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Design and evaluation of an Intelligent Transport System (ITS) through IoT and Artificial Intelligence (AI) techniques

Romain Atangana[1, 2, 3], Epiphanie Lauriane KenneTsakmo[3], Vivien Loick Beyala Kamgang[3,], Amstrong Emini Me Zenanga[3,] Emmanuel BABA[3,4,5], Daniel Tchiotsop[1], Godpromesse Kenne[1]

[1] Unité de Recherche d'Automatique et d'Informatique Appliquée (UR-AIA) , IUT of Bandjoun, University of Dschang –Cameroun P. O Box 134 Bandjoun

[2] Unité de Recherche de Matière Condensée d'Electronique et de Traitement du Signal (UR-MACETS), Faculty of Science, University of Dschang-Cameroun, P;O Box 67 Dschang

[3] Department of Computer Science, Higher Teacher Training College, University of Bertoua-Cameroun P.O Box 652 Bertoua

[4]Mathematical and Computer Science Department, LaRi Lab. University of Maroua –Cameroon P.O Box 814 Maroua-Cameroon

[5] CREATIVE Lab. University of Garoua –Cameroon P. O Box 346 Garoua- Cameroon

[6]Department of Mathematics, statistic and computer sciences, the University of Bertoua –Cameroon P.O Box 416 Bertoua

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Abstract

Rapid urbanization and the substantial growth of the vehicular population in Bertoua, particularly along the corridor connecting the MTN building to the Governor's Office, have resulted in critical traffic congestion, impaired mobility, and a progressive deterioration in urban quality of life. To address these emerging challenges, this study proposes the design and performance evaluation of an intelligent urban traffic monitoring and guidance system. The proposed framework integrates Internet of Things (IoT)-based technologies for real-time traffic data acquisition with Artificial Intelligence (AI) approaches, notably Long Short-Term Memory (LSTM) networks, for traffic flow prediction and classification. This paper presents the overall system architecture, the methodologies adopted for data collection and preprocessing, and the AI models implemented for traffic analysis and decision support. Experimental results demonstrate the effectiveness of the proposed system in enhancing traffic fluidity and optimizing urban mobility management. Performance evaluation using standard classification metrics achieved an accuracy of 92.43%, highlighting the robustness and predictive capability of the developed model. Furthermore, the limitations associated with dataset diversity and scenario coverage are critically discussed. Overall, this work provides a significant contribution toward the development of intelligent transportation solutions for rapidly growing urban environments with similar infrastructural and mobility constraints.

Keywords : Traffic management, IoT, Artificial Intelligence, Neural networks, Traffic prediction, Smart cities, Bertoua.

INTRODUCTION

Population growth and urban expansion in cities like Bertoua, quarter head of East Region of Cameroon, which is situated in the midway of the Douala Djamena corridor are accompanied by an exponential increase in the number of vehicles. This dynamic puts pressure on existing road infrastructure, leading to major challenges such as chronic congestion, increased road insecurity, and environmental degradation due to waste of time due to traffic congestion. The MTN building - Governor's Office axis in Bertoua, crucial for economic and administrative activities, exemplifies this issue, characterized by frequent traffic jams, difficulties in navigation, and long queues for users. In response to these challenges, Intelligent Transport Systems (ITS) are emerging as promising solutions, leveraging Information and Communication Technologies (ICT) to optimize traffic management. These systems enable real-time data collection, in-depth analysis, and informed decision-making to dynamically regulate traffic flows. The integration of the Internet of Things (IoT) for detection and communication, combined with Artificial Intelligence (AI) for predictive and prescriptive analysis, offers an innovative approach to transforming urban mobility. This article aims to design and evaluate an intelligent traffic control and guidance system specifically adapted to the context of Bertoua. The goal is to improve traffic flow, reduce travel times and fuel consumption, and enhance user safety. We hypothesize that such a system, based on real-time data collection and analysis and integrating a dynamic guidance system, can significantly optimize traffic flow management and facilitate transportation.

LITTERATURE REVIEW

The advent of the Internet of Things (IoT) has revolutionized many sectors, including transportation. IoT enables the connection of physical objects equipped with sensors and actuators, giving them the ability to collect and exchange data. In the context of traffic management, IoT facilitates real-time monitoring and the collection of detailed data on road conditions. A Connected Object (CO) is a device capable of collecting, processing, and transmitting data via a network, without direct human intervention [Roxin and Bouchereau, 2017]. The IoT architecture is typically structured in several layers: the perception layer (infrared sensors, cameras), the network layer (data transmission), the data processing layer (storage and analysis), the application layer (user interfaces), and a cross-cutting security layer [Mouhoub et al., 2015]. Recent work, such as that of [Dupont et al., 2023], has explored optimizing these architectures for complex urban environments, focusing on resilience and scalability. Communication technologies are essential for IoT. Short-range technologies like Bluetooth and Wi-Fi are useful for local connectivity, while long-range technologies such as cellular networks (4G/5G) and LPWANs (LoRa, Sigfox) are crucial for data transmission over large urban areas [Roxin and Bouchereau, 2017] [Martin and Petit, 2024] recently compared the effectiveness of different LPWAN technologies for real-time traffic monitoring, highlighting the advantages of LoRa for low-cost and low-power deployments. IoT platforms, such as AWS IoT or Thingspeak, play a central role by providing the necessary services for the collection, storage, analysis, and utilization of data from connected objects [Thiam, 2023].

Artificial Intelligence (AI) has become a cornerstone for smart traffic management, particularly for flow prediction and the optimization of signaling systems. Time series, which represent sequences of data indexed by time (such as hourly traffic volume), are at the heart of these applications. AI-based time series prediction models are varied. Artificial Neural Networks (ANNs), and more specifically recurrent neural networks (RNNs) like Long Short-Term Memory (LSTM) networks, are particularly effective at capturing complex temporal dependencies in traffic data [Al Malawi, 2024]. Recent studies, including that of [Chen et al., 2023], have demonstrated the superiority of Deep Learning models (LSTM, CNN LSTM) compared to traditional statistical models (ARIMA) for short-term traffic prediction, especially under fluctuating traffic conditions. Convolutional Neural Networks (CNNs) are also used for the analysis of spatial traffic data, for example by processing images or traffic density matrices as input data [BENSRHAIR and VIENNEY, 2021]. The integration of CNN and LSTM (CNN-LSTM) allows for simultaneous modeling of spatial and temporal traffic dependencies, providing more accurate predictions [Wang and Li, 2022].

Related works and comparison of solutions

Many intelligent traffic management systems have been developed around the world. For example, systems based on computer vision and deep learning have been proposed for vehicle detection and traffic density estimation [Garcia et al., 2023]. Other work has focused on the adaptive optimization of traffic lights based on real-time traffic conditions.

FERHAT and MERABET (2025) "Traffic Management System in a Smart City" uses data collected in real time through sensors, surveillance cameras, and traffic lights. Their methodology is based on the design, simulation, and testing of devices such as adaptive traffic lights, optimized lighting, smart speed bumps, and parking through computer vision using the Arduino platform and specialized software. The models employed are intelligent algorithms for anticipating traffic flows and computer vision models for parking management. The implicit limitations lie in the fragility of the Arduino board, requiring validation in real-world deployment. Despite this, the results obtained demonstrate a significant improvement in traffic flow, road safety, and energy efficiency, contributing to more sustainable urban mobility

Ruiz-Guirola et al. (2024) "Modeling IoT Traffic Patterns: Insights from a Machine Type Communication Dataset" Methodology: This study adopts a statistical approach to model communication flows in IoT networks through classical distributions. The authors use statistical goodness-of-fit tests (Kolmogorov-Smirnov, chi-square, etc.) to verify the relevance of the proposed models. The data comes from the Smart Campus of the University of Oulu, a connected environment in which various IoT sensors provide regular measurements. The models used include the Poisson distribution, used to model random events such as network requests, and the quasi-periodic distribution, used to model cyclical sensor updates. The models show a good fit with error rates of 11% for the Poisson model and 7% for the quasi-periodic model. Thus, the study remains descriptive with no predictive capability, no traffic control application is being considered.

Idriss Moumen, Jaafar Abouchabaka, Najat Rafalia (2023) Department of Computer Science, Faculty of Sciences, Ibn Tofail University, Kenitra, Morocco. To improve urban mobility, the authors propose a data collection system from IoT devices on the road that includes three key components: the IoT router, the IoT platform, and the data center, which then feed machine learning (ML) and deep learning (DL) models to predict short- and long-term traffic. These data are generated by observing traffic between two specific points. The dataset contains 25,092,093 data points with 9 attributes, recorded every 5 minutes. It includes raw data (number of vehicles, average speed, measurement time) and metadata (sensor position, distance), all coming from the city of Aarhus, Denmark. As a result, several methods have been used to predict traffic patterns, including: Linear regression is a statistical model that analyzes the linear relationship between a dependent variable and a set of independent variables. K-nearest neighbors (KNN) is an algorithm that makes predictions based on the features of the k nearest neighbors of a data point. Support vector regression (SVR) is a variant of the support vector machine designed for regression tasks. Long short-term memory (LSTM) is a type of recurrent neural network (RNN) designed to handle the vanishing gradient problem, making it effective for time series data such as traffic. Finally, the implementation was carried out using deep learning frameworks such as TensorFlow and PyTorch. The study results are promising. The dataset was split into training, validation and testing (70%, 20%, and 10%). Here are the results of the machine learning models: linear regression with 41% accuracy, support vector regression with 46% accuracy, and K-nearest neighbors with 43% accuracy. Results of the deep learning model (LSTM) After several iterations, the LSTM model achieved an accuracy of 91%, demonstrating its effectiveness in predicting the number of vehicles in real time and future traffic patterns. Like any study, this article has its limitations; among others, the study focuses mainly on linear regression, k-nearest neighbors, and support vector regression, which are simpler machine learning models. The article acknowledges that these models have limited accuracy and are not sufficiently effective for complex traffic forecasts.

ASTM (2024) "Autonomous Smart Traffic Management System" This project proposes an autonomous traffic management system based on a dual approach: real-time vehicle detection and flow prediction through deep learning. The whole system is tested in the CARLA simulation environment, known for its realistic scenarios. The data provide simulated videos from CARLA for vehicle detection, as well as simulated traffic history for training the predictive model. YOLOv5 is used for real-time vehicle detection in video streams, and LSTM for predicting the expected number of vehicles at a given intersection. The MAP (Mean Average Precision) achieved for detection is 0.885. RMSE (Root Mean Square Error): 2.232 for the prediction. Vehicle flow improved by +50%; waiting times reduced by 70%. However, all results are obtained in simulation; no validation in real-world conditions.

Bhatt et al. (2025) "Architecting Digital Twins for Intelligent Transportation Systems" This work focuses on the development of a digital twin, called DigIT, to model and simulate a real-time intelligent traffic management system. It integrates sensors, data streams, and predictive analytics modules powered by ML algorithms, all orchestrated in an MLOps pipeline for continuous model updates. Although not described in detail, the system is assumed to operate with: Historical traffic data, real-time streams captured via traffic lights, road sensors, and connected vehicles. Predictive machine learning algorithms, integration of monitoring and deployment tools in an MLOps pipeline are the models used. The results indicate that the system is capable of providing accurate, real-time predictions while remaining modular, flexible, and computationally efficient. Like any work, this article has limitations: no tests were conducted in a real urban environment, and the results remain essentially qualitative, without comparative performance metrics.

METHODOLOGY

Implemented architecture of the system

Inspired by modern intelligent transportation systems (ITS) (as presented in the works of Bhatt et al. 2025 or Moumen et al. 2023), the implemented architecture relies on IoT sensors, real-time data processing, and visualization tools that allow the optimization of traffic flow and the improvement of urban traffic.

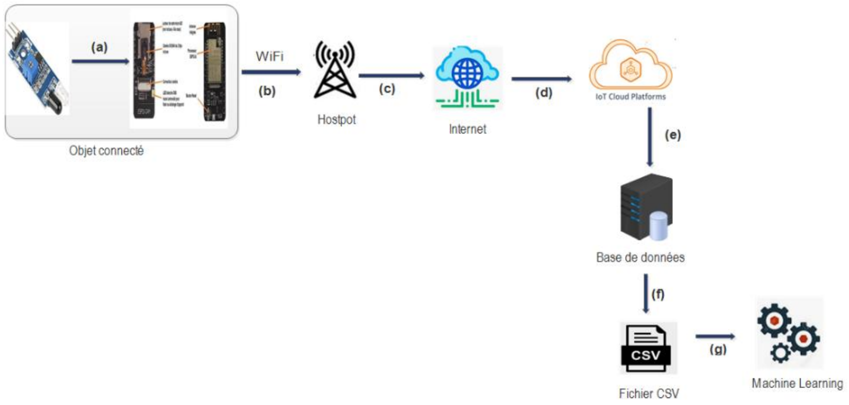

Figure 1: Architecture of intelligent transportation system

Physical sensors: Inductive loops, radars, cameras for traffic detection, an ESP32 for connectivity. (b), (c), and (d) Embedded IoT sensors (OBU) and fixed sensors (RSU): for vehicle-to-infrastructure communication. (e), (f), and (g) Traffic Control Center (TCC): processing interface, data centralization, AI algorithm execution. This architecture follows an Edge-to-Cloud model, combining edge processing (Edge AI) and centralized modeling.

Description of dataset

The dataset used comes from CSV files of road traffic, containing 4,696 road segments and 24 variables, including:

- Geospatial variables: start and end coordinates of segments (xD, yD, zD, xF, yF, zF);
- Road signs: length, type of road, concessions, coordinates;
- Target variable : AADT (Annual Average Daily Traffic);
- In-depth data engineering was carried out:
  Type conversion (from strings to float).
- Encoding categorical variables using OneHotEncoder.
- Creation of a 'Euclidean distance' feature between start and end points.
- Removal of incomplete data.

Generalities on LSTM

The detailed architecture of the LSTM classification model [Van Houdt et al (2020)], optimized for high accuracy, is as follows: Input Layer: Input(shape=(N_STEPS, X_train_seq_class.shape[2])): Defines the shape of the input data, which are sequences of N_STEPS time steps, each step having X_train_seq_class.shape[2] features. First LSTM Layer: LSTM(512, activation='relu', return_sequences=True): An LSTM layer with 512 units. The ReLU activation is used to introduce non-linearity. return_sequences=True is crucial because the output of this layer is a sequence that will be passed to the next LSTM layer. First Batch Normalization Layer (BatchNormalization): BatchNormalization(): Normalizes the activations of the previous LSTM layer, which helps to stabilize and speed up the training of the deep network. First Dropout Layer: Dropout(0.5): Randomly disables 50% of the neurons in the previous layer during training. This reduces overfitting by preventing neurons from overly co-adapting.

Second LSTM Layer: LSTM (256, activation='relu', return_sequences=True): Another LSTM layer with 256 units. return_sequences=True is also used here. Second Batch Normalization Layer: BatchNormalization(): Normalization of activations. Second Dropout Layer: Dropout (0.5): Randomly disables 50% of the neurons.

Third LSTM Layer: LSTM (128, activation='relu'): A third LSTM layer with 128 units. return_sequences is omitted (or implicitly False), which means it only returns the final output of the sequence, not the full sequence.

Third Batch Normalization Layer (BatchNormalization): BatchNormalization(): Normalization of activations. Third Dropout Layer: Dropout(0.4): Randomly disables 40% of the neurons. First Dense Layer: Dense(128, activation='relu'): A fully connected (dense) layer with 128 neurons and ReLU activation. It allows the model to learn complex combinations of the features extracted by the previous layers.

Fourth Batch Normalization Layer (BatchNormalization): BatchNormalization(): Normalization of activations. Fourth Dropout Layer: Dropout(0.3): Randomly disables 30% of the neurons. Second Dense Layer: Dense(64, activation='relu'): A second dense layer with 64 neurons and relu activation.

Fifth Batch Normalization Layer: BatchNormalization(): Normalizes the activations. Fifth Dropout Layer: Dropout(0.2): Randomly disables 20% of the neurons. Output Layer: Dense(1, activation='sigmoid'): The final output layer. For binary classification, it has a single neuron and uses the sigmoid activation, which produces a probability between 0 and 1. A probability above 0.5 is generally interpreted as the positive class ('high' traffic).

This deep architecture and the integration of regularization techniques (Dropout) and stabilization (Batch Normalization) are designed to allow the model to learn complex patterns in sequential data, while minimizing the risk of overfitting, in order to achieve high accuracy.

Fonctionnalités of the system

The intelligent road control and guidance system, based on the described methodological approach, offers the following main features:

1. Real-Time Data Collection: Infrared sensors are deployed along the Maison MTN-Governor Service axis to continuously collect data on vehicle volume, speed, and potentially their type. This raw data is transmitted by microcontrollers (ESP32 CAM) through IoT communication technologies (Wi-Fi, cellular, LoRa) to a central platform.
2. Data Preprocessing and Storage: The received data undergoes a preprocessing pipeline (cleaning, type conversion, missing value imputation, temporal and spatial feature engineering, encoding, scaling). The preprocessed data is then stored in a database ready to be used by machine learning models.
3. Predictive Traffic Modeling: ADT Prediction: The Traffic Classification LSTM Model (Binary Classification): The LSTM classification model categorizes traffic in real-time into two states: 'high traffic' or 'low traffic.' This binary classification is essential for quick decision-making
4. Decision-Making and Dynamic Guidance: Based on traffic predictions and classifications, the system can recommend actions to optimize flow. For example: Dynamic adjustment of traffic lights to prioritize certain flows. Suggestion of alternative routes for drivers via dynamic display signs or a mobile app. Alerts in case of imminent congestion or incidents.
5. Performance Monitoring and Reporting: The system generates regular reports on model performance (accuracy, F1-Score, confusion matrix for classification; R^2, MSE, MAE for regression). Visualizations (loss curves, accuracy curves) are produced to allow operators to monitor model health and identify the need for retraining or adjustment.
6. Class Imbalance Management: For classification, the system includes the ability to handle class imbalance by applying class weights during training, ensuring that the model does not bias its predictions toward the majority class.

RESULTS AND DISCUSSION

Implemented models and processing Preliminary spectral analysis

The goal is to study AADT distributions through interpolation and spectral transformation. We obtained as results the frequency curves useful for peak detection and class segmentation.

Binary classification task

Predict whether the AADT value for a segment is above or below the median (supervised approach). The model used is LSTM with: One hidden layer, A sigmoid function at the output, 10-fold cross-validation for generalization, Split: 80% training / 20% testing.

Evaluation : Accuracy : 92.43 %, F1-score : 0.92, AUC ROC : 0.95

Real time visualization

Figure 2: Status of road

Classification (traffic status)

For traffic state classification (e.g., smooth, moderate, congested), the LSTM model has also shown promising performance. The learning curves illustrate convergence. The Confusion Matrix provides a detailed view of performance by class. (a) Training accuracy (Classification).

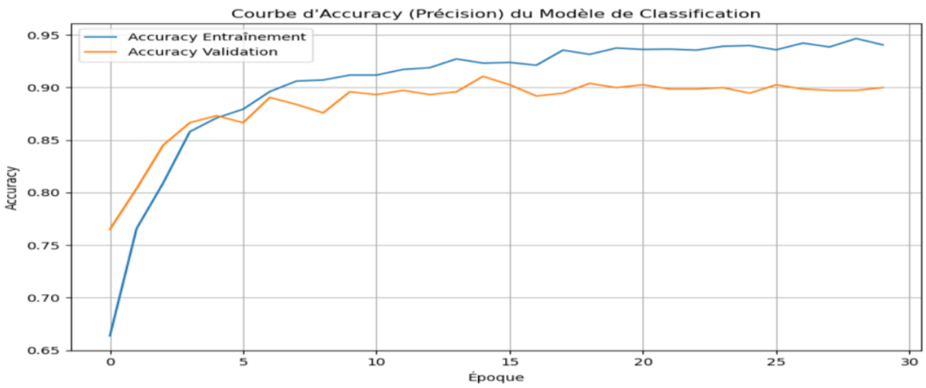

Figure 3: Learning curve of classification

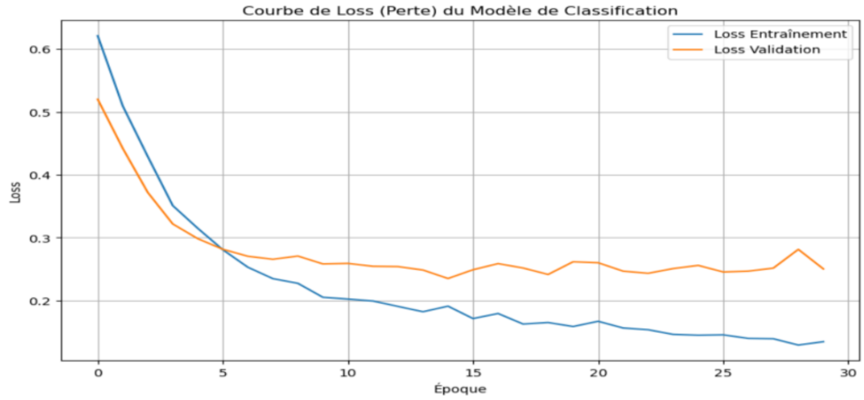

Figure 4: Loss curve

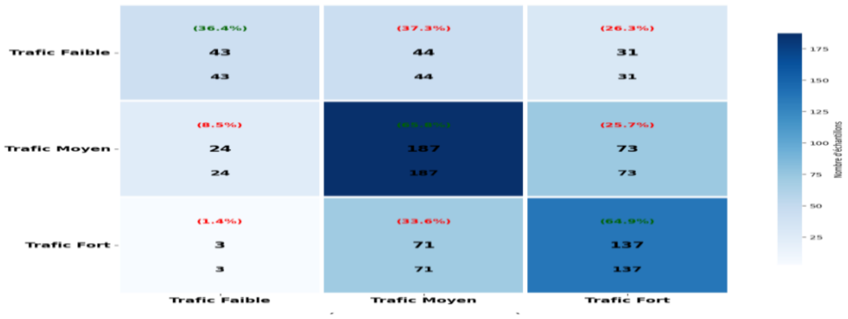

Figure 5: Confusion Matrix for three states of road

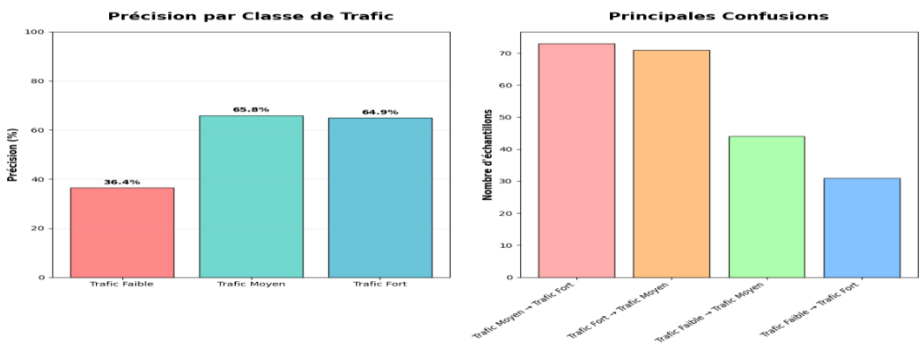

Figure 6: Confusion Matrix of the model of classification

The choice of LSTM for classification was justified by its ability to learn complex patterns in traffic data and to provide a reliable classification of congestion states.

DISCUSSIONS

References	Methodology	Dataset	Models	Results	Draubacks
FERHAT et MERABET 2025	Design, the simulation and tests	Sensors, surveillance cameras and adaptive traffic lights	Intelligent algorithms and computer vision models	-	Fragility of the Arduino board

Ruiz-Guirola 2024	Statistical analysis	Campus Oulu MTC	Fish/quasi-periodic	Error <11 %	No AI/prediction
Moumen et al. 2023	Edge sensors and ML/DL	Urban Edge IoT	SVM, LSTM, etc.	Greather to baselines	Unspecified dataset
ASTM 2024	Simulation CARLA	Simulated more images	YOLOv5, LSTM	+50 % flux, –70 % deadlines	Simulations only
Bhatt et al. 2025	Digital twin plus... MLOps	Historical plus real-time	ML predictif	Architecture efficience	No precision
Our Work (2025)	AADT distributions via interpolation and spectral transform	CSV of road traffic	LSTM	92.43 % precision	Interpretability

LIMITATIONS OF THE DATA AND MODELS USED

In addition to the dataset limitations mentioned earlier, those of the models include: Generalization: Models trained on a specific area may not generalize well to other parts of the city with different traffic characteristics without retraining or more diverse data.

Complexity of Rare Events:

Models may have difficulty predicting or correctly classifying rare or unexpected traffic events (major accidents, large-scale breakdowns) due to their underrepresentation in the training data.

Interpretability: Neural network models, although powerful, are often 'black boxes,' making it difficult to interpret the decisions made by the system.

Conclusion et perspectives

This article presented the design and evaluation of an intelligent system for controlling and directing urban traffic in the city of Bertoua, relying on the Internet of Things and Artificial Intelligence. We have demonstrated the system's capability to collect real-time traffic data and to use neural network models (LSTM) for predicting traffic volume and classifying traffic conditions. The results obtained are encouraging and validate the relevance of this approach for alleviating road congestion and improving urban mobility.

In terms of prospects, several research and development directions can be considered:

- Deployment Expansion;
- Integration of Heterogeneous Data;
- Advanced AI Models;
- Traffic Light Optimization.

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