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Intelligent Traffic Analysis System Using Deep Learning

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Abstract

Due to the rapid increase in both vehicle traffic and urbanization, effective traffic control systems are now essential. This review paper integrates Intelligent Traffic Analysis Systems (ITAS) with Convolutional Neural Networks (CNNs), a deep learning technology, to provide accurate and real-time data analysis. Advanced technologies used by ITAS monitor, analyze, and reduce traffic flow. Specifically designed deep learning models for object detection and tracking are employed to recognize and monitor cars, trucks, and other relevant entities in the recorded data. Transfer learning from previously trained models is used to train the proposed CNN architecture, which is modified for traffic analysis. This approach enhances efficiency and helps avoid road traffic congestion.

Keywords: *Artificial Neural Network, Deep Learning technology, Convolutional Neural Networks (CNNs), Machine Learning.*

1. Introduction

In our consistently growing metropolitan cities, the flow of traffic has become a difficult challenge. Road traffic management systems frequently struggle to adapt to the dynamic and complex nature of daily traffic situations. To address this, Intelligent Traffic Analysis Systems (ITAS) have emerged as a robust analysis system, utilizing the capabilities of Deep Learning, particularly Convolutional Neural Networks (CNNs), to transform how traffic information is captured, analyzed, and used for insightful decision-making. Currently, the number of vehicles has increased globally, especially in large urban areas. Traffic refers to the number of vehicles moving along roads. Managing the increasing number of streets, which is growing daily, has become truly challenging. This situation affects our lives in many ways, such as health issues, pollution, and wasted fuel [1-3]. There are numerous reasons for traffic, including disabled vehicles, sudden emergencies, and accidents that can block one or more roadways. We should engage in more activities to reduce traffic congestion, such as implementing adaptive signal technology, encouraging the use of public transportation as much as possible, and using AI to alert traffic management systems. Heavy road traffic is a condition on transport networks that occurs as usage increases and is characterized by slower speeds, longer travel times, and increased vehicular queuing. When traffic demand is significant enough that the interaction between motor vehicles slows the pace of traffic, this results in congestion. While congestion is possible for any mode of transportation, counting vehicles provides the data needed to understand the flow of traffic in any observed region [4]. Along with this, the main information we have attempted to gather is counting vehicles from various libraries' available traffic recordings. ITAS represents a transformative approach to traffic management, offering unprecedented insights and capabilities through the fusion of deep learning and transportation engineering. By optimizing traffic flow and reducing stop-and-go conditions, ITAS not only improves the efficiency of transportation networks but also contributes to a more livable and resilient urban environment. Moreover, we highlight the potential benefits of ITAS, ranging from reduced travel times and fuel consumption to enhanced road safety and environmental sustainability. Furthermore, we examine the key components of ITAS, including real-time traffic monitoring, predictive analytics, anomaly detection, and adaptive signal control. We discuss how these components work in tandem to facilitate dynamic traffic management, proactively identifying bottlenecks, accidents, and other disruptions, and suggesting optimal rerouting strategies to minimize congestion and improve overall traffic flow [5-7].

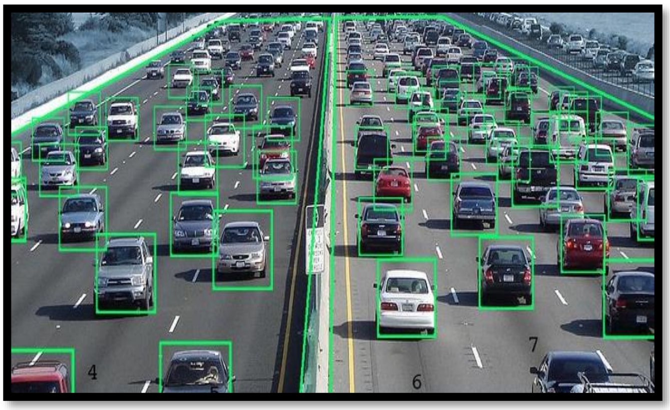

Figure 1 Detected Vehicles from Videos

In this paper, we delve into the architecture, capabilities, and potential impact of ITAS in revolutionizing urban traffic management. We explore how deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are employed to extract meaningful patterns from raw traffic data, including vehicle movements, congestion patterns, and anomalous events [8].

2. Recent Related Work

2.1. Application Progress of Intelligent Traffic Analysis System Using Deep Learning

Anomaly Detection in Traffic Surveillance: Deep learning algorithms have been employed for anomaly detection in traffic surveillance systems. By analyzing patterns in traffic data, such as vehicle speeds, densities, and trajectories, these models can identify abnormal events such as accidents, breakdowns, or road obstructions, enabling timely intervention and mitigation [9].

Integration of Multi-Modal Data for Comprehensive Traffic Analysis: Recent efforts have focused on integrating data from multiple sources, including traffic cameras, GPS devices, and social media platforms, to perform comprehensive traffic analysis. Deep learning methods are employed to extract insights from diverse data modalities, enhancing the accuracy and robustness of traffic management systems.

Privacy-Preserving Techniques for Traffic Data Analysis: With growing concerns about privacy and data security, recent research has explored privacy-preserving techniques for traffic data analysis. Deep learning models are being developed to analyze encrypted or anonymized traffic data while preserving the privacy of individual users, ensuring compliance with privacy regulations and enhancing public trust in traffic management systems. **Real-Time Traffic Monitoring with Convolutional Neural Networks (CNNs):** Recent research has explored the use of CNNs for real-time traffic monitoring from video streams captured by traffic cameras. These models can detect and track vehicles, estimate traffic density, and identify congestion hotspots, providing valuable insights for traffic management authorities.

Deep Learning-Based Traffic Flow Prediction: Recent studies have focused on using deep learning techniques, such as recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks, for traffic flow prediction. These models leverage historical traffic data to forecast future traffic conditions, aiding in proactive traffic management and congestion avoidance.

Adaptive Traffic Signal Control Using Reinforcement Learning: Deep reinforcement learning techniques have been applied to optimize traffic signal control in urban environments. By learning from real-time traffic data and feedback loops, these models can dynamically adjust signal timings to minimize congestion, reduce delays, and improve overall traffic flow efficiency. These recent advancements highlight the growing adoption of deep learning techniques in the development of Intelligent Traffic Analysis Systems, paving the way for more efficient, adaptive, and sustainable urban transportation networks.

2.2. Current Situation of Intelligent Traffic Analysis System Using Deep Learning

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Real-World Deployments: Many cities around the world are deploying ITAS solutions to address traffic congestion, enhance road safety, and improve overall transportation efficiency. These systems often leverage a combination of traffic cameras, sensors, and other IoT devices to collect real-time traffic data, which is then analyzed using deep learning algorithms to derive actionable insights.

Integration of Multi-Modal Data: There is a growing trend towards integrating data from multiple sources, including traffic cameras, GPS devices, and social media platforms, to perform comprehensive traffic analysis. Deep learning methods are employed to extract insights from diverse data modalities, enhancing the accuracy and robustness of ITAS solutions.

Traffic Flow Prediction: ITAS systems continue to focus on traffic flow prediction, utilizing historical traffic data to forecast future traffic conditions. By accurately predicting traffic patterns, authorities can proactively implement traffic management strategies to alleviate congestion and improve traffic flow. **Advancements in Deep Learning Techniques:** Deep learning algorithms, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and reinforcement learning, are being further refined and optimized for traffic analysis tasks. Researchers are exploring novel architectures and training methodologies to improve the accuracy and efficiency of ITAS models.

Privacy and Security Considerations: With the increasing deployment of ITAS systems, there is a growing emphasis on privacy-preserving techniques for traffic data analysis. Researchers are developing methods to analyze encrypted or anonymized traffic data while preserving the privacy of individual users, ensuring compliance with privacy regulations.

Anomaly Detection and Incident Management: Deep learning-based anomaly detection algorithms are being used to identify abnormal events in traffic data, such as accidents, breakdowns, or road obstructions. These systems enable authorities to quickly respond to incidents, minimize disruptions, and ensure the safety of commuters.

Anomaly Detection and Incident Management: Machine learning-based anomaly detection algorithms play a crucial role in identifying abnormal events in traffic data, such as accidents, breakdowns, or road closures. These algorithms analyze patterns in traffic flow, vehicle trajectories, and other sensor data to detect deviations from normal behavior and trigger timely interventions and incident management responses.

Real-World Deployments and Pilots: Many cities and transportation agencies worldwide are actively deploying or piloting ITAS solutions to address traffic congestion, enhance road safety, and optimize transportation networks. These systems often leverage data from a variety of sources, including traffic cameras, sensors, GPS devices, and historical traffic data, to provide real-time insights and decision support to traffic management authorities.

Integration of Data Sources: There is a growing emphasis on integrating data from multiple sources, including traffic sensors, social media, weather data, and public transportation schedules, to perform comprehensive traffic analysis. Machine learning algorithms are employed to process, integrate, and analyze diverse data sources, enabling holistic insights into traffic patterns and trends.

Privacy and Security Considerations: With the increasing deployment of ITAS systems, there is a heightened focus on privacy and security considerations. Machine learning models are being developed with privacy-preserving techniques to analyze traffic data while protecting sensitive information about individuals and ensuring compliance with privacy regulations. **Traffic Flow Prediction:** Machine learning models are extensively used for traffic flow prediction, leveraging historical traffic data to forecast future traffic conditions. These models employ techniques such as regression, time-series analysis, and deep learning to capture complex patterns in traffic data and predict traffic volumes, speeds, and congestion levels with high accuracy.

Real-Time Traffic Monitoring: Machine learning techniques, including computer vision and pattern recognition, are widely used for real-time traffic monitoring from video streams captured by traffic cameras. These models can detect and track vehicles, estimate traffic density, identify congestion hotspots, and provide actionable insights to traffic management

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authorities in real-time. Advancements in Machine **Learning Techniques:** Machine learning algorithms, including supervised learning, unsupervised learning, and reinforcement learning, are being increasingly applied in ITAS for various tasks such as traffic flow prediction, anomaly detection, and adaptive signal control. Researchers and practitioners are continuously exploring new algorithms and methodologies to improve the accuracy and efficiency of traffic analysis. Overall, the current situation of Intelligent Traffic Analysis Systems using machine learning reflects a dynamic landscape of ongoing research, technological innovation, and real-world deployments aimed at improving urban mobility, safety, and sustainability through data-driven decision-making and proactive traffic management strategies.

Real-Time Traffic Monitoring: ITAS systems employ CNNs and other deep learning models for real-time traffic monitoring from video streams captured by traffic cameras. These models can detect and track vehicles, estimate traffic density, and identify congestion hotspots, providing valuable insights for traffic management authorities to make data-driven decisions. Overall, the current situation of Intelligent Traffic Analysis Systems using deep learning reflects a dynamic landscape of ongoing research, technological innovation, and real-world deployments aimed at improving urban mobility, safety, and sustainability.

3. Analysis of Intelligent Traffic Analysis System Using Deep Learning

Integration of Multi-Modal Data: This parameter analyzes how effectively the system integrates data from diverse sources, including traffic cameras, GPS devices, and social media platforms, to perform comprehensive traffic analysis. It examines the effectiveness of deep learning methods in processing and fusing multi-modal data for enhanced insights and decision-making.

Anomaly Detection Performance: This parameter evaluates the system's ability to detect abnormal events in traffic data, such as accidents, breakdowns, or road obstructions. It examines the precision, recall, and F1-score of deep learning-based anomaly detection algorithms in identifying and classifying anomalies.

Real-Time Monitoring Efficiency: This parameter assesses the system's capability to monitor traffic conditions in real-time using data from traffic cameras and sensors. It evaluates the speed, accuracy, and scalability of deep learning models, such as convolutional neural networks (CNNs), in analyzing video streams and extracting relevant traffic information.

Privacy and Security Compliance: This parameter assesses the system's adherence to privacy regulations and security standards in handling sensitive traffic data. It evaluates the effectiveness of privacy-preserving techniques, such as data encryption and anonymization, in protecting user privacy while ensuring the integrity and confidentiality of traffic data.

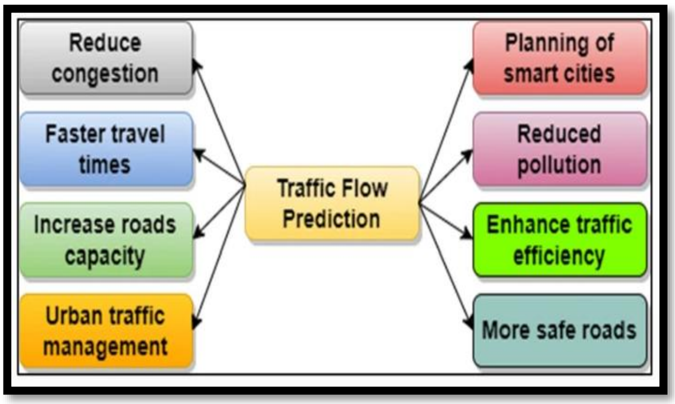

Figure 2 AI Based Traffic Flow Predictions

Traffic Flow Prediction Accuracy: This parameter assesses how accurately the system predicts future traffic conditions based on historical data. It measures the effectiveness of deep learning models, such as recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks, in forecasting traffic patterns.

Scalability and Robustness: This parameter examines the system's scalability and robustness in handling large-scale traffic data and operating under varying environmental conditions. It analyzes the performance of deep learning models in scaling to

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accommodate increasing data volumes and adapting to changing traffic dynamics and conditions.

Adaptive Signal Control Performance: This parameter evaluates the system's effectiveness in optimizing traffic signal control using reinforcement learning techniques. It assesses the ability of deep reinforcement learning models to dynamically adjust signal timings based on real-time traffic data and feedback loops to minimize congestion and improve traffic flow efficiency.

4. Prediction and Analysis of Intelligent Traffic Analysis System Using Deep Learning

4.1. Traffic Flow Prediction

Formula: Traffic Flow Prediction = f(Historical Traffic Data)

In this step, historical traffic data, such as vehicle counts, speeds, and congestion levels, is fed into a deep learning model (e.g., Recurrent Neural Network or Long Short-Term Memory network). The model learns patterns and relationships in the data to forecast future traffic conditions, such as traffic volumes, speeds, and congestion levels, at specific time intervals or locations.

4.2. Anomaly Detection

Formula: Anomaly Score = g(Current Traffic Data)

Anomaly detection algorithms, such as Isolation Forest or Autoencoder, analyze current traffic data in real-time. The algorithm computes an anomaly score for each data point, indicating its deviation from normal traffic behavior. Anomalies are identified based on predefined thresholds or statistical properties of the anomaly scores.

4.3. Real-Time Traffic Monitoring

Formula: Traffic Density = h (Video Stream)

Video streams from traffic cameras are processed using deep learning models, such as Convolutional Neural Networks (CNNs). The CNNs detect and track vehicles, estimate traffic density, and identify congestion hotspots in real-time.

4.4. Integration of Multi-Modal Data

Integrated Traffic Analysis = α(Traffic Data) + β(Weather Data) + γ(Social Media Data)

Explanation

Data from various sources, including traffic sensors, weather stations, and social media platforms, are integrated into a unified dataset. Machine learning algorithms are applied to process and analyze the integrated data, extracting insights into traffic patterns, weather impacts, and public sentiment.

4.5. Adaptive Signal Control

Formula: Signal Timing Adjustment = δ (Current Traffic Conditions)

- Reinforcement learning algorithms, such as Q-learning or Deep Q-Networks, optimize traffic signal timings based on real-time traffic conditions.
- The algorithm learns from feedback loops and adjusts signal timings to minimize congestion, reduce delays, and improve overall traffic flow efficiency.

These formulas provide a basic framework for understanding how deep learning is utilized in an ITAS for prediction and analysis tasks. Actual implementations may involve more complex models, data preprocessing techniques, and system architectures tailored to specific traffic management objectives and operational requirements.

Anomaly Detection: Deep learning-based anomaly detection algorithms are utilized to identify abnormal events in real-time traffic data. These algorithms analyze traffic flow patterns, vehicle trajectories, and sensor data to promptly detect anomalies such as accidents, breakdowns, or road obstructions. By swiftly identifying anomalies, ITAS enables rapid intervention and incident management, thereby minimizing disruptions and ensuring commuter safety.

Integration of Multi-Modal Data: ITAS integrates data from various sources such as traffic sensors, GPS devices, weather stations, and social media platforms to perform comprehensive traffic analysis. Deep learning algorithms process and analyze this multi-modal data, extracting insights into traffic patterns, weather impacts, and public sentiment. By integrating diverse data sources, ITAS offers holistic insights for informed decision-making and strategic planning.

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Traffic Flow Prediction: ITAS employs deep learning models, such as recurrent neural networks (RNNs) or Long Short-Term Memory (LSTM) networks, to forecast future traffic conditions based on historical data. By analyzing patterns in past traffic flows, including vehicle counts, speeds, and congestion levels, ITAS predicts traffic volumes, speeds, and congestion patterns at specific locations and times. This enables proactive decision-making to alleviate congestion and optimize traffic flow efficiency.

Real-Time Traffic Monitoring: ITAS leverages deep learning techniques like computer vision and pattern recognition to monitor traffic conditions in real-time using video streams from traffic cameras. These models detect and track vehicles, estimate traffic density, and identify congestion hotspots, providing actionable insights to traffic management authorities instantaneously. Continuous real-time monitoring enables timely decision-making and proactive traffic flow management.

Adaptive Signal Control: ITAS employs deep reinforcement learning techniques to optimize traffic signal control in real-time. These algorithms learn from real-time traffic data and feedback loops to dynamically adjust signal timings, minimizing congestion, reducing delays, and improving overall traffic flow efficiency. By adapting signal control based on current traffic conditions, ITAS optimizes traffic signal systems to respond dynamically to changing traffic dynamics and conditions. An efficient artificial intelligence (AI) model is required to classify malicious and non-malicious sensor data so that the OR network endures only non-malicious data from the SHS. Reinforcement learning is also emerging as a technology that enhances the security of sensor communication by adopting better decision policies. The authors of [10] address energy theft issues in smart home systems, integrating AI schemes to filter out abnormalities and improve the decision capabilities of the sensors. To enhance the security of low-power IoT devices in smart homes, [11 & 12] introduced an intrusion detection system to detect and classify multiple routing attacks in a single run. They utilize the signature and behavior-based detection rule to detect anomalies in the network traffic. The aforementioned solutions, however, do not confront data integrity and data tampering issues that thwart the performance of smart homes. Therefore, there is a need for a conspicuous technology, i.e., blockchain, to securely store the correctly classified sensor data from the OR network. The authors of [13] proposed a combinatorial approach by combining the authentication scheme and smart contracts that adhere to the data security and priacy goals for smart homes. Their proposed method outperforms against tampering, denial-of-service (DoS), and data scraping attacks. Further, to enhance the energy efficiency and data privacy of the SHS, [14-17] presented a distributed approach to optimally manage the energy via blockchain smart contracts. The results show that their approach is computationally inexpensive. However, storing large transactions inside the blockchain can significantly increase the computational cost of the system.

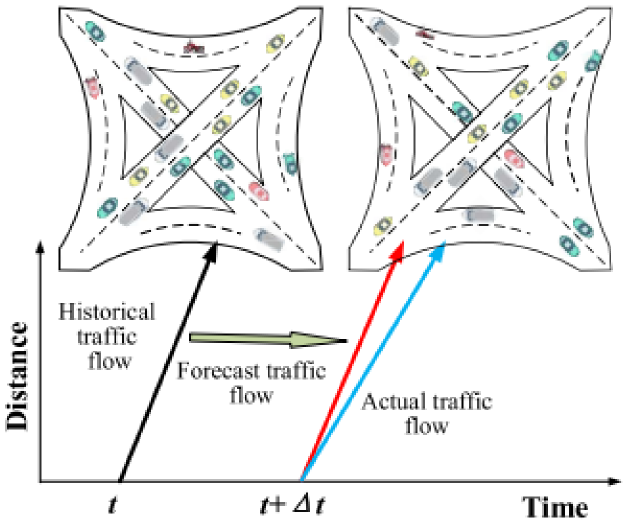

Figure 3 **Schematic Diagram of Short-Term Traffic Flow Prediction**

While constructing the smart city, urban transportation has become a complex and changeable system [18-20]. To solve the current urban development problems during road network congestion, road congestion, and other emergencies, it is more necessary to predict the urban transportation system, thus making the subsequent urbanization process change in a more

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intelligent way. The prediction of medium and short-term traffic flow in the smart city can improve the current situation of urban road congestion and ensure people's travel safety [21]. It is extremely important for the development of the smart city to prevent the occurrence of traffic congestion in urban road network areas and further improve travel efficiency. For 5G IoV, the location of vehicles will change with time, and the location of the mobile edge computing (MEC) server is fixed in the roadside unit. Thus, after a period of time, the vehicle will drive out of the coverage of the MEC server currently connected to it [22]. It is assumed that in this scheme, the vehicle will not drive out of the coverage of the MEC server. If the link upload speed between vehicle i and the MEC server j is Rv, then Rv can be expressed in (1) as follows. Traffic flow refers to the flow of people and vehicles passing through the traffic network. Short-term traffic flow prediction refers to the prediction of the number of actual vehicles passing through a certain road section that are detected by the observation points of the road section in a certain period t to t + t (t represents the set prediction interval). Figures 1 to 3 presents the prediction of short-term traffic flow.

$$R_v = B\log_2\left(1 + \frac{p_v h_{ij}^2}{\sigma^2}\right)$$

In (1), B is the bandwidth between the server and the vehicle, pv refers to the transmission power of the vehicle, σ2 represents the noise power, and h2 ij indicates the channel gain between the vehicle and the server. The upload delay Tv for uploading the task Qi by vehicle i to server j can be expressed in (2) as follows.

$$T_v = \frac{s_i}{R_v}$$

Equation (2) suggests that the time of uploading the task Qi to the server is related to the size of the task itself. When the calculation task is completed on the server, the calculation result is much smaller than the task size. Therefore, the time required to return the task result and the corresponding energy consumption can be ignored [23]. When Xi = 0, the task Qi will be sent to MEC server j for calculation. The time required to complete the task is related to the amount of calculation required by the task and the server's computing capacity. The calculation time T c m can be expressed in (3) as follows.

$$T_m^c = \frac{w_i}{f_j^m}$$

wi refers to the number of resources required to complete the task Qi and f m j suggests the computing power of the MEC server. Thus, when the task is unloaded to the MEC server for processing, the total time required T m tot is as follows:

$$T_{tot}^m = T_v + T_m^c$$

When Xi = 1, the task Qi will be sent to the cloud server to continue processing, and its computing time can be expressed in (5) as follows.

$$T_c^c = \frac{w_i}{f^c}$$

fc indicates the computing power of the cloud server. Therefore, when a task Qi is sent to the cloud server for processing, the total time required Tc tot is as follows:

$$T_{tot}^c = T_v + T_c^c$$

The calculation of the size Stot of the final task Qi can be modeled as follows in (7).

$$\begin{aligned} &\min_{\forall Q_i, \forall A_i} S_{tot} = \sum_{i=0}^{A} X_i T_{tot}^c + (1 - X_i)\, T_{tot}^m \\ &s.t.\ C1: w_i \le w^c, \quad \forall i < A \\ &C2: X_i \in (0, 1) \\ &C3: T_{tot}^c \le t^{\max}, T_{tot}^m \le t_{\max} \end{aligned}$$

The constraint condition C1 indicates that the resources required by the task must be less than the maximum number of resources provided by the cloud server. The constraint condition C2 indicates that the unloading decision can only be unloaded to the cloud server or the MEC server, which also indicates that the time required to complete the task cannot exceed the maximum tolerable time of the task [24]The delay and energy consumption mainly come from three parts: data upload, task calculation, and task migration. For the traffic scene of multi-vehicle and multi MEC service nodes, the guide network v = {V1, V2, Vm} is used to represent the collection of driving vehicles, and R = {R1, R2..., Rt} indicates the MEC

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service nodes on both sides of the road. The vehicles and MEC server are connected by many wireless communication channels in communication technology, expressed as N = {N1, N2, Nn}. The total delay dtotal i and total energy consumption total i are expressed in (9) and (10) as follows.

$$d_i^{total} = d_{(m,n)}^{tran} + d_i^{com} + d_R^{mig}$$
$$e_i^{total} = e_{(m,n)}^{tran} + e_i^{com} + e_{(T,R_t)}^{mig}$$

The issue can be described as follows.

$$\min_{R_1,R_2,\ldots,R_t} C_n^m = \min_{R_1,R_2,\ldots,R_t} \left(\alpha e_i^{total} + \beta d_i^{total}\right)$$
$$\alpha + \beta = 1$$

And n represent vehicle and channel, respectively, and Cm n represents the cost of vehicle m accessing channel n. α and β indicate the weight parameters of delay and energy consumption, and their relationship is shown in (12) [25], [26]. It is further simplified, and the minimum cost in the process of vehicle task load sharing can be obtained as follows:

$$\min \sum_1^n \sum_1^m C_n^m X_n^m \quad S.T.\ X_n^m \in \{0,1\}$$
$$\sum_1^n X_n^m \le 1$$
$$\sum_1^m X_n^m = 1$$

Get a vehicle task-sharing cost matrix with m rows and n columns. Xm n ∈ {0, 1} determines the vehicle channel connection, indicating whether the task of vehicle m is transmitted to the v-MEC service node through channel n. If it is, then Xm n = 1; if it is not, then Xm n = 0. n 1 Xm n ≤ 1 has at most one wireless communication channel between the vehicle and MEC service node, and m 1 Xm n = 1 means that each wireless channel can only upload one vehicle computing task at this time.

5. Traffic Flow Detection Algorithm Based On Yolov3 and Deep sort

In this section, we present an edge traffic flow detection scheme based on deep learning. The scheme is primarily driven by real-time object detection and MOT. We divide our scheme into three parts. Firstly, we improved the YOLOv3 algorithm to detect individual vehicles, training the network in a lab workstation which is treated as a simulated cloud computing center. Then, we introduced a dense connection structure into the backbone network and carried out sparse training and channel pruning on the network. Secondly, we integrated the appearance information of object candidates from object-detection CNNs with a fast improved Deep SORT MOT method to extract motion features and compute trajectories in the lab workstation. We used the result of the object detection and tracking to count the number of vehicles in the lab workstation and achieve the purpose of traffic flow statistics. Thirdly, we migrated and deployed the object detection, multiple-object tracking, and counting algorithm to the edge device.

5.1.Vehicle Object Detection Based on Improved YOLOv3

The detection network of YOLOv3 is Darknet-53 with reference to ResNet, which solves the problem of gradient disappearance and network degradation. It uses a large number of 1 × 1 convolution kernels and 3 × 3 convolution kernels instead of maximum pooling to reduce the number of parameters. However, for the detection of fewer classes of objects, the Darknet-53 network is too complex and redundant. The large number of parameters increases training complexity and reduces detection speed. To achieve real-time detection of vehicles, we need to design a feature extraction network structure with fewer parameters.

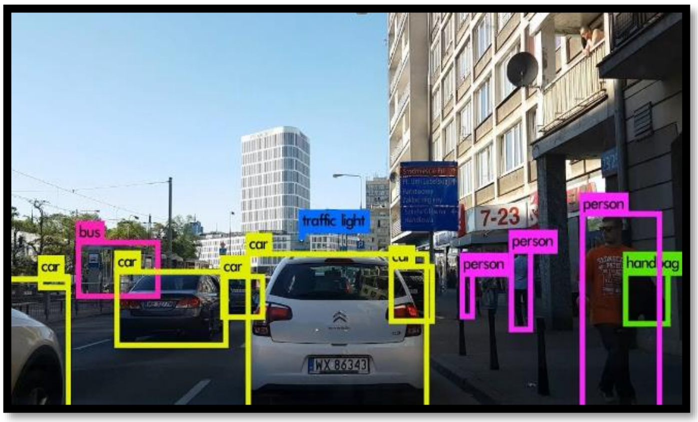

Figure 4 **Vehicle Object Detection**

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The original model of YOLOv3 is based on the COCO dataset and designed to classify 80 kinds of objects. However, we switched to the car dataset, reducing the number of target categories to 13 and thus reducing feature complexity. We changed the combination of the residual network to extract image features in groups of 4. We improved YOLOv3's backbone network, Darknet-53, by introducing dense connections. First, based on the adjustment of the module combination described above, we replaced the residual modules with dense blocks. This enhances the end-to-end connection, reuses the feature graph, and reduces the loss of feature information and gradient information during transmission. Meanwhile, as shown in Fig.4, we added a maximum pooling layer with a stride of 2 as the transition module between the dense blocks. The function of the transition module is to reduce and denoise the feature map. This dense connection of Darknet-53 is called Darknet-Dense. The targets were detected at three different scales by the up sampling and fusion of the characteristics at different layers. When the vehicles are far from the shooting point, their sizes in the picture are very small. To address this situation, we improved the header of YOLOv3 and extended the original 3-scale detection to 4-scale detection. Some finer anchor boxes are used in the larger feature map to detect the target. We took the intersection over union ratio (IoU, expressed by IoU R) of the rectangular frame as the similarity, using K-Means clustering to obtain the anchor box sizes of all targets in the vehicle training set. We chose 12 sizes corresponding to 4 detection scales. The distance function of K-Means clustering is as follows:

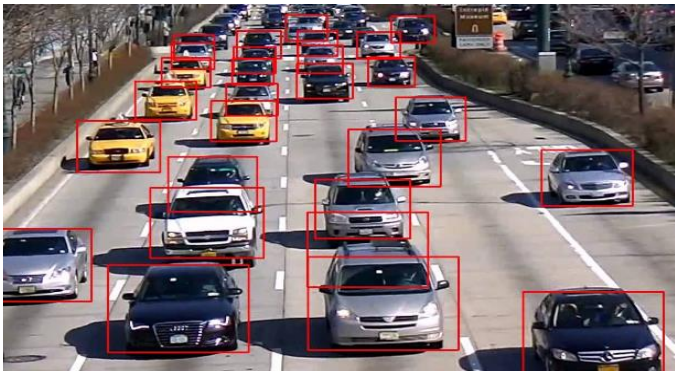

Figure 5 Parallel Fusion

At the same time, we improved the original method of lateral connection of multiscale features and adopted the method of dense connection to fuse the multiscale features, as shown in Fig.5. The parallel fusion was changed to cascaded fusion, which retained more original feature information. Where B is the size of the rectangular box, C is the center of the rectangular box, and RIoU(B,C) represents the IoU of the two rectangular boxes.we added a maximum pooling layer with a stride of 2 as the transition module between the dense blocks. The function of the transition module is to reduce and denoise the feature map. This dense connection of Darknet-53 is called Darknet-Dense. The targets were detected at three different scales by the up sampling and fusion of the characteristics at different layers. When the vehicles are far from the shooting point, their sizes in the picture are very small. To address this situation, we improved the header of YOLOv3 and extended the original 3-scale detection to 4-scale detection. Some finer anchor boxes are used in the larger feature map to detect the target. We took the intersection over union ratio (IoU, expressed by IoU R) of the rectangular frame as the similarity, using K-Means clustering to obtain the anchor box sizes of all targets in the vehicle training set.

Conclusion

To summarize, this literature review holds great promise for revolutionizing traffic management, enhancing safety, and optimizing transportation networks. Through advanced data analytics and predictive capabilities, ITAS can offer real-time insights into traffic conditions, enabling authorities to make informed decisions and implement proactive interventions to alleviate congestion, reduce travel times, and improve overall mobility.

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