic control and route planning. By providing useful information, the system enhances the usefulness of current navigation tools and acts as a supplementary solution. Future research will concentrate on enhancing model robustness to manage changing climatic circumstances, growing the dataset to encompass more varied and minimal scenarios, and scaling the system deployment to cover wider geography and integrate with broader traffic management systems.

References

[1] Shan Hu, Jiansheng Wu and Ling Xu, "Real-time traffic congestion detection based on video analysis", Journal of Information and Computational Science, vol. 9, no. 10, pp. 2907-2914, 2012.

[2] Amina Riaz and Shoab A Khan, "Traffic congestion classification using motion vector statistical features", International Conference on Machine Vision, pp. 90671A-90671A, 2013.

[3] Hanlin Tan, Yongping Zhai, Yu Liu and Maojun Zhang, "Fast anomaly detection in traffic surveillance video based on robust sparse optical flow", IEEE International Conference on Acoustics Speech and Signal Processing, pp. 1976-1980, 2016.

[4] N. Zarei, P. Moallem and M. Shams, "Fast-Yolo-Rec: Incorporating Yolo-Base Detection and Recurrent-Base Prediction Networks for Fast Vehicle Detection in Consecutive Images", IEEE Access, vol. 10, pp. 120592-120605, 2022.

[5] C. -J. Lin and J. -Y. Jhang, "Intelligent Traffic-Monitoring System Based on YOLO and Convolutional Fuzzy Neural Networks", IEEE Access, vol. 10, pp. 14120-14133, 2022.

[6] Alomari Ahmad, Lebdeh Enas, Awad Bashar, Hawamdeh Mohammed, Karasneh Mohammad, Al-Qudah Sara, et al., Autonomous Real-Time Multiple Vehicles Detection and Tracking System, 2021.