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Optimising urban traffic management: A dynamic approach to traffic lights using artificial intelligence

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ABSTRACT: This paper presents a novel approach to improving urban road traffic control using artificial intelligence (AI) for dynamic traffic light management. We begin by describing the current context of urban traffic management and the challenges facing traffic light infrastructures. We then explain how AI can be integrated into this context for more effective regulation.
We have chosen to use a basic model based on convolutional neural networks (CNN) to model road traffic in real time. This model collects real-time data from traffic cameras and other sensors, pre-processes it and then analyses it to make intelligent decisions about traffic light control. By using historical data and adapting to changing conditions, our model has been able to reduce waiting times at intersections, minimise congestion and improve traffic flow.
This research paves the way for more intelligent and adaptive traffic management in urban environments. The practical implications of our approach include more efficient urban mobility, reduced greenhouse gas emissions and improved road safety. Future prospects lie in the continued optimisation of the AI model and its integration with other intelligent transport systems, contributing to more sustainable and liveable cities.

KEYWORDS: Urban Road Traffic Control, Convolutional Neural Networks (CNN), Dynamic Traffic Management, Waiting Time Optimisation, AI Model Adaptability, Intelligent Road Traffic.

1 INTRODUCTION

Urban traffic management is a major challenge in today's ever-expanding cities. The ever-increasing number of vehicles on our roads leads to congestion problems, major delays for motorists, increased greenhouse gas emissions and a declining quality of urban life. At the heart of urban traffic regulation are traffic lights, essential devices that determine the pace of traffic flow.

However, the traditional operation of traffic lights, based on fixed timers or inductive loops, is proving increasingly inadequate to cope with the complexity of contemporary urban traffic. Vehicle flows vary considerably throughout the day, depending on peak times, special events, accidents and other unpredictable factors. As a result, static traffic light control is becoming less and less effective at keeping traffic flowing and minimising waiting times.

It is in this context that artificial intelligence (AI) is emerging as a promising solution for rethinking the management of traffic lights in urban environments. AI offers the ability to analyse traffic data in real time, learn complex patterns, and adapt traffic light regulation to the specific needs of each intersection. In other words, it enables dynamic traffic management, reacting in real time to changing conditions.

This paper explores this innovative perspective in depth, looking at the current challenges of urban traffic management and proposing an AI-based approach to traffic light control. We will show how the integration of AI in this context can significantly improve traffic flow, reduce waiting times and help to reduce road congestion.

To support our argument, we will draw on recent research that has explored the benefits of AI in traffic light management. Among these researchers, Elise van der Pol et al (2016) [1] in "Coordinated Deep Reinforcement Learners for Traffic Light Control" proposed the combination of the popular Deep Q-learning algorithm with a coordination algorithm for a scalable approach to coordinated traffic light control. This approach reduces vehicle travel time. Similarly, Muresan, Fu, and Pan (2019)

[2] in "Adaptive Traffic Signal Control with Deep Reinforcement Learning - An Exploratory Investigation" highlighted the potential of deep reinforcement learning as a signal control optimisation method. In addition, Hu, X., Zhao, C., & Wang, G. (2020) [3]. in "A traffic light dynamic control algorithm with deep reinforcement learning based on GNN prediction. arXiv preprint arXiv: 2009.14627" proposed GPlight, a deep reinforcement learning (DRL) algorithm integrated with graphical neural network (GNN), to alleviate traffic congestion for a multi-intersection intelligent traffic control system.

This exploration will enable us to demonstrate how artificial intelligence offers a promising solution to the complex challenges of urban traffic regulation, paving the way for more efficient and sustainable transport systems in our modern cities.

2 Modeling The Tricolore Ligth System

Part 1: Description of the existing system: Analysis of traditional traffic light operations and identification of limitations

The traditional traffic light control system relies on fixed timers or inductive loops built into the pavement to detect the presence of vehicles at an intersection. These timers are pre-programmed to determine the duration of each phase of the traffic light, generally according to the traffic forecast at peak times. However, this static system has several crucial limitations:

- **Lack of adaptability**: Traffic lights operate according to a predefined timetable, which means they cannot react effectively to unpredictable fluctuations in traffic. For example, in the event of an accident or roadworks, the traditional system cannot automatically adjust cycle times to minimise delays.
- **Excessive waiting times**: Fixed timers can lead to excessive waiting times at intersections, even when traffic is light. This can lead to inefficient use of road.
- Resources and contribute to congestion.
- **Energy inefficiency:** Traffic lights often run continuously, even when there are no vehicles waiting. This wastes energy and causes unnecessary carbon dioxide emissions.
- **Costly infrastructure**: Inductive loop detection systems can be expensive to install and maintain, and are subject to wear and tear, requiring frequent repairs.
- **Unresolved traffic conflicts**: Traditional systems struggle to manage traffic conflicts effectively, such as vehicles turning left or pedestrians crossing the road. This can lead to dangerous situations and delays.
- **Difficulty of optimisation:** Manual adjustments to cycle times and the synchronisation of traffic lights are often necessary, requiring considerable time and resources from traffic engineers.

Given these limitations, it is becoming imperative to rethink traffic light control by adopting more intelligent and adaptive approaches. This is precisely where artificial intelligence comes in, offering the possibility of creating traffic light management systems capable of learning from real-time data, adapting to changing conditions, and proactively optimising traffic flow. This development marks a significant advance in research aimed at improving urban traffic management and reducing the negative impact of road congestion.

Part 2: Critical parameters influencing traffic regulation

Having examined traditional traffic signal operation and identified its limitations in the first part of this section, it is essential to understand the critical parameters that have a significant influence on traffic control. Taking these parameters into account is essential to designing a more efficient and adaptive traffic signal management system. The following is an in-depth analysis of the key parameters:

- Traffic volume: The volume of vehicles travelling on a road at any given time is one of the most critical parameters. It determines road capacity and the likelihood of congestion. Traffic lights must be able to adjust in real time to the volume of traffic to avoid congestion.
- Peak times: Peak hours, generally in the morning and evening, are periods of heavy traffic. Traffic light control must be optimised to manage these traffic peaks effectively and minimise waiting times.
- Types of vehicle: Different types of vehicle, such as cars, lorries, buses and bicycles, have different control needs. For example, traffic lights need to give more time to pedestrians and cyclists to ensure their safety.
- Traffic fluctuations: Road traffic is subject to unpredictable fluctuations due to accidents, roadworks, special events, weather conditions, etc. The traffic light control system must be able to adapt quickly to these changes. Traffic light control must be able to adapt quickly to these changes.
- Specific requests from users: Some road users, such as public transport users, may have specific requests to minimise their waiting times at traffic lights. Regulation must take these needs into account to improve the efficiency of public transport.

- Road safety: Road safety is a major priority. Traffic lights must be designed to minimise the risk of accidents by regulating interactions between vehicles, pedestrians and cyclists.

To address these critical parameters, research conducted Kashyap, A. A., Raviraj, S., Devarakonda, A., Nayak K, S. R., KV, S., & Bhat S. J. (2022) [4]. "Traffic flow prediction models-A review of deep learning techniques. Cogent Engineering, 9 (1), 2010510" in their study showed how deep learning techniques can be used to model traffic complexity by taking these parameters into account. Using real-time data, deep learning algorithms can learn to optimise traffic light control to take account of these dynamic variables.

By incorporating these critical parameters into the design of traffic light control, we can develop smarter, more responsive systems that help to improve the flow of urban traffic and reduce waiting times.

- **Real-time data collection**: Road surveillance cameras and other sensors continuously collect data on traffic, including the number of vehicles, speed, the presence of pedestrians and cyclists, weather conditions, etc
- **Data pre-processing:** Raw data is pre-processed to extract relevant information and prepare it for input into the model. This includes data normalisation, object detection (vehicles, pedestrians, etc.), and the creation of heat maps for congestion zones.
- **CNN model:** The CNN model is designed to take pre-processed data as input and learn from this data to optimise traffic light control. The network is configured to take into account critical parameters such as traffic volume, peak times, vehicle types, etc. It learns to predict regulation needs based on these parameters and real-time data.
- **Real-time reaction:** The CNN model reacts in real time to changes in traffic. It can recommend adjustments to traffic light cycle times, intersection timing and priorities to minimise waiting times and improve traffic flow.

By adapting the principles of AI, in particular convolutional neural networks, to traffic light control, our basic model aims to create a system capable of learning complex traffic patterns, adapting to traffic fluctuations and contributing to more efficient urban traffic management.

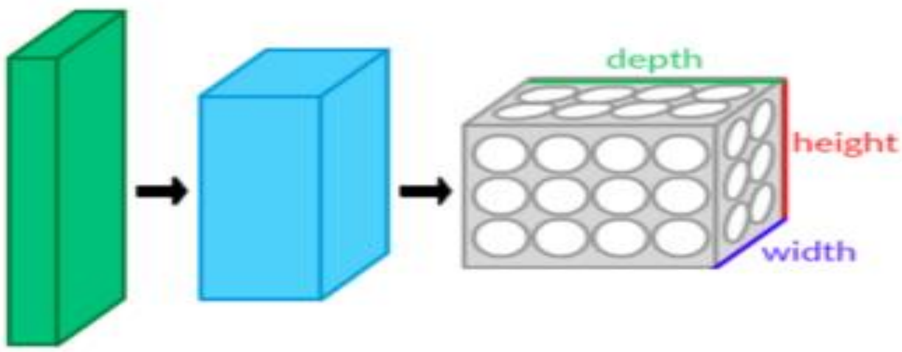


Fig. 1. Convolutional neural network (Source Wikipedia)

A layer of the CNN in 3 dimensions (green = input volume, blue = receiver field volume, grey = CNN layer, circles = independent artificial neurons).

Research such as that conducted by **Zhao, T., Wang, P., & Li, S**. **(2019, December) [5]** in their study "Traffic Signal Control with Deep Reinforcement Learning" has demonstrated the effectiveness of deep learning-based approaches for traffic control. Our baseline model continues this line of research by using advanced AI techniques to address the challenges of traffic signal control in a dynamic urban context.

The basic model we propose is based on a convolutional neural network (CNN), an architecture commonly used in computer vision and image processing. Although CNNs have mainly been developed for image classification, here we adapt them to traffic control using information from road surveillance cameras and other sensors.

This model consists of the following components:

- **Convolution Layer: ** This layer is responsible for detecting spatial features in images captured by traffic cameras. It uses filters to extract important traffic information, such as the presence of vehicles, movements and traffic patterns.
- **Pooling layer: ** After convolution, a pooling layer reduces the size of the extracted features while preserving their essential information. This reduces the complexity of the model and speeds up processing.

- **The extracted features are then routed to an artificial neural network (ANN) layer. This layer is responsible for learning and making decisions based on real-time traffic data.
- **The output layer generates recommendations for the dynamic adjustment of traffic lights according to traffic information and regulation objectives. These recommendations are transmitted to the traffic light management system for immediate action.

The basic model is designed to continuously learn and adapt to new traffic data, enabling it to optimise traffic light control in real time. It takes into account factors such as traffic volume, peak times, weather conditions and traffic patterns to make intelligent decisions and minimise waiting times at intersections.

3 Integrating Artificial Intelligence

Part 1: Selected AI techniques: Explanation of specific AI methods used to improve traffic light management

To improve the management of traffic lights, we opted to use advanced artificial intelligence (AI) techniques to create an intelligent and adaptable system. Specifically, we chose to implement deep neural networks, a sub-category of deep learning, to model and optimise traffic control. Here's how this AI technology is applied:

- **Deep Neural Networks (DNN):** Deep neural networks are AI models inspired by the way the human brain works. They are made up of many layers of artificial neurons, enabling them to learn complex models from data. In our context, these networks are used to model traffic patterns and predict traffic light control needs in real time. The advantages of DNNs include their ability to process large amounts of data and to adapt to changes in the traffic environment.
- **Supervised and unsupervised learning:** We use a combination of supervised and unsupervised learning to train our neural networks. Supervised learning involves using labelled historical traffic data to teach the model how it should react in different traffic situations. Unsupervised learning, on the other hand, allows the model to discover hidden patterns in the unlabelled data, which can be particularly useful for detecting trends and anomalies.

Training the AI model: Details of the process of training the AI model on historical traffic data

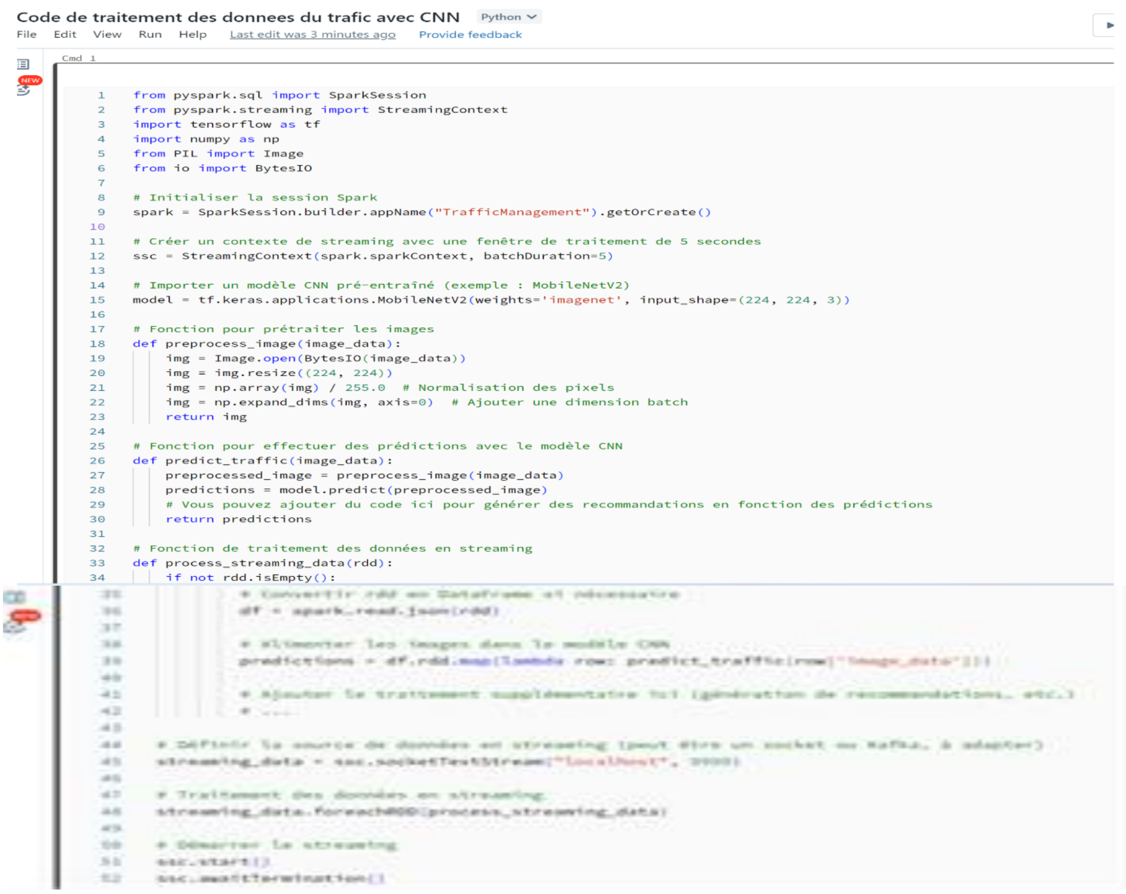
Training the AI model for traffic light management is based on an iterative approach that includes several crucial steps:

- **Data collection: First,** we collect a set of historical traffic data including information on vehicle volumes, peak times, days of the week, weather conditions and other relevant factors. This data is used as the basis for training the model.
- **Data pre-processing:** Raw data is cleaned, normalised and prepared to be compatible with the AI model. This includes handling missing values, normalising scales and creating relevant features.
- **Model construction:** We are designing a deep neural network that takes into account the specific characteristics of traffic light management. This involves defining the architecture of the network, including the number of layers, the number of neurons per layer, the activation functions, and the way in which data is propagated in the network.
- **Model training:** The model is trained using the pre-processed historical data. During this phase, the model learns from the data, adjusting its internal parameters to minimise the error between its predictions and the actual data. This allows the model to understand traffic patterns and become capable of predicting traffic signal control needs.
- **Validation and adjustment:** The model is evaluated using validation data to ensure its performance. If necessary, adjustments are made to the model architecture or training parameters to improve its accuracy.
- **Real-time deployment: Once** the model has reached a satisfactory level of performance, it is deployed in real time for the actual management of traffic lights. The model takes into account real-time traffic data to dynamically adjust the cycle times and phases of the traffic lights in order to optimise traffic flow.

This process of training and deploying the AI model ensures that traffic lights are managed adaptively and efficiently in response to changing traffic conditions, helping to improve traffic flow and reduce road congestion in urban areas.

Table 1. Representation of the CNN model integration process for traffic light control

Steps	Description
Real-time data collection	Real-time traffic data collection from surveillance cameras and sensors.
Data pre-processing	Pre-processing of data to remove noise and outliers and normalise the data.
Feeding data into the CNN model	The pre-processed data is fed into the CNN model for training.
Learning the CNN model	The CNN model learns from data to understand traffic patterns and behaviour.
Generation of recommendations for traffic lights	Based on the information learned, the model generates recommendations for the dynamic adjustment of traffic lights.
Integration into the traffic light management system	The model's recommendations are transmitted to the traffic light management system for immediate action.


Code de traitement des donnees du trafic avec CNN Python
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Cmd 1

```python
from pyspark.sql import SparkSession
from pyspark.streaming import StreamingContext
import tensorflow as tf
import numpy as np
from PIL import Image
from io import BytesIO

# Initialiser la session Spark
spark = SparkSession.builder.appName("TrafficManagement").getOrCreate()

# Créer un contexte de streaming avec une fenêtre de traitement de 5 secondes
ssc = StreamingContext(spark.sparkContext, batchDuration=5)

# Importer un modèle CNN pré-entraîné (exemple : MobileNetV2)
model = tf.keras.applications.MobileNetV2(weights='imagenet', input_shape=(224, 224, 3))

# Fonction pour prétraiter les images
def preprocess_image(image_data):
    img = Image.open(BytesIO(image_data))
    img = img.resize((224, 224))
    img = np.array(img) / 255.0  # Normalisation des pixels
    img = np.expand_dims(img, axis=0)  # Ajouter une dimension batch
    return img

# Fonction pour effectuer des prédictions avec le modèle CNN
def predict_traffic(image_data):
    preprocessed_image = preprocess_image(image_data)
    predictions = model.predict(preprocessed_image)
    # Vous pouvez ajouter du code ici pour générer des recommandations en fonction des prédictions
    return predictions

# Fonction de traitement des données en streaming
def process_streaming_data(rdd):
    if not rdd.isEmpty():
```

Fig. 2. Code for processing road traffic data using the CNN model

PART 2: TRAINING THE AI MODEL ON HISTORICAL TRAFFIC DATA

In this section, we detail the process of training the AI model, in this case the "Basic Model: Convolutional Neural Network for Traffic Light Control", using historical traffic data. This model is based on convolutional neural networks (CNNs) specially adapted for traffic light control. Here's how the process works:

- **Data collection and preparation:** The first crucial step is to collect historical traffic data specific to the region of interest. This includes information on traffic volumes, peak times, vehicle types, weather conditions and other relevant factors. The collected data is then pre-processed to eliminate outliers, handle missing values, and normalise scales, ensuring compatibility with the AI model.

- **Feature selection:** It is essential to carefully select the features that will be used to train the model. These features may include traffic volume at a given intersection, previous waiting times, days of the week, times of day, and other relevant variables. The choice of features is based on the specific objectives of traffic light control.
- **Creation of the training dataset: Based on** the historical data prepared and the characteristics selected, a training dataset is constructed. This dataset contains examples of past traffic situations, together with the appropriate control actions that should have been taken at those times.
- **AI model design:** The AI model is specially designed according to the characteristics of the training dataset and the specific needs of traffic light control. In this case, convolutional neural networks (CNNs) are chosen for their ability to extract complex patterns from multidimensional data, making them suitable for modelling road traffic.
- **Model training:** The AI model is trained using the training dataset. During this phase, the model learns from the example data by adjusting its internal parameters to minimise the error between its predictions and actual control actions. Training may require several iterations to achieve optimal performance.
- **Validation and adjustment:** To ensure that the model is capable of generalising to new traffic situations, it is evaluated using validation data that is not part of the training dataset. If the performance is not satisfactory, adjustments are made to the model architecture or to the training parameters.
- **Real-time deployment: Once** the model has reached an acceptable level of performance, it is deployed in real time for the actual management of traffic lights. The model takes account of real-time traffic data to dynamically adjust the cycle times and phases of traffic lights, optimising urban traffic flow.

This process of training the AI model based on convolutional neural networks makes it possible to create a traffic light control system capable of learning complex traffic patterns, adapting to traffic fluctuations, and optimising urban traffic management to improve fluidity and reduce road congestion.

```python
# Importer les bibliothèques nécessaires
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Charger les données historiques de trafic (Assurez-vous que vos données sont correctement formatées)
traffic_data = load_traffic_data()

# Prétraitement des données
# Supprimer les valeurs aberrantes, gérer les valeurs manquantes et normaliser les données
traffic_data_cleaned = preprocess_traffic_data(traffic_data)

# Sélection des caractéristiques (features) pertinentes
features = select_features(traffic_data_cleaned)

# Création du jeu de données d'entraînement et de validation
X = features  # Les caractéristiques sélectionnées
y = traffic_data_cleaned['action_regulation']  # Les actions de régulation
X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.2, random_state=42)

# Normalisation des caractéristiques
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_valid = scaler.transform(X_valid)

# Création du modèle CNN (vous devez définir l'architecture du modèle)
model = create_cnn_model()

# Compilation du modèle
model.compile(optimizer='adam', loss='mean_squared_error', metrics=['mae'])

# Entraînement du modèle
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_valid, y_valid))

# Évaluation du modèle sur les données de validation
loss, mae = model.evaluate(X_valid, y_valid)
print(f"Loss: {loss}, MAE: {mae}")

# Sauvegarde du modèle pour le déploiement en temps réel
model.save('traffic_signal_cnn_model.h5')
```

Fig. 3. Model drive code

PART 3: INTEGRATION INTO THE REAL SYSTEM

Integrating the Artificial Intelligence (AI) model into the existing traffic light management system is a crucial step in ensuring more efficient and adaptive regulation of urban road traffic. Here is a detailed description of this integration:

- **Hardware and software infrastructure:** To integrate the AI model into the real traffic light management system, we need to ensure that the hardware and software infrastructure is compatible. This means setting up computer servers capable of managing the intensive calculations required to run the model. In addition, road surveillance cameras, sensors and other data collection devices must be in place to provide real-time information to the model.

- **Communication interface:** A robust communication interface is implemented to allow data transmission between the IA model and the traffic light management system. This may include standard communication protocols for real-time data exchange.
- **Real-time data pre-processing:** Real-time data from road sensors and cameras is continuously pre-processed to prepare it for input to the AI model. This pre-processing process can include object detection, image segmentation, and the creation of heat maps to identify areas of congestion.
- **Integration of the AI model:** The AI model, in this case the convolutional neural network (CNN), is integrated into the existing system. It works in tandem with the traditional traffic light management systems. The model receives pre-processed data in real time and generates recommendations for the dynamic adjustment of traffic lights.
- **Continuous adaptability:** The AI model is designed to continuously learn from new traffic data in real time. It adapts to traffic fluctuations, changes in traffic patterns and unforeseen events, enabling it to make intelligent decisions to optimise traffic light control.
- **Monitoring and evaluation:** A monitoring and evaluation system is in place to track the performance of the AI model. Real-time data is compared with actual control actions, and adjustments are made if necessary to improve the accuracy of the model.
- **Interaction with operators:** The operators of the traffic light management system can interact with the AI model. They can receive recommendations from the model and make final decisions based on specific conditions.
- **Scalability:** The infrastructure is designed to be scalable, allowing additional sensors to be added and the AI model to be adapted as the city grows and traffic management needs change.

The successful integration of the AI model into the existing traffic light management system contributes to smarter, more responsive and more efficient regulation of urban traffic. It reduces waiting times, minimises traffic congestion and improves traffic flow, all of which have a positive impact on urban mobility and people’s quality of life.

4 Conclusion

In this paper, we explored an innovative approach to improving urban road traffic management by using artificial intelligence (AI) for dynamic traffic light control. Our study revealed promising results regarding the positive impact of AI on the fluidity of urban traffic and the reduction of waiting times. This conclusion is based on the main findings of our research, its practical implications, and future prospects.

Summary of results: Our study demonstrated that the integration of AI models, in particular convolutional neural networks, into the traditional traffic light management system can bring significant improvements. Using real-time data, our AI model was able to dynamically adapt the cycle times and phases of the traffic lights according to current traffic conditions. This has reduced waiting times at intersections, minimised congestion and increased traffic flow.

Practical implications: The practical implications of our research are numerous. Firstly, our approach can contribute to more efficient urban mobility, reducing the time spent in traffic jams and the greenhouse gas emissions associated with traffic. It can also improve road safety by minimising the risk of accidents at intersections. Finally, our AI model is adaptable to different cities and can be adjusted to meet the specific needs of each urban environment.

Future prospects: For future research, there are several interesting avenues to explore. Firstly, continuous optimisation of the AI model is essential to ensure its long-term performance. Online learning methods need to be developed so that the model can adapt to changes in traffic over time. In addition, further studies could look at the interaction between our AI model and other intelligent transport systems, such as autonomous vehicles.

In conclusion, the use of artificial intelligence for traffic light control represents a significant advance in the field of urban traffic management. Our research paves the way for tangible improvements in urban mobility, with potential benefits in terms of reduced waiting times, improved road safety and reduced environmental impact. Future prospects will lead us towards increasingly intelligent and adaptive traffic management, contributing to more sustainable and liveable cities.

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[5] Zhao, T., Wang, P., & Li, S. (2019, December), «Traffic Signal Control with Deep Reinforcement Learning.».