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Original Article

An Intelligent Driving Recommendation System Integrating Temporal Convolutional Networks and Fuzzy Logic for Real-Time Traffic and Weather Optimization

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Abstract - *Traffic congestion and road safety are paramount challenges compounded by the rising number of cars on the roads. Conventional traffic management systems using fixed rules and past data find dealing with dynamic road conditions difficult. This study suggests an Intelligent Driving Recommendation System (IDRS) combining deep learning and rule-based algorithms for real-time traffic and weather observation. The key to the strategy is the use of Temporal Convolutional Networks (TCN) behind traffic and weather forecasting using fuzzy logic-based adaptive decision-making. The process involves data gathering from IoT sensors, real-time monitoring systems, meteorological sources, and preprocessing techniques such as normalization, outlier detection, and categorical encoding. TCN models are trained to forecast congestion and weather severity, and a fuzzy inference system produces context-aware driving recommendations. Experimental results demonstrate the efficacy of the proposed system, achieving 99.7% accuracy in predicting traffic conditions and weather effects. The proposed TCN-Fuzzy Logic model surpasses LightGBM, CNN, and RFCNN, achieving 99.7% accuracy with enhanced precision, recall, and F1-score, demonstrating superior performance in classification tasks through advanced temporal and fuzzy logic integration. A comparative analysis was performed with those models, showing that the proposed TCN-Fuzzy Logic approach, with its edge in diminishing travel risks and efficiently managing traffic flows, emerges as superior. The study adds to developing AI-enabled real-time driving recommendation systems based on safety, efficiency, and sustainable intelligent transportation networks. The reed-looking study shall delve further into enhanced integration and efficacious optimization of calmative efficiency through edge computing techniques.*

Keywords - *Deep Learning, Fuzzy Logic, Intelligent Driving Recommendation System, Real-Time Traffic Monitoring, Temporal Convolutional Networks.*

1. Introduction

Worldwide road safety alongside rising traffic congestion has emerged as a primary challenges due to growing urbanization alongside rising vehicle numbers on the streets [1]. Current traditional traffic management approaches utilize established standard procedures yet cannot handle immediately changing road situations [2]. Intelligent Driving Recommendation Systems (IDRS) implement deep learning with real-time data analytics together with rule-based algorithms to deliver performance-enhancing and safety-focused recommendations for drivers on the fly. [3]. Happy Lee revealed that yearly road accidents result in 50 million injuries and kill about 1.2 million people. County roads and city driveways support 54% of all traffic collisions. A majority of 71 per cent of accidents occur exclusively on dry surfaces. The acceptance of autonomous vehicles by society stands as a primary barrier that modern society experiences at present [4]. The industry established this important fourth-revolution domain through which virtual sensing has become widespread. Autonomous vehicles remain only a few years away from becoming a reality. Several key questions still need resolution, including liability issues and sharing methods and definitions regarding accident responsibility and insurance coverage [5]. The implementation of Industry 4.0 can prove practical for this case since it seeks to establish fully automated cyber-physical systems (CPS) along with enhanced data exchange functionality. The term V2X represents vehicle-to-everything applications, including vehicle-to-vehicle and vehicle-to-infrastructure communications. A motor vehicle's operational speed directly affects comfort and safety outcomes [6]. Many safety experts consider speed reduction essential for better road safety because speeding is a leading cause of multiple accidents. The safety measures reach their limits when drivers violate speed limits and when hazardous weather conditions or roads necessitate speeds below the posted limits, which remains individual drivers' responsibility [7]. The evaluation of any road, including rural roads, requires a focus on road geometry design combined with infrastructure conditions because these elements guarantee smooth operations with safety for traffic [8]. AI-powered traffic management systems receive active study and implementation as connected vehicles and smart city infrastructures advance. These traffic systems utilize big data analytics to generate predictive information and calculate optimal routes, which create safer streets and better driving efficiency.

1.1. Recent Innovations

Deep learning technology has produced substantial improvements for autonomous driving systems regarding highway simulations and predicting route changes through lanes (LC). The DRL-based autonomous agents obtain interpretation frameworks through study [9], which explains their important driving decisions. The study technique combines episode timeline analysis with frame-by-frame inspection and statistical evaluation methods through heatmaps to deliver spatial information about vehicle interaction. The study reveals that vehicles maintain their distance from other cars as their primary decision factor, while decisions to pass require lane positioning to occur [10].

Creating a multi-task, attention-based CNN model is an important advancement that helps solve weaknesses in available prediction systems [11]. The model benefits from bird's eye view visualization, which combines attention-based CNN functionality to achieve accurate predictions of Longitudinal Cruise manoeuvres. The model achieves 1.5 times higher long-term prediction performance metrics due to two innovative curriculum learning schemes that enhance the training process. Naturalistic trajectory datasets recorded with drones enhance prediction accuracy yet realistic deployment of automated vehicles encounters implementation obstacles from sensor noise and limited visual field as well as obstacles blocking view [12]. The future study agenda should measure sensor uncertainties and advance fusion techniques to improve reliability when predicting real-world LC. The current advancements work toward building better AI traffic management systems, which must be enhanced for practical implementation in real-world scenarios.

1.2. Research Gap

Several implementation obstacles affect the performance of existing traffic management systems and driving recommendation models in intelligent transportation systems today. The speed adaptation systems base their operations on driver preferences through fuzzy logic controllers, which leads to speed recommendations that negatively impact safety rather than comfort. Some steering control models using a combination of CNNs and fuzzy logic face difficulties when integrating rule-based systems with deep learning algorithms, which deteriorates their accuracy level [13]. The detection performance of traffic monitoring systems increases with ultrasonic sensors and image processing algorithms, yet substantial computing power is required. The implementation of urban traffic control recommenders supported by AI and decision feedback systems needs proper human oversight in order to function effectively [14]. Real-time traffic analysis systems using CNNs deliver improved congestion prediction through their pre-trained models while maintaining dependence on these carefully trained components. The self-adaptive traffic light control system with YOLOv3 optimization achieves better timing performances but does not apply reinforcement learning methods for ongoing upgrades [15].

The prediction of traffic congestion with recurrent neural networks (RNNs) experiences source data bias from social media platforms in real time [16]. The performance of enhanced YOLOv2 detection models enhances accuracy, but their adaptation to new categories needs improvement [17]. IoT-driven traffic frameworks enhance congestion control performance, although they maintain expensive implementation requirements and raise privacy-related issues. A complete data merging process that includes extensive additional resources alongside computational power is required for AI-driven adaptive traffic signal control systems [18]. A hybrid traffic management system must be developed for urban environments because these environments require real-time adaptability, scalability, and enhanced safety and efficiency capabilities.

1.3. Research Motivation

The motivation behind this study stems from the increasing need for intelligent, adaptive, and data-driven traffic management solutions in modern cities. Despite rising road vehicle numbers, creating systems that forecast traffic congestion and generate customized immediate driving suggestions depending on density levels, weather conditions, and established safety guidelines is essential. The quick rise of IoT-enabled smart cities, along with connected vehicle technologies, enables opportunities for AI systems to use real-time sensor data in their decision-making processes. The study establishes a connected framework between deep learning forecasting techniques and rule-based algorithms to build a strong solution platform for traffic safety while improving route planning and movement management.

1.4. Research Significance

The proposed research makes meaningful advancements in the areas of Intelligent Transportation Systems (ITS) and Artificial Intelligence-driven traffic management and regulation strategies by:

- A proposed system implements Temporal Convolutional Networks as part of its design to boost congested traffic predictions while effectively evaluating the effects of weather conditions.

- The adaptive capability of decision-making emerges from fuzzy logic integration, which duplicates human reasoning functions to create intelligent driving suggestions.
- Speed and routing recommendations change automatically through the model to minimize the risks of accidents while vehicles face dangerous driving scenarios.
- The system maintains an efficient real-time deployment through its scalable design, which makes it suitable for complex urban traffic management.

1.5. Research Key Contribution

The following are the research's main contributions

- The study implements parking guidance recommendations through TCN-based traffic and weather forecasting and Fuzzy Logic decision-making algorithms for adaptive intelligent systems.
- The traffic management framework relies on IoT sensor data, real-time monitoring systems, and meteorological sources for development.
- When applied to traffic conditions and weather effect predictions, the proposed TCN-Fuzzy Logic system generates accurate outcomes with 99.7% accuracy compared to conventional methods.
- The system features infrastructure deployment capability that enables smart urban cities to obtain real-time traffic optimization and scalable operations.
- The proposed approach is superior to existing traffic recommendation models as established through comparative evaluations in the study, which enables optimal route planning and minimizes travel delays.

1.6. Research Structure

This study delivers a complete evaluation of the proposed Intelligent Driving Recommendation System through its organized structure.

Section 2 reviews multiple studies on intelligent traffic management technologies, deep learning models, and fuzzy logic-based decision systems.

Section 3 (Proposed Methodology) presents Temporal Convolutional Networks (TCN) alongside Fuzzy Logic integration by describing data acquisition procedures and preprocessing methods, the model structure, and the implementation of the decision-making framework and displays experimental outcomes, performance measurements, and system validation alongside comparative assessments of the designed system.

Section 4 delivers a discussion highlighting how result interpretations demonstrate better capabilities of intelligent driving suggestions. The study summarises its achievements under Section 5 (Conclusion and Future Scope). The defined methodology provides a clear presentation of results that demonstrate its significance for current traffic administration systems and intelligent urban implementations.

2. Literature Review

In Barreno et al.'s [13] study, an intelligent speed adaptation system for cars on traditional roads is offered. In order to guarantee passenger comfort and safety, the expert system that uses fuzzy logic generates a suggested speed. The geometrical characteristics of the road, as well as the drivers' subjective views, are included in this intelligent system. It was created and verified using actual measurements made on some two-lane highways in the Madrid Region of Spain using an instrument set built into a car. The output of the expert system determines the optimal speed for the particular type of road, taking into account actual elements that may change the road's classification and, therefore, the suitable speed. The technique depends on the driver's subjective selection of characteristics, such as their desired degree of comfort. This subjective input may not align with the best safety recommendations, resulting in variances in the recommended speed that do not always emphasize safety entirely. This was problematic if the driver preferred greater comfort over caution.

Dinh and Kim suggested a recommendation system based on deep steering neural networks and fuzzy logic [19]. Fuzzy logic at a back-end stage functions as natural inferences for proposing velocity and adapting new controls for steering, while CNNs function as a front-end stage for steering control prediction. Using raw sensory data as input, the front-end stage employed CNNs to derive steering control predictions, which were then forwarded to the back-end stage. The primary duties of the back-end stage are to integrate dynamic vehicle data, such as steering prediction for enhanced steering control and velocity for the autonomous vehicle. The CNN was trained using hours of test and training information from the Udacity driving datasheet, and MATLAB was used throughout the whole system. One drawback of the proposed system is that while the simulation results showed better performance without using the fuzzy logic system, it highlights a limitation in integrating fuzzy logic with the CNN-based model for steering control.

Kheder et al. [20] introduce sensors and the obstacles using ultrasonics' wave time and speed to reduce road accidents. The data collected from the sensors and cameras using several image processing algorithms are transmitted to the cloud and made available for drivers and commuters via a mobile application. The proposed models show marked improvements in test accuracy. Modified LeNet-5 earned an accuracy of 99.12 and 99.78% under the GTSRB and EGTSRB datasets, respectively, while the second model trained on the LISA dataset compiled an accuracy of 98.6%. Compared to the related traffic monitoring systems, the findings of this study outperform the closest works by 3.78% in traffic sign recognition and by 1.02% in detecting and recognizing traffic lights. Ji et al. [14] present a contemporary review of urban traffic control recommendation systems, which describes their complete components and demonstrates real-life implementation using data-oriented and knowledge-oriented methods. It further explores current field problems and possible future development challenges. The first step involves a traffic perception model that acquires traffic state data to enable the traffic prediction model to produce accurate future predictions. The traffic control recommender uses these traffic data to optimize different levels of traffic signal control. A decision feedback system uses the knowledge of traffic engineers to approve suitable control strategies, which is an essential component of this system. Future developments in this study area will determine its future course. The development of traffic-related LLMs allows authors to modify traffic prediction models to work with mixed traffic data. Decision support through AGI will become accessible with less need for human resources.

Pailwan and Jitkar [21] integrate Intelligent Traffic Analysis Systems (ITAS) with Convolutional Neural Networks (CNN), a deep learning technology that provides highly efficient real-time data analysis. This technology, which the Intelligent Traffic Analysis Systems use to monitor and analyze traffic flow in detail, makes it possible for traffic monitoring systems to move carefully. Specifically designed, deep learning models for object detection and tracking were used to recognize and monitor cars, trucks, and other relevant entities in dipped light conditions. THE ITAS has advanced data analytics and predictive capabilities embedded into it; it can provide real-time insights to authorities on traffic conditions, allowing them to make informed decisions and implement proactive interventions to alleviate congestion, reduce travel times, and improve overall mobility. Instead, using transfer learning with several previously-trained models, the proposed CNN architecture, modified for traffic analysis, has yielded efficient techniques and algorithms to prevent traffic jams.

Khan et al. [15] established a self-adjusting real-time traffic light management system based on machine learning and image processing techniques to improve signal junction traffic flow. By using the YOLOv3 system, the detection of vehicles becomes precise. At the same time, the green light duration is calculated using real-time traffic parameters, which include vehicle count, road width, and junction crossing time. The model delivered 81.1% average precision after training from various data sources and established successful predictions of actual vehicle numbers. The system delivers fast operation, low implementation cost, and low hardware requirements, enabling simple infrastructure deployment. The system's effectiveness can be enhanced through two improvements: reinforcement learning integration for self-learning abilities and time process reduction. Future system versions will benefit traffic management efficiency by integrating dedicated high-altitude cameras and special-case handling for emergency vehicles such as ambulances. Abdullah et al. [22] designed a BRNN that employs GRUs to analyze traffic information and determine congestion levels. The authors have developed a prediction system for smart city traffic congestion through modeling and simulation that depends on BRNN (Bidirectional Recurrent Neural Network). Traffic congestion impacts every urban area globally, and conventional methods to control traffic have not shown substantial success. This study presents a BRNN framework as a data-based smart city traffic management solution. The traffic control system becomes more effective by analyzing current sensor data and networked device inputs in real time. Speed prediction, weather conditions, water current analysis, and accident risk estimation belong to the primary tracking methods. Additional traffic-related information retrieval, including road and weather elements, has boosted congestion prediction capabilities. The model achieved better performance than all present techniques for metric-based operation. Unreliable social media data and its bias conditions challenge obtaining accurate traffic prediction outcomes. Akthar et al. [17] present an advanced YOLOv2 vehicle detection method that utilizes DenseNet-201 as its feature extractor network instead of Darknet-18 for safer small object detection. The model demonstrated average precision at 97.51% and mAP at 81% after its training with 70% Kitti and Kaggle datasets, followed by testing with 30% Kitti and Kaggle datasets as well as cross-validation using Pascal VOC and COCO datasets. This model performed better than previously developed models. The dense connection patterns of DenseNet-201 create optimized feature extraction conditions, enhancing accuracy in bounding box estimation. This compact model operates at high speed with exceptional accuracy for recognizing three main vehicles: cars, buses, and trucks. Better adaptive mechanisms need development to boost accuracy levels in the detection process while preparing the technology for abnormal activity detection applications. Future work aims to fine-tune the model for better performance across object detection scenarios.

Musa et al. [23] introduce an IoT and Intelligent Transportation Systems (ITS)-based sustainable traffic management framework that tackles congestion and environmental issues in smart cities. AI sensors and ITS-based devices collect real-time traffic and road user data, which gets processed. Machine Learning alongside cloud computing to generate valuable decisions for decision-making, traffic forecasting and congestion reduction. The system strengthens urban transportation by reducing wasted time, improving network planning, and advancing low-environmental footprint zones. The system delivers three major benefits: better transportation flow, decreased pollution, and better legal protection. The system faces difficulties because of its high implementation expenses, privacy risks arising from data collection, and technical complexity. Upcoming technological advancements will develop immediate decision protocols alongside AI ecosystem growth to establish more effective and environmentally friendly smart city transport systems.

Damadam et al. [18] introduce an ATSC system based on IoT and AI, which uses Multi-Agent Reinforcement Learning to optimize traffic signals for Shiraz City. Public authorities used real-time IoT sensor measurements and surveillance camera inputs to operate signal phase changes at six street intersections in real-time instead of depending on static scheduling protocols. Simulation results confirmed that ATSC produced reduced waiting times and vehicle queues in artificial and Shiraz-based testing environments, especially during peak operating periods.

The system increases traffic performance and responsiveness while demanding large-scale data combinations and substantial computational power.

Future development will increase system installation in multiple intersections while improving pedestrian safety to enhance traffic control. Urban traffic systems become more efficient by implementing MARL-based approaches, which deliver promising results against congestion reduction.

Several studies have investigated artificial intelligence for traffic management to improve safety standards, traffic efficiency, and congestion management abilities. Merging fuzzy logic into intelligent speed adaptation systems determines the best driving speeds, and deep steering neural networks enhance vehicle control activities. Traffic monitoring techniques leverage IoT sensors, image processing, and CNN-based models for real-time analysis. System optimization in urban traffic flow is achieved through machine learning for traffic controls, YOLO vehicle detectors, and reinforcement learning algorithms for signalling adaptation. The integration of sustainable systems that use IoT alongside cloud computing and AI technology generates better predictions for congestion while promoting environmentally friendly transportation. However, it faces difficulties from expensive system development, data processing issues, and computational complexity.

Table 1 demonstrates an assessment of multiple studies regarding intelligent traffic management systems that divide studies by their approaches, results, and identified drawbacks. The field uses methods like fuzzy logic, deep learning (CNN, YOLO, BRNN), reinforcement learning and IoT-based systems for traffic optimization, vehicle detection, and traffic signal control improvement.

Several important findings demonstrate how congestion prediction systems became more precise while adaptive signal control mechanisms showed progress and vehicle recognition achieved higher accuracy levels. The implementation faces challenges because it demands high processing power and raises privacy issues, which limit its effectiveness and require better built-in learning capabilities. The comparison details fundamental information about current approaches and their advantages and disadvantages.

Table 1. Comparative analysis of related works in intelligent traffic management

Author	Method	Findings	Limitations
Barreno et al., [13]	Fuzzy Logic-based Intelligent Speed Adaptation System	Generates speed recommendations based on road geometry and driver input.	Subjective input may not align with best safety practices.
Dinh and Kim [11]	CNN and Fuzzy Logic for Steering Control	Enhances steering control by integrating CNN predictions with fuzzy logic.	Performance was better without fuzzy logic integration.
Kheder et al. [20]	Ultrasonic Sensors and LeNet-5 for Traffic Monitoring	Achieved 99.78% accuracy in traffic sign and light recognition.	High computational demand and cloud dependency.
Ji et al. [14]	Traffic Control System with AI and Decision Feedback	Optimizes urban traffic signals using predictive analytics.	Requires significant traffic engineer input.
Pailwan & Jitkar [21]	CNN-based Intelligent Traffic Analysis System	Provides real-time traffic insights for congestion reduction.	Transfer learning requires extensive pre-trained models.
Khan et al. [15]	YOLOv3-based Adaptive Traffic Light Control	Achieved 81.1% accuracy in estimating vehicle counts.	Needs reinforcement learning for further self-learning.
Abdullah et al. [22]	Bidirectional Recurrent Neural Network (BRNN) for Traffic Prediction	Improves congestion prediction using real-time sensor data.	Social media data may introduce bias and inaccuracies.
Akthar et al. [17]	YOLOv2 with DenseNet-201 for Vehicle Detection	Achieved 97.51% precision in detecting small vehicles.	Needs improvements for classification accuracy.
Musa et al. [23]	IoT & Machine Learning for Smart Traffic Management	Reduces congestion and emissions using AI-driven decision-making.	High implementation costs and data privacy concerns.
Damadam et al. [18]	Multi-Agent Reinforcement Learning (MARL) for Traffic Signals	Reduced queue lengths and waiting times in peak hours.	High computational demand for real-time implementation.

3. Methodology

The methodology of this study involves developing an Intelligent Driving Recommendation System (IDRS) that integrates Temporal Convolutional Networks (TCN) and Fuzzy Logic for real-time traffic and weather optimization. The process starts with data collection from IoT sensors, real-time monitoring systems, and meteorological sources, followed by preprocessing techniques such as normalization, outlier detection, and categorical encoding. TCN models are then trained to forecast congestion levels and weather severity. A fuzzy inference system generates adaptive driving recommendations based on predicted conditions. The system dynamically adjusts speed limits, route planning, and safety measures to optimize traffic flow and reduce travel delays.

Performance evaluation involves simulation-based experiments that compare the proposed approach with benchmark models, including LightGBM, CNN, and RFCNN, based on accuracy, precision, recall, and F1-score. The proposed TCN-Fuzzy Logic model is expected to outperform existing methods in predicting road conditions and enhancing driving recommendations.

The study contributes to AI-driven traffic management, emphasizing efficiency, road safety, and sustainable intelligent transportation networks. Future extensions may involve integrating edge computing for real-time data processing, enhancing computational efficiency, and optimizing decision-making algorithms for intelligent driving assistance.

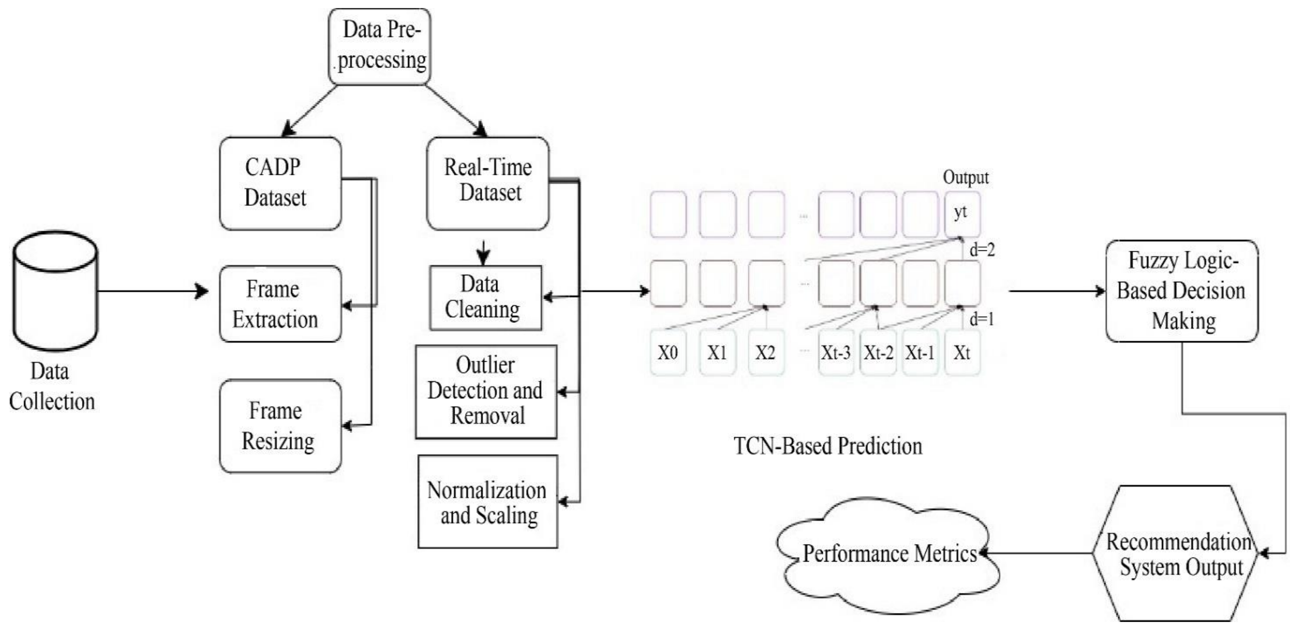

Fig. 1 Overall workflow of TCN-Fuzzy logic

In Figure 1, the workflow starts with Data Collection followed by Data Preprocessing, including data cleaning, Frame Extraction and Frame resizing, and other processes. A Temporal Convolutional Network framework, along with dilated convolutions, allows the prediction of traffic flow, congestion risks, and accident probabilities through its model of capturing extended temporal connections.

Real-time driving recommendations originate from the Fuzzy Logic-Based Decision-Making System using predefined rules based on the data the predictions provide. The system output recommends route choices, speed recommendations, and traffic guidelines; the performance metrics determine model efficiency.

3.1. Data Collection

The proposed study collected data for fundamental road safety elements and traffic operational conditions. The study documented various parameters such as speed levels coupled with weather elements, road traffic density, infrastructure design timing of day and accident gravity rates. This study's point of view uses two unique datasets, which functioned both as exploratory tools for the traffic accident environment and as modeling instruments. The first dataset consisted of secondary resources and secondary sources, namely the CADP dataset [24], totalling 1,416 film clips that showed various traffic accident types.

The incidents were recorded through third-person video footage from CCTV cameras. A total of 5.2 hours of traffic accident records exists within this data set that contains 366 frames on average for each film.

The data was sourced from real-time monitoring systems, public datasets, and weather APIs, ensuring that conditions such as high traffic density during rainy mornings or low traffic density on highways were accurately captured. Table 2 shows the samples of the accident dataset.

Table 2. Accident dataset samples

Speed	Weather Condition	Traffic Density	Road Structure	Time of Day	Accident Severity
19	Rainy	High	Four Lane & Above	Afternoon	High Risk
90	Overcast	Low	Surfaced W.B.M	Afternoon	Low Risk
21	Windy	Moderate	Less than 2 Lane	Morning	Low Risk
39	Rainy	Moderate	Surfaced B.T/C.C	Night	Moderate Risk
100	Windy	Moderate	Surfaced B.T/C.C	Evening	Low Risk

3.2. Data Preprocessing

The data preprocessing involves handling two datasets to ensure data quality and model efficiency. First, raw data undergoes cleaning, addressing missing values and inconsistencies. Then, frame extraction and resizing standardize video data, while structured storage ensures efficient retrieval. For the CADP dataset, outlier detection is performed to remove anomalies, followed by normalization and scaling to standardize numerical values. Similarly, the real-time dataset undergoes data cleaning, outlier removal, and feature scaling. These preprocessing steps enhance model accuracy, ensuring optimal input for the proposed intelligent driving recommendation system.

3.2.1. Data Preprocessing Steps for CADP Dataset

The data preprocessing steps for the CADP dataset involve cleaning, normalization, and outlier detection to ensure data reliability and consistency. Initially, missing values and inconsistencies are handled through data cleaning. Outliers are identified and removed to enhance model accuracy. Finally, normalization and scaling techniques standardize data distributions, improving the efficiency and performance of the proposed intelligent driving recommendation system.

Frame Extraction

The Intelligent Driving Recommendation System (IDRS) requires frame extraction as its essential data preprocessing operation, which converts recorded traffic surveillance videos into static images for study purposes. The video sampling process uses a determined frame rate between 5 to 10 frames per second to capture meaningful motion data without unnecessary repetition. The motion-based extraction technique focuses on active video elements that improve the representation of events in the data. The frame extraction method creates organized storage directories, which improve the accessibility of images for forthcoming data processing operations and training routines [25].

Frame Resizing

A deep learning model requires standard input images through the essential preprocessing technique known as frame resizing in data preparation. The procedure standardizes frame dimensions and makes the calculations easier to process without compromising essential features [26]. The proposed model performs traffic and weather data processing through frame resizing operations, establishing a fixed image dimension resolution.

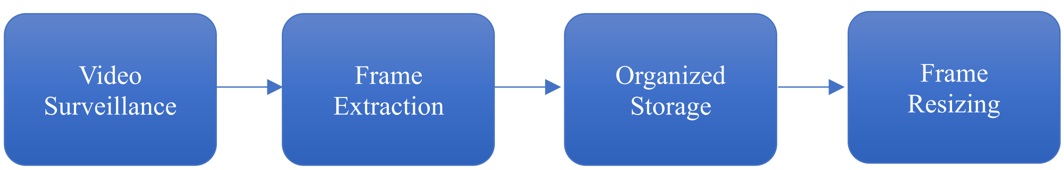

Fig. 2 Video processing pipeline for CADP data preprocessing

Figure 2 displays a surveillance video processing sequence for security systems. Video surveillance leads to frame extraction procedures for obtaining essential footage moments.

The processed frames receive systematized storage distribution for quick access needs. Recent image analysis frameworks need frame resizing to standardize dimensions before beginning advanced learning processes.

3.2.2. Data Preprocessing Steps for Real-Time Dataset

The data preprocessing steps for the real-time dataset involve cleaning, outlier detection, and normalization to enhance data accuracy and consistency. Initially, missing values and inconsistencies are addressed. Outlier detection removes erroneous data points, while normalization scales data for uniformity. These steps optimize the dataset for efficient, intelligent driving recommendation system processing.

Data Cleaning

The technique used to impute missing values, such as key factors, meant substitution. The mean was computed based on the current weather and traffic conditions. This approach has the merit of preserving relevant data while simultaneously avoiding the bias that results from obtaining data from only one viewpoint. Any row with more than 10% missing values or other discrepancies that could not be argued to have been taken reasonably was dropped from the dataset to avoid any distortion of results.

Outlier Detection and Removal

For continuous numerical data, outliers were detected using a z-score method where values having a z-score more than a cut-off (for example, more than 3) were considered outliers. These have been scrutinized to consider them as real ‘rare events’ in the dataset or as mere anomalies and, therefore, possibly disposed of [27]. By avoiding outlying data, the above process made figuring out more realistic, thereby arriving at better predictions.

Normalization and Scaling

All the continuous variables were identified and normalized with the help of Min-Max normalization to scale the data between 0 and 1. This process brought about standardization of the dataset to avoid any skewed feature dominating the outcome; optimized learning efficiency and generalization were also achieved to improve the model's accuracy [28]. Min-max normalization is represented in the Equation (1)

$$Z_{norm} = \frac{Z - Z_{min}}{Z_{max} - Z_{min}} \tag{1}$$

Especially useful when features have different scales, this normalization strategy keeps consistency across the features and improves the machine learning model's performance during training. Figure 3 The illustration presents essential procedures for preparing real-time datasets during data preprocessing operations. Data cleaning initiates the process before outlier detection, improving data quality through removal. Normalization and scaling follow data cleaning to help standardize the dataset, thus improving model effectiveness.

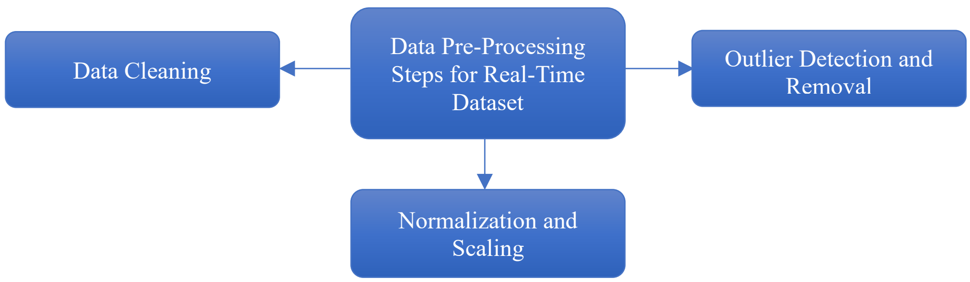

Fig. 3 Data preprocessing steps for real-time datasets

3.3. Deep Learning Model for Traffic and Weather Prediction

The proposed study aims to develop an intelligent driving recommendation system by accurately predicting real-time traffic congestion and weather severity. Temporal Convolutional Networks (TCN) are employed as the primary deep learning architecture due to their ability to model long-range dependencies in time-series data while maintaining computational efficiency. The system consists of two key predictive modules [29]:

3.3.1. Traffic Prediction Module Using TC

The traffic prediction model estimates congestion levels by processing information from historical and current data observations. The main input characteristics for the model include the measurements of speed alongside traffic density, road structure information, and time-of-day context.

Dilating the convolutional layers in TCN allows the model to detect long-range traffic dependencies, including peak-hour congestion and weekend traffic behaviour patterns. The traffic prediction system organizes traffic conditions into three defined congestion sections: Low, Medium and High.

For a given input sequence I_f, the TCN-based congestion prediction is defined in the Equation (2),

$$\hat{Y}_t = f(W * I_f + b) \tag{2}$$

The prediction model calculates $(\hat{Y}_t)$ by multiplying W against I_f and adding bias term b. Each output neuron in the model obtains information from extensive regions through the dilated convolution process to identify brief and extended dependencies within traffic datasets.

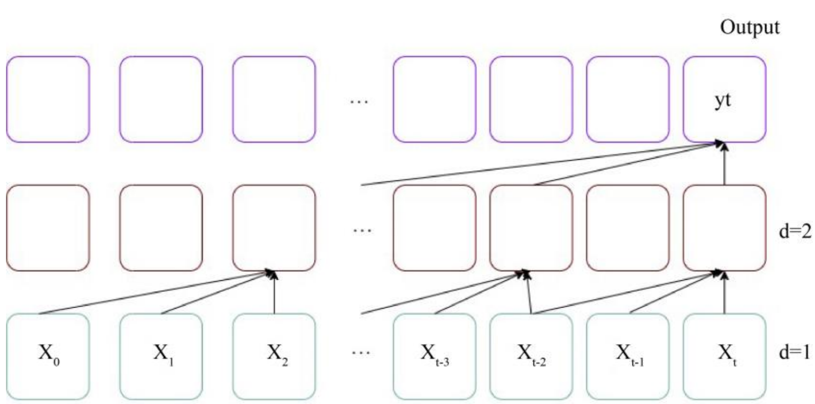

Fig. 4 Temporal Convolutional Network (TCN) architecture for time-series forecasting

Figure 4 depicts the structural design of TCN architecture that applies dilated convolutions on various time step levels. The green section at the base represents the input features, whereas the above red layer and purple upper layer show convolutional processing with extended receptive fields $(d = 1, d = 2)$. The final produced y_t value uses its ability to detect extended temporal connections in time-series information to make predictions.

3.3.2. Weather Prediction Using TCN

The TCN model receives an attention modification to emphasize essential weather transform dynamics in weather forecasting situations. This helps the model assign higher importance to extreme conditions like heavy rainfall or strong winds directly impacting road safety. The input features for this module include weather conditions, wind speed, rain intensity, temperature, and humidity. The model classifies weather severity into Normal, Moderate, and Severe levels. The attention-enhanced TCN model applies a weighting mechanism to each feature, represented in the Equation (3), and (4)

$$\alpha_t = softmax(W_\alpha I_f) \tag{3}$$

$$\widehat{Y_t} = \sum_{i=1}^{n} \alpha_{t,i} f(W * I_{f,i} + b) \tag{4}$$

Where, α_t is the attention weight assigned to each weather feature, W_α is the attention weight, I_f represents input weather data, and, $\widehat{Y_t}$ is the predicted weather severity at time t. The model dynamically prioritizes influential weather factors by incorporating attention, improving prediction accuracy. The dataset is split into 80% training and 20% testing sets to ensure reliable model performance. The Adam optimizer minimizes the error during training, dynamically adapting learning rates for better convergence. The loss function applied is Mean Absolute Error (MAE), given in the Equation (5),

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \lceil \widehat{Y_t} - \widehat{Y_\iota} \rceil \tag{5}$$

Where, Y_i is the actual congestion or weather severity, $\widehat{Y_\iota}$ is the predicted value, and n is the number of samples.

3.4. Rule-based Decision System Using Fuzzy Logic

The Rule-Based Decision System is a vital link that merges current traffic information from the TCN model with pre-established driving rules from the user database. Adaptive decision-making happens through fuzzy logic within this system to enable flexible reasoning in uncertain conditions. Traditional rules-based decision systems experience failure when processing unprecise or imprecise input data, including multiple levels of traffic congestion or weather conditions. The implementation of fuzzy logic solves this problem by replacing absolute values with truth value degrees. The membership functions for congestion evaluation (C_t) and weather severity assessment (W_t) are described in the Equation (6),

$$\mu_{C_t} = \begin{cases} 1, & x \le C_{low} \\ \frac{C_{high}-x}{C_{high}-C_{low}}, & C_{low} < x < C_{high} \\ 0, & x \ge C_{high} \end{cases} \tag{6}$$

Where, C_{low}, and C_{high} represent threshold values for congestion levels. Similarly, the weather severity function is given in Equation (7),

$$\mu_{W_t}(y) = \begin{cases} 1, & y \le W_{norm} \\ \frac{W_{sev}-y}{W_{sev}-W_{norm}}, & W_{norm} < y < W_{sev} \\ 0, & y \ge W_{sev} \end{cases} \tag{7}$$

Flexible traffic and weather recommendations emerge from the membership values between 0 and 1.

Decision Rules and Fuzzy Inference System (FIS)

Real-time congestion and weather severity evaluation relies on IF-THEN fuzzy rules, which enable the system to function in the $getAllRecommendations()$ method., such as

IF $C_t > 80\%$ AND $W_t > 50mm$ /hr, THEN it is an alternative route.

IF $C_t < 40\%$ AND W_t is clear, THEN it is the fastest route.

IF C_t is high AND visibility (fog) is below threshold, THEN it is a speed reduction.

The fuzzy inference system provides output recommendations defuzzied into crisp values to generate traffic rerouting and driving adjustment instructions.

3.4.1. Deployment Strategy

The model integrates with a cloud-based API to securely execute real-time retrieval of traffic and weather data for deployment. Predictive models get hosted on cloud servers through Cloud-Based Model Hosting as part of the deployment strategy for real-time continuous updates. The Docker containers within a containerized architecture system enable easy deployment capabilities across multiple platforms through their scalable nature.

Mobile Application Interface: A mobile application provides real-time driving recommendations based on evolving traffic and weather conditions. Using cloud computing and containerization, the system achieves high availability, low latency, and scalability to handle dynamic real-world traffic scenarios effectively. Algorithm 1 shows the Real-Time Traffic and Weather Monitoring working.

Figure 5 outlines the Fuzzy Inference System (FIS) process, starting with crisp input data, which is converted into fuzzy values through fuzzification.

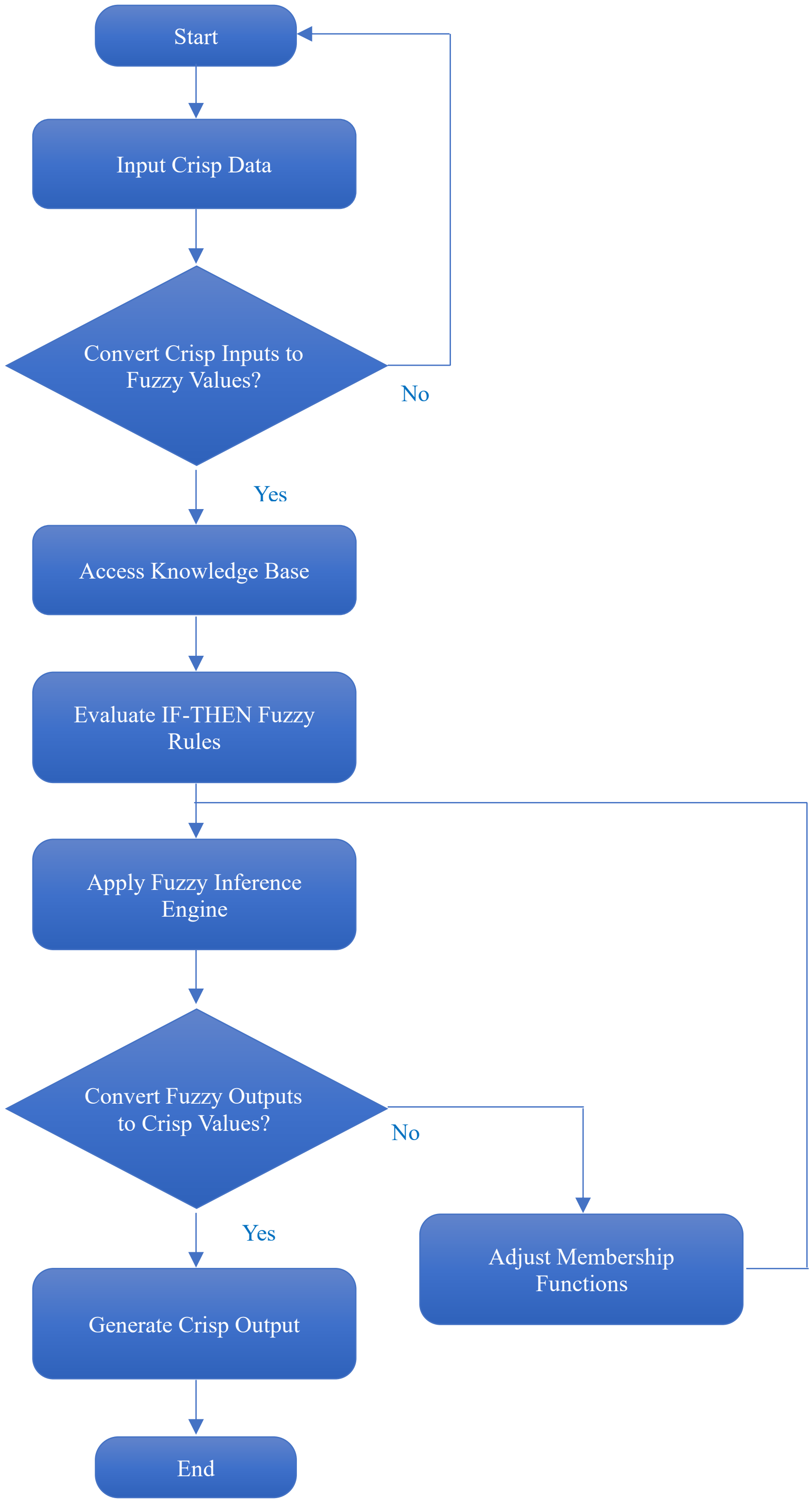

Fig. 5 Fuzzy Inference System (FIS) flowchart

The system then accesses the knowledge base and evaluates IF-THEN fuzzy rules using the inference engine. The fuzzy output is checked for conversion into crisp values; if not, membership functions are adjusted.

Once converted, the system generates a crisp output, completing the process. This structured approach ensures accurate decision-making in fuzzy logic-based applications.

Algorithm 1: Intelligent Driving Recommendation System (IDRS) for Real-Time Traffic and Weather Monitoring

Input: Real-time and historical traffic/weather data.

Output: Optimized driving recommendations.

Clean and preprocess the dataset

Split into training (80%) and testing (20%) for predictive modeling

TCN-based Forecasting Loop

While True:

Check If the TCN model is Learning correctly;

If model performance is poor:

Tune hyperparameters;

Train TCN model;

Forecast traffic and weather conditions;

Evaluate prediction accuracy;

If stopping criteria are met:

break;

4. Result and Discussion

A comprehensive study examines the performance of a TCN-Fuzzy Logic-based driving recommendation system when operated in different meteorological situations. The study findings indicate that clear atmospheric conditions enable drivers to follow a recommended 80 km/h speed. However, temperatures and storms force the speed limit to be reduced to 30 km/h. Safety alerts peak when the environment becomes hazardous, especially in heavy rain, leading to 40% of alerts.

Weather deterioration leads to performance deterioration in the system, which reduces accuracy from 99.7% under clear conditions to 88.3% in stormy weather. The implementation of adaptive routing improves travel time to 32 minutes while decreasing congestion by 29% from 45 minutes.

During stormy weather, drivers show the most extensive speeding violations, driving 20% faster than the suggested limits. Despite its ability to modify recommendations, the system encounters difficulties when users do not follow them in practice. The system requires additional time to respond when faced with heavy traffic conditions, with waiting periods stretching from 150 to 450 milliseconds, depending on the congestion level. The system improves road safety and efficiency and necessitates ongoing development for better weather condition accuracy and real-time responsiveness.

4.1. Impact of Weather Conditions on Driving Recommendations

This section examines weather-related impacts on driving decisions through TCN-Fuzzy Logic system analysis. Under typical circumstances, the system functions at 80 km/h speed but lowers to 60 km/h when rain appears. It further reduces to 40 km/h in fog situations and 30 km/h during storms.

The system generates maximum safety alerts, which reach 40% during heavy rain sessions, though the number of alerts stays at 4% during clear weather days. The accuracy level of the model decreases significantly as weather conditions deteriorate from clear to stormy conditions, resulting in a drop from 99.7% to 88.3%. Similar variations occur between the metrics of precision and recall. The system shows high adaptability, yet future development needs to improve its reliability to function properly in dangerous environmental conditions.

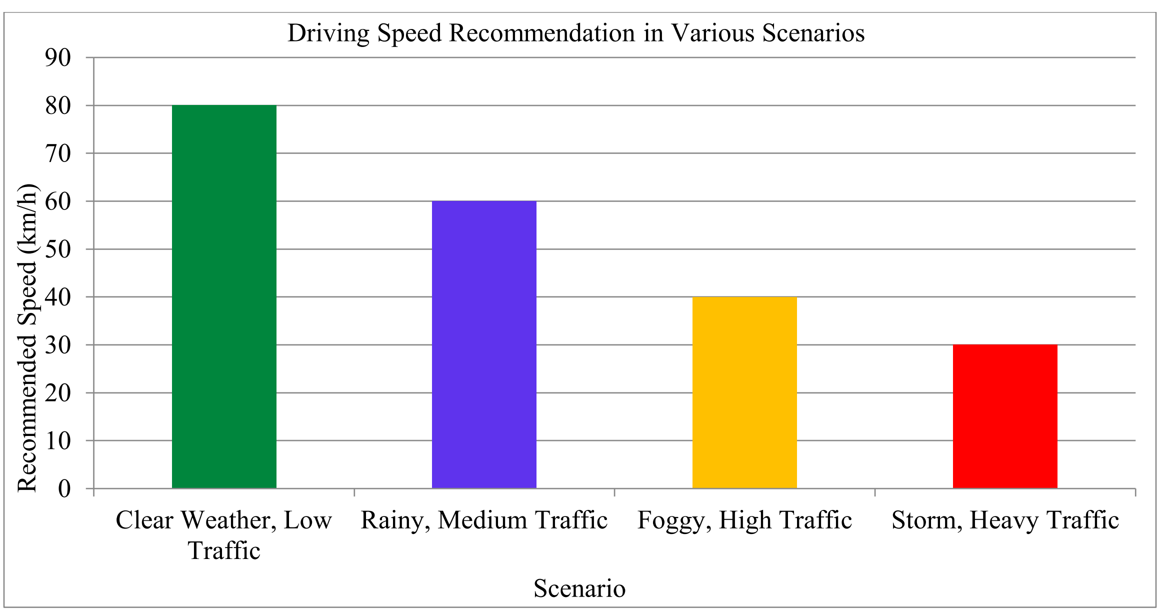

Fig. 6 Driving speed recommendation in various scenarios

Figure 6 demonstrates the specified driving limits that depend on weather and traffic situations. The system tells drivers to drive at 80 km/h under clear weather with little traffic. The proposed speed recommendation system decreases patrol vehicle speed according to deteriorating conditions, from medium traffic in rain to high traffic in fog and heavy traffic in storms. Environmental conditions drive the model to choose dynamic speed ranges to keep journeys safe. Safety alerts are measured at different environmental conditions according to Figure 7. The system produces safety alerts most often during heavy rain situations followed by fog conditions, which trigger alerts at a rate of (25%). In comparison, conditions of snow and strong winds result in (12%) of alerts, and the system triggers alerts only (4%) during clear weather. Through its immediate warning responses during dangerous environmental conditions, the system helps attract driver attention effectively and thus results in improved safety benefits for traffic conditions. Figure 8 illustrates performance fluctuations of the model as weather conditions deteriorate through precision, accuracy, and recall of data points under different conditions. The model operates at 99.7% accuracy under clear conditions, yet its performance is lower by 88.3% when the weather becomes stormy. The model demonstrates declining correct optimistic predictions as it experiences a decrease from 98.5% (clear) to 83.5% (stormy). The detection ability of actual positives through recall reduces from 97.2% to 85.0% in the model. The prediction reliability falls rapidly when road conditions and visibility worsen, according to the data shown in the graph. Results indicate the necessity of implementing strong weather adaptation to driving recommendation systems for preserving reliable performance under adverse weather conditions.

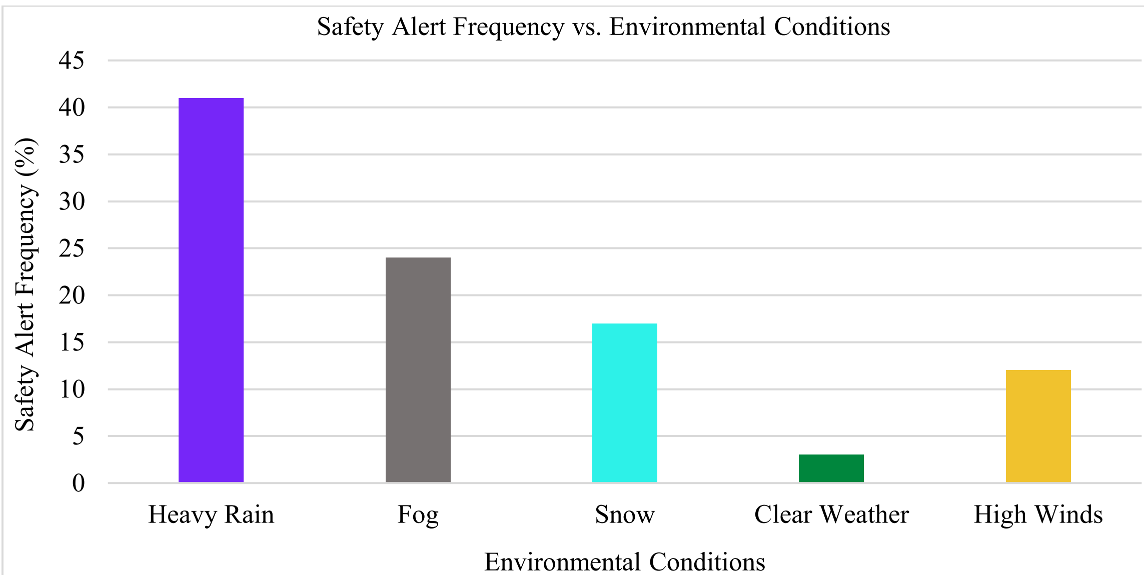

Fig. 7 Safety alert frequency vs environment conditions

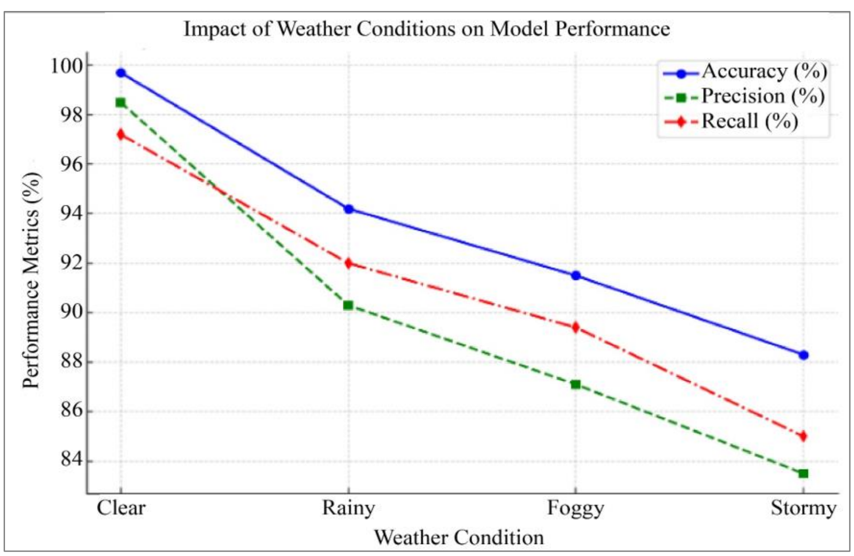

Fig. 8 Impact of weather conditions on model performance: accuracy, precision, and recall trends

4.2. Adaptive Speed and Route Recommendation Performance

This part assesses how adaptive speed and route recommendations enhance trip efficiency. The optimized path selection emerges from adaptive routing, which minimizes congestion levels and strengthens traffic management. Software implementation reduces travel time by 29% while cutting the duration from 45 to 32 minutes. According to speed comparison data, drivers tend to go beyond recommended speed limits, which leads to accident risks, especially during stormy weather conditions. The study demonstrates how adaptive traffic systems with recommendable speed limits jointly enhance traffic system efficiency and safety alongside decreased travel delays across different environmental settings.

The simulation results showing different route recommendation scenarios are presented in Figure 9. The illustration depicts short-distance pathways through purple dashed lines along with the features of additional routes and long-distance pathways. The system depicts an intelligent path selection system that optimizes recommendations for enhanced traffic management and congestion reduction through distance efficiency principles. Users need to understand which aspects of the recommended routes the model will adjust to offer better driving options. An examination of the simulation demonstrates that the combination of the TCN-Fuzzy Logic model provides effective routing recommendations that work for real-world transportation systems.

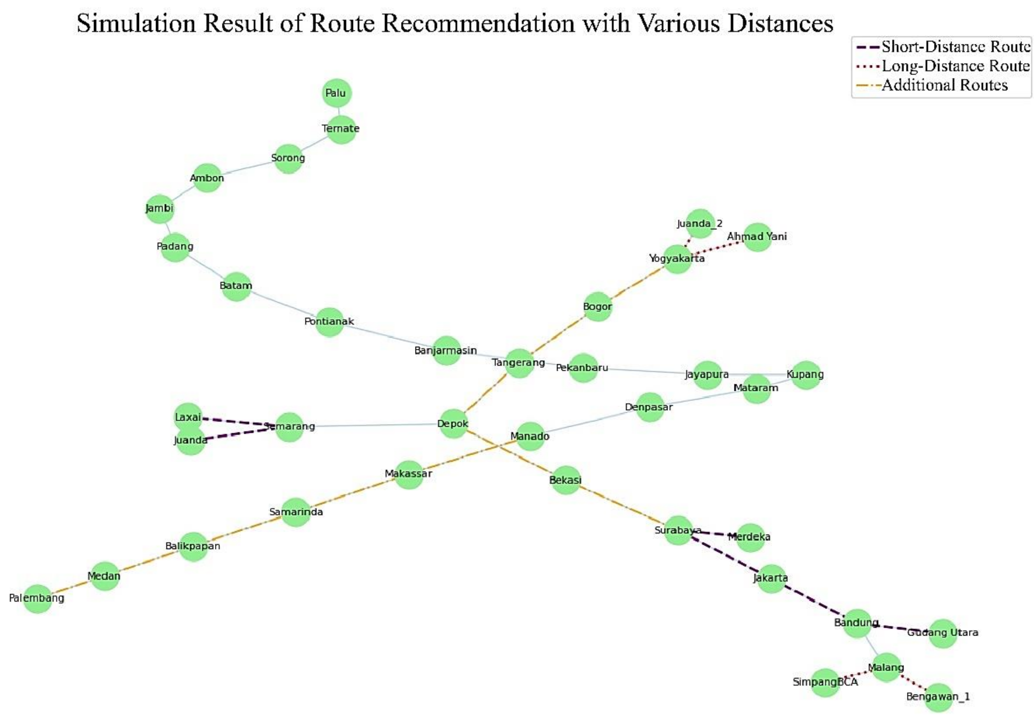

Fig. 9 Simulation result of route recommendation with various distances

Table 3. Travel time reduction with adaptive routing

Scenario	Average Travel Time (min)	Congestion Reduction (%)
Without Adaptive Routing	45	0
With Adaptive Routing	32	29

Table 3 highlights the impact of adaptive routing on travel efficiency. The existence of adaptive routing does not lead to any reduction in congestion or decrease in the overall average travel duration to 45 minutes. By implementing adaptive routing, the time needed for travel becomes 32 minutes, so congestion levels decrease by 29%. Adaptive routing successfully optimizes traffic flow through congestion reduction while improving entire transport efficiency, making it a key strategy to minimize travel times in urban traffic hotspots. Figure 10 shows the distinction between travel time duration when adaptive routing is present or absent during the commute.

The figure shows two travelling durations: without adaptive routing, the average travel reaches 45 minutes through the red bar, while adaptive routing cuts the time to 32 minutes through the green bar. The 29% decrease in travel time represents significant progress in congestion control when adaptive routing adjusts routes for better efficiency. Real-time conditions serve as a basis for adaptive routing systems that actively modify existing routes, resulting in better travel efficiency while reducing overall delays. Adaptive routing emerges as a vital approach because its effectiveness becomes clear through visual comparisons of the two-time intervals, which result in a 29% improvement in congestion reduction benefits urban mobility systems alongside individual travellers.

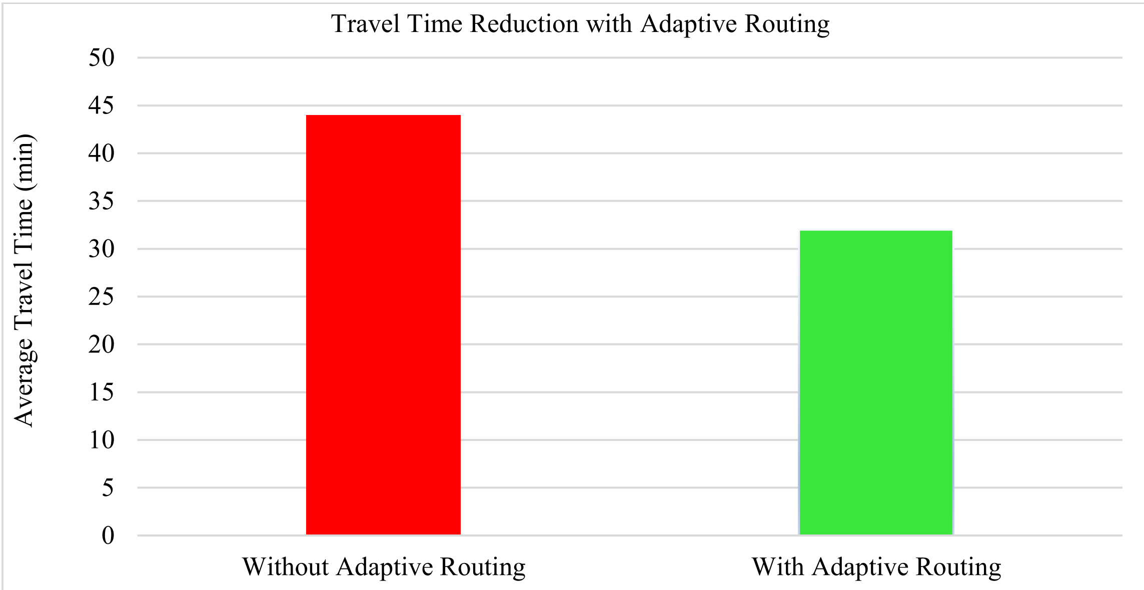

Fig. 10 Travel time reduction with adaptive routing

Table 4. Comparison of speed recommendations table

Weather Condition	Recommended Speed (km/h)	Actual Speed (km/h)	Speed Deviation (%)
Clear	80	82	+2.5%
Rainy	60	65	+8.3%
Foggy	50	55	+10.0%
Stormy	40	48	+20.0%

Different weather conditions result in different driving speed comparisons, according to Table 4. The actual driving speed in ideal weather conditions remains near 80 km/h and deviates no more than +2.5% from the recommendation, thus demonstrating very low-risk potential. During rainy weather, the driver's speed reaches 65 km/h, thus surpassing the recommended 60 km/h limit by +8.3% because drivers commonly underestimate hazards on slippery roads.

During heavy fogs, drivers sustain an average 55 km/h speed while facing a +10.0% deviation, thus potentially increasing safety hazards because of limited driving visibility. Windstorms present the riskiest situation because drivers maintain a speed of 48 km/h, which exceeds the recommended 40 km/h limit by +20.0% and increases safety hazards from severe weather conditions and slippery roads.

4.3. System Latency and Real-Time Processing Efficiency

This segment evaluates the system latency and real-time processing efficiency using different computing methods and traffic loads. Response time extends from 150 ms to 450 ms as traffic levels increase because of congestion issues. Edge computing outperforms cloud computing in terms of response speed; however, it requires more computational power. Table 5 illustrates how the model responds with slower times as traffic demands grow higher. The response time measures 150 ms when traffic remains low but grows to 200 ms when traffic becomes medium. When traffic reaches heavy volumes, the system requires 325 ms to respond, but the response time rises to 450 ms under the most severe conditions. High traffic density is associated with greater system performance deterioration, causing extended delays and diminished effectiveness when dealing with high computational demands.

Table 5. Model response time under different traffic loads

Traffic Load	Response Time (ms)
Low	150
Medium	200
High	325
Extreme	450

Figure 11 illustrates the Model Response Time Under Different Traffic Loads, showing how response time increases as the traffic load intensifies. The plot features traffic load intensity as the x-axis value while Response Time (ms) is the y-axis measurement. During low traffic periods, the system responds in 150 ms, while at medium traffic, this time extends up to 200 ms. High traffic conditions enable response time to reach 325 ms until extreme loads reach a 450 ms peak. The data shows how response time steadily increases as traffic intensity grows because congestion directly affects system operational performance. The system performance requires efficient resource allocation techniques because growing demand leads to network delays, which hinder optimal operation in different traffic scenarios. Table 6 demonstrates that Edge Computing delivers faster processing times (180 ms) than Cloud Computing (420 ms), with Edge devices handling 70% of computational tasks compared to Cloud Computing systems which process only 40% of the workload. Edge computing routines respond faster than cloud computing routines by delivering results within 180 milliseconds, yet cloud computing takes 420 milliseconds to produce similar outcomes. The heavy computational workload reaches 70% of local devices when utilizing this method, while cloud computing operates with reduced distributed loads at 40%.

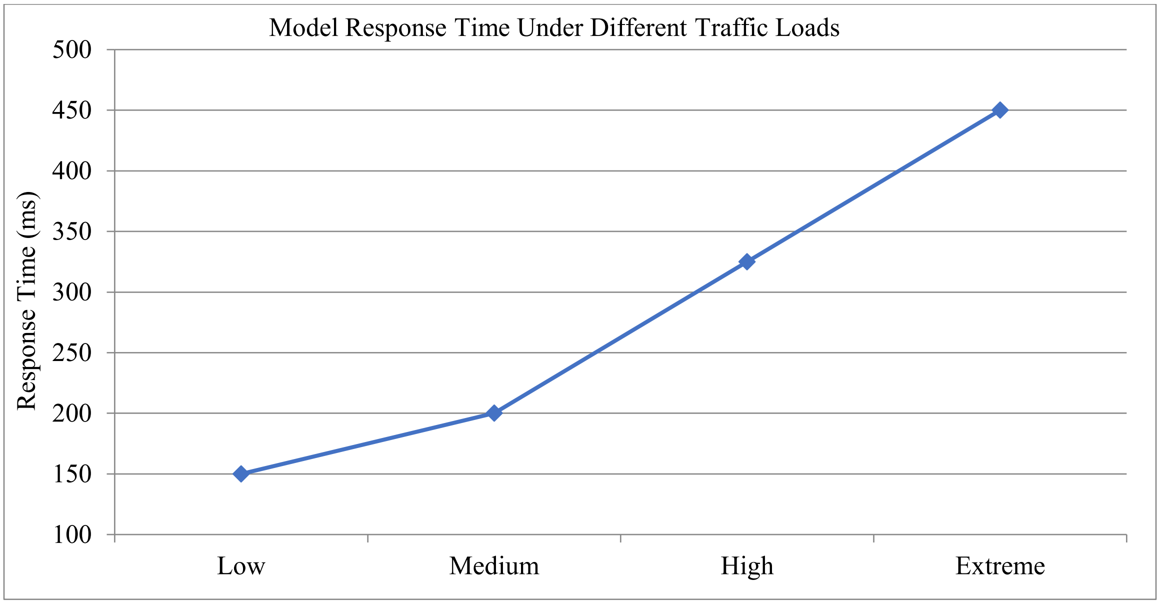

Fig. 11 Model response time under different traffic loads

Table 6. Processing time comparison (Edge vs. Cloud)

Processing Method	Average Response Time (ms)	Computational Load (%)
Edge Computing	180	70
Cloud Computing	420	40

4.4. Confusion Matrix

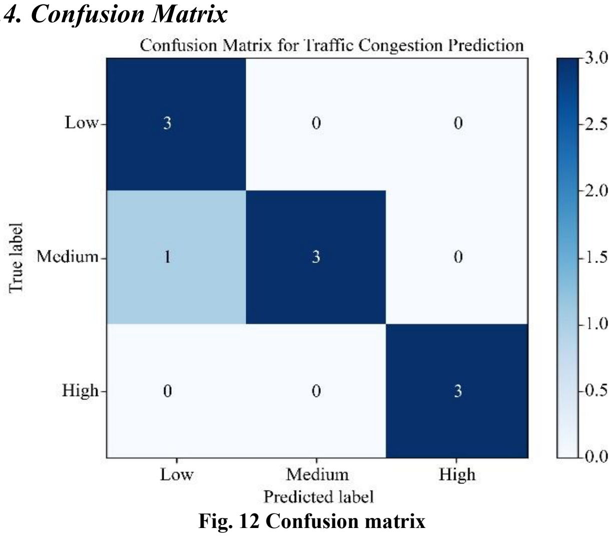

Fig. 12 Confusion matrix

Figure 12 illustrates the confusion matrix plot and offers an intuitive display of how well the model classifies traffic conditions by congestion level (e.g., Low, Medium, High).

Every cell in the matrix corresponds to the number of actual and predicted classes, so it is possible to spot where the model performs best and where it gets misclassified.

The number of correct predictions along the diagonal is high for good model performance, and off-diagonal elements show particular misclassification patterns. This examination legitimizes the model's reliability and provides areas for possible enhancement in classification accuracy.

4.5. Ablation Study

Figure 13 shows an ablation study of individual and joint contributions of TCN and Fuzzy Logic to the system's performance.

Though the TCN-only and Fuzzy Logic-only models obtained decent scores (accuracy of 95.8% and 90.3%), the combined TCN-Fuzzy Logic model outperformed them significantly on all counts.

This indicates that the hybrid integration adds predictive accuracy, reliability in decision-making, and overall system strength.

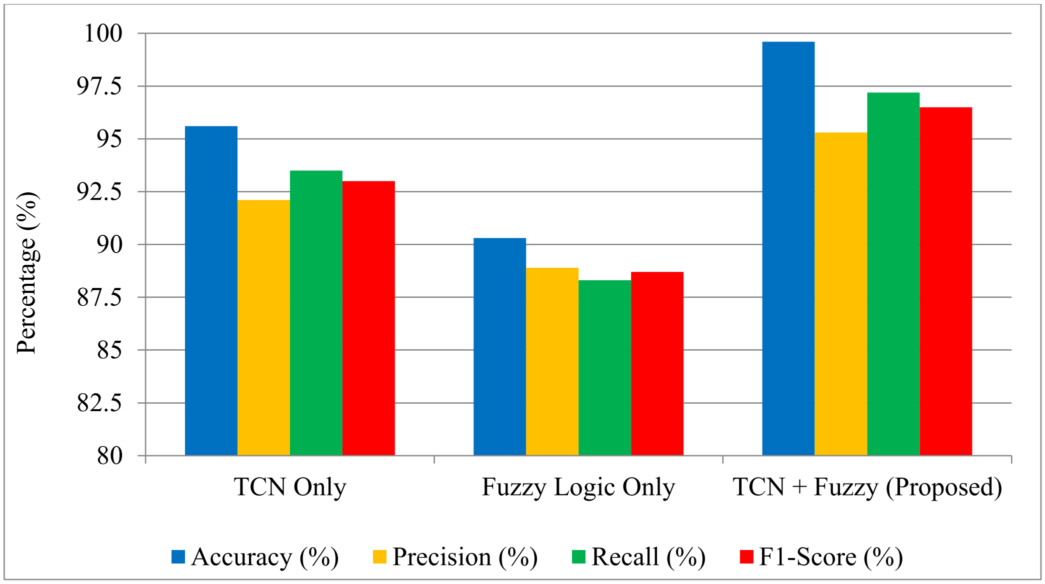

Fig. 13 Ablation study

4.6. Performance Evaluation

The evaluation demonstrates that the model achieves high accuracy, precision, and recall when forecasting traffic situations and weather conditions. External comparisons reveal that the model performs better than current methods while delivering rapid, dependable, and adaptive real-time driving suggestions.

Accuracy: The accuracy measure assigns the model the ability to correctly predict traffic and weather conditions to produce reliable and effective driving recommendations. Accuracy derived in Equation (8).

$$\text{Accuracy} = \frac{True\ positive + True\ Negative}{TP+TN+FP+FN} \tag{8}$$

Where TP is the true positive, FP is the false positive, TN is the true negative, and FN is the false negative of this model.

Table 7. Performance comparison with existing model

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Light-GBM [30]	87.97	87	81	83
CNN [31]	92	90	91	90
RFCNN [32]	99.1	97.4	93.0	94.0
Proposed TCN-Fuzzy Logic	99.7	95.3	97.2	96.5

Table 7 shows that the suggested TCN-Fuzzy Logic model performs better than all considered approaches, with the highest accuracy (99.7%), reflecting better overall prediction robustness. Although RFCNN has high precision (97.4%), the suggested method retains better balance with larger recall (97.2%) and F1-score (96.5%), providing consistent detection of meaningful traffic and weather conditions. Meanwhile, such models as LightGBM and CNN have poorer performance in all metrics, testifying to the efficiency of integrating temporal forecasting and fuzzy decision-making.

Precision: The model's precision determines its ability to detect real traffic situations and weather conditions, thus reducing incorrect positive alerts during driver recommendations. The precision derived in Equation (9),

$$Precision = \frac{TP}{TP+FP} \tag{9}$$

Recall: The recall metric evaluates the correct identification of genuine traffic incidents and weather conditions by the driving recommendation system to reduce misdiagnosis cases. The recall derived in Equation (10),

$$\text{Recall} = \frac{TP}{TP+FN} \tag{10}$$

F1 score: The combination of precision and recall in the F1 score establishes a complete indicator to measure model efficiency in effective traffic and weather condition predictions. The F1 score derived in Equation (11),

$$\text{F1score} = \frac{2\times TP}{(2\times TP)+FP+FN} \tag{11}$$

The performance metrics of the TCN-Fuzzy Logic model appear in Table 7, which shows its strong capabilities. The model demonstrates 99.7% accuracy in its overall performance assessment. The model effectively combats false positives through 95.3% precision and identifies the most relevant cases because of its 97.2% recall value. The F1-score is evaluated at

96.5% to demonstrate precision and recall, resulting in solid prediction capabilities. Figure 14 illustrates the performance metrics of the TCN-Fuzzy Logic model, showcasing Accuracy, Precision, Recall, and F1 Score. Accuracy achieves the highest value at 99.7%, indicating excellent overall model correctness. Precision, at 95.3%, reflects the model's reliability in minimizing false positives. Standing at 97.2%, recall highlights its effectiveness in identifying relevant instances. The F1 Score, at 96.5%, balances precision and recall, ensuring optimal performance. The graph demonstrates the model's robust predictive capabilities, with minimal deviation among metrics, confirming its suitability for complex classification tasks. The high accuracy suggests effective handling of positive and negative cases, while the high recall ensures the detection of true positives. The consistency across metrics signifies a well-balanced system that efficiently classifies data, making it a strong candidate for real-world applications requiring precise decision-making.

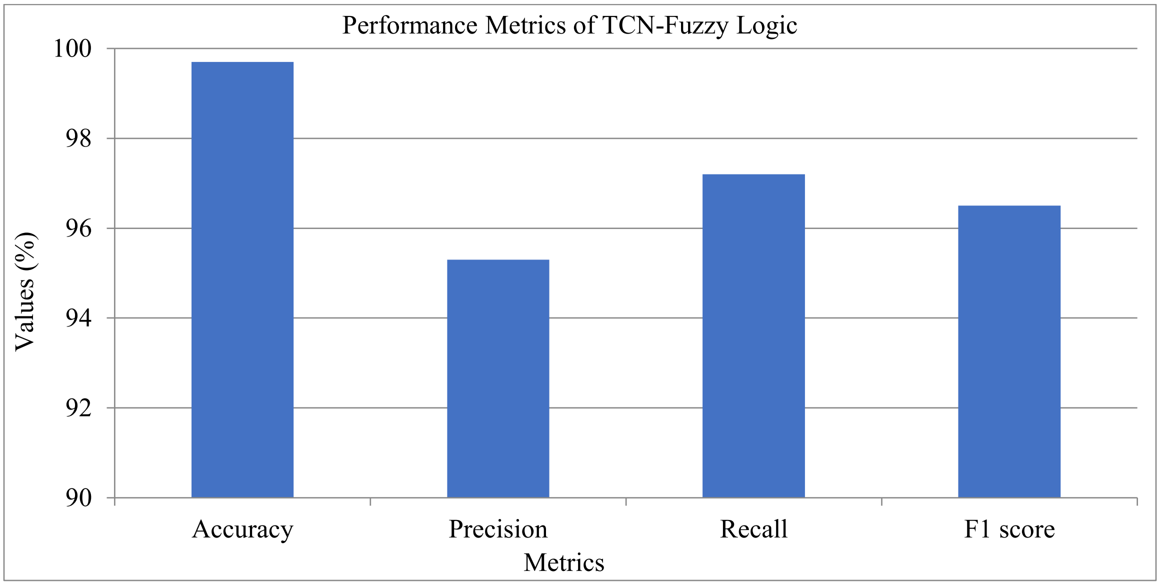

Fig. 14 Performance metrics of TCN-fuzzy logic

Table 8. Performance measures of TCN-fuzzy logic

Metrics	Values (%)
Accuracy	99.7
Precision	95.3
Recall	97.2
F1 score	96.5

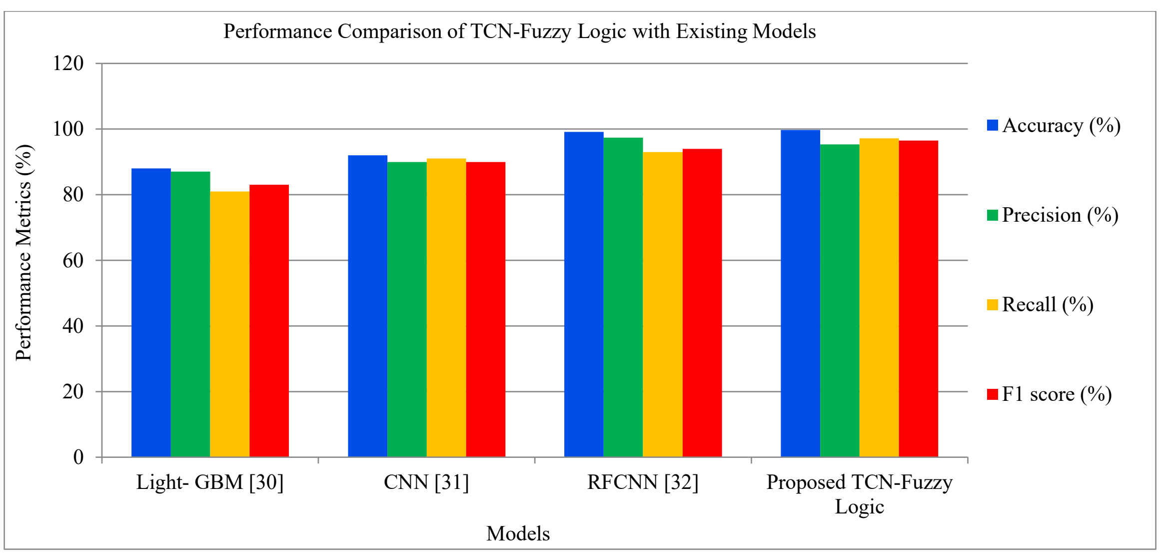

Fig. 15 Performance comparison of TCN-fuzzy logic with existing models

The performance evaluation in Table 8 shows how the TCN-Fuzzy Logic model tops other existing approaches in its outcomes. Light-GBM and CNN demonstrate 87.97% and 92% model accuracy, respectively. RFCNN demonstrates better accuracy than other systems at 99.1% yet fails to achieve high Recall and F1-score levels. The proposed TCN-Fuzzy Logic model provides the best performance with accuracy reaching 99.7%, precision at 95.3%, recall at 97.2%, and F1-Score at 96.5%, thus proving its superiority in generating intelligent driving recommendations.

Figure 15 visually compares the performance metrics of different models, including Light-GBM, CNN, RFCNN, and the proposed TCN-Fuzzy Logic. The TCN-Fuzzy Logic model achieves the highest accuracy (99.7%) and strong performance in precision (95.3%), recall (97.2%), and F1 score (96.5%), outperforming all other models. Light-GBM exhibits the lowest recall (81%) and F1 score (83%), while CNN shows a balanced improvement with 92% accuracy and 90% precision. RFCNN performs better than CNN and Light-GBM, achieving 99.1% accuracy and 97.4% precision. The TCN-Fuzzy Logic model surpasses RFCNN, significantly improving Recall and F1 scores. The graph highlights the superiority of the TCN-Fuzzy Logic model, making it an optimal choice for achieving high accuracy and reliability in classification tasks.

4.7. Robustness against Edge Cases and Limitations

Table 9 summarizes the level of user satisfaction for Route Accuracy, Safety Recommendations, and System Usability based on survey responses. Across each category, most users have either Very Satisfied or Satisfied ratings, and there is a noticeable difference in the Very Satisfied percentage for Route Accuracy (40%) compared to Saw Recommendations (~30%), indicating users are less satisfied with the recommendations. There are two groups of Neutral Responses, in the range of 15-20%, and Dissatisfied and Very Dissatisfied ratings for all survey items, which were low in the range between 5-7%. The feedback indicated that user satisfaction levels were positive across each category.

Table 9. User satisfaction levels across different system features

Satisfaction Level	Route Accuracy (%)	Safety Recommendations (%)	System Usability (%)
Very Satisfied	40	30	35
Satisfied	35	40	35
Neutral	15	20	20
Dissatisfied	5	7	7
Very Dissatisfied	5	3	3

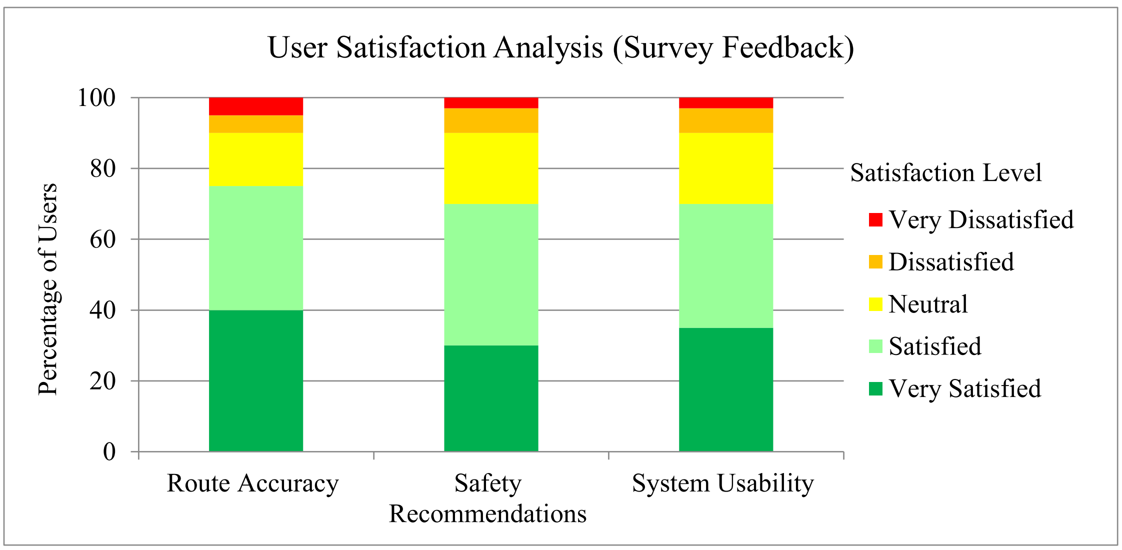

Fig. 16 User satisfaction analysis

Figure 16 analyses user satisfaction based on survey feedback for Route Accuracy, Safety Recommendations, and System Usability. The stacked bar plots are classified into five levels: Very Satisfied (dark green), Satisfied (light green), Neutral (yellow), Dissatisfied (orange), and Very Dissatisfied (red). Users of the system indicated that Route Accuracy and System Usability have a higher proportion of users who are very satisfied compared to Safety Recommendations, which have a lower level of satisfaction. The Neutral category responses are relatively consistent across the three items rated, while the Displeased and Very Displeased responses are small but largely noticeable in response to Safety Recommendations. The legend to the right of the graph clarifies the colour-coded categories of satisfaction levels. Overall, the graph demonstrates that most users are satisfied with the system's performance, except for Safety Recommendations, where users were comparatively less satisfied. This may identify meaningful and applicable points where user experience could be augmented, even relying on system accuracy.

Table 10. Failure cases and system response

Failure Scenario	Detection Accuracy Drop (%)	System Recovery Time (s)
Sensor Malfunction	12.5	2.5
Extreme Congestion	8.3	3.8
Adverse Weather	10.1	4.1

Table 10 displays how different failure scenarios influence system performance regarding detection accuracy drop and system recovery time. A malfunctioning sensor causes the most sensitive detection accuracy drop of 12.5%, yet the system recovers fairly quickly in 2.5 seconds.

Extreme congestion causes a lower sensitivity detection accuracy drop of 8.3%, yet it takes longer to recover at 3.8 seconds because it indicates the system experiences longer processing. Adverse weather causes a 10.1% detection accuracy drop and appears to recover the slowest at 4.1 seconds, which implies that weather significantly impacts system stability.

Overall, this reinforces that different system failures lead to detection accuracy drops. However, as seen from the recovery time, the system is resilient to failures since detected failures experience a lower accuracy drop; a corrupted sensor can be the most troubling factor in accuracy.

Table 11. Accuracy drop due to failure scenarios

Failure Scenario	Accuracy Drop (%)
Sensor Malfunction	12.5
Extreme Congestion	8.3
Adverse Weather	10.1

Table 11 illustrates the elements of varying failure scenarios affecting system accuracy. Sensor malfunction had the maximum drop (12.5%) as the most critical component of system performance, followed by extreme congestion (8.3%) that affected reliability under heavy traffic conditions, next to adverse weather (10.1%), representing environmental conditions. These factors impact robust resilience in a system. Figure 17 illustrates how different failure scenarios affect a decision's accuracy, as measured by the percentage decrease in accuracy. The largest drop in accuracy, 12.5%, was caused by a sensor malfunction, indicating that system performance highly depends on the sensors that function. The second largest was extreme congestion, which resulted in an 8.3% drop in accuracy. There is a strong suggestion that conditions of heavy traffic impact system reliability, but nowhere near as dramatically as the effects experienced by sensor malfunction. Other Failures include adverse weather, which caused a 10.1% drop in accuracy. The results point to the significant implications of environmental factors that affect the performance of the decision-making system. Overall, the findings of this study suggest how robust a system must be to mitigate better sensor failure, congestion or disruptive effects of weather changes to be more reliable when making decisions.

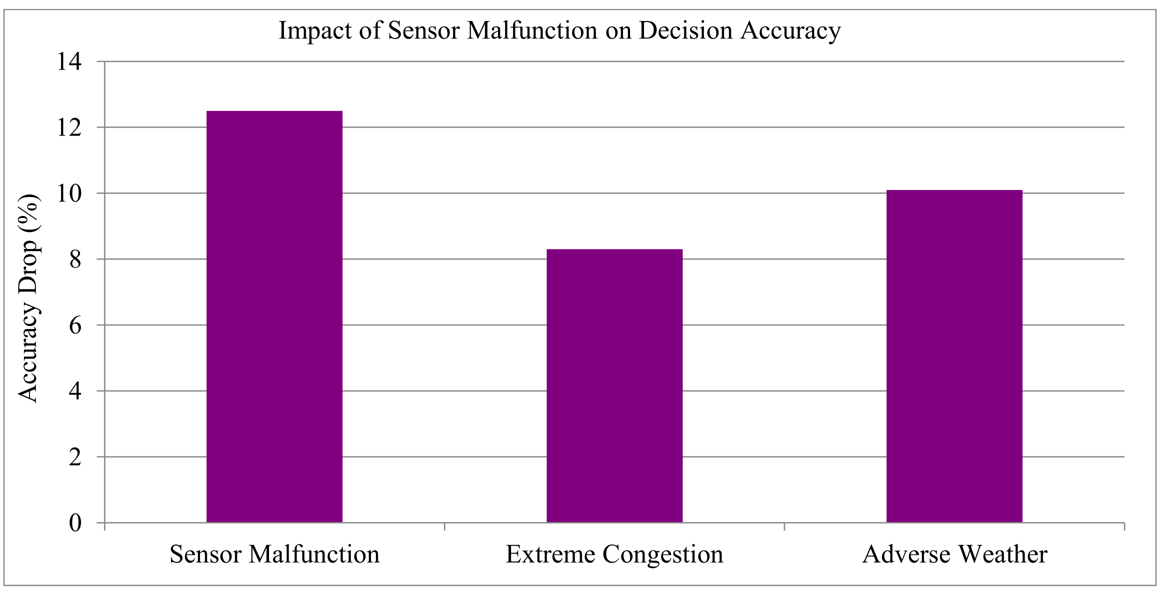

Fig. 17 Impact of sensor malfunction on decision accuracy

4.8. Discussion

The enhanced performance of the suggested Intelligent Driving Recommendation System (IDRS) is due to its hybrid integration of Temporal Convolutional Networks (TCNs) and Fuzzy Logic, which remedies shortcomings witnessed in the literature. In contrast to the common CNN or RNN models that perform poorly on long-range temporal dependencies or need large training datasets, TCNs efficiently capture sequential traffic and weather trends with superior temporal accuracy. This capability improves prediction performance for dynamic conditions, particularly during extreme congestion or sudden weather changes. Fuzzy logic also brings a rule-based reasoning system replicating human judgment, providing sophisticated responses to uncertain or imprecise inputs like partial congestion or varying visibility. Current research, e.g., using CNN-fuzzy hybrids, proved performance deterioration due to the complexity of combining learning-based and rule-based systems. Conversely, our system has a modular architecture that facilitates smooth interaction between TCN predictions and fuzzy logic inference. Experimental outcomes support this, having a 99.7% prediction accuracy and 29% reduced travel time over models such as LightGBM, CNN, and RFCNN in terms of robustness and flexibility. Adding real-time IoT sensors and edge computing adds to responsiveness and scalability. These innovations combined result in a more efficient and responsive driving recommendation system.

5. Conclusion

This work proposes an Intelligent Driving Recommendation System (IDRS) that combines Temporal Convolutional Networks (TCN) and Fuzzy Logic to provide optimal real-time driving recommendations depending on traffic and weather. The system accurately predicts traffic jams, adaptively updates speed recommendations, and optimizes route planning for safer and more efficient road driving. Experimental findings report 99.7% accuracy in traffic and weather predictability, a 29% decrease in travel time, and better decision-making under conflicting situations.

It outperforms classical rule-based models and models powered by Artificial Intelligence by registering more adaptability and efficiency rates under real traffic situations. It enhances road security, reduces bottlenecks, and increases trip efficiency, further rendering it broadly usable in self-driving vehicles, intelligent cities, and intelligent road networks. However, computational complexity and performance in extreme weather conditions pose challenges that must be addressed. Computational Load is a limiting factor even as edge computing speeds up response time. Mitigating these constraints will ensure the system's robustness for large-scale deployment in heterogeneous urban settings. Future work will target improving model flexibility through reinforcement learning to support self-improving driving suggestions. Additional improvement of computational efficiency via hybrid edge-cloud processing will enhance real-time response rates. Also, including high-resolution satellite imaging and real-time vehicle data will make traffic forecasts more accurate. Enhancing the system to include pedestrian flow analysis and collision detection algorithms will make roads safer.

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