Assignment 3

Case Study Analysis on Edge-Computing Video Analytics for Real-time Traffic Monitoring in a Smart City

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February 11, 2025

Analysis Report: Edge-Computing Video Analytics for Real-Time Traffic Monitoring in a Smart City

a. Introduction and Objectives:

The Liverpool Smart Pedestrians project, a collaboration between the Liverpool City Council and the University of Wollongong was initiated to develop innovative and non-intrusive urban planning solutions using edge-computing technologies. By implementing edge-computing sensors across Liverpool’s town center, the project sought to analyze traffic flows, assess urban redevelopment impacts, and enhance data-driven decision-making for a more sustainable and efficient city. The urban planning challenges addressed are:

- Traffic Management: Real-time monitoring of pedestrians, cyclists, and vehicles to optimize traffic flow.
- Infrastructure Integration: Upgrading existing CCTV networks with smart sensors for cost-effective data collection.
- Scalability & Interoperability: Enabling seamless integration with smart city technologies and future sensor expansion.
- Privacy Compliance: Processing data on-site and transmitting only anonymized metadata.
- Environmental Impact: Monitoring traffic alongside air and noise pollution to assess urban sustainability.
- Data-Driven Planning: Providing insights to enhance infrastructure, traffic management, and pedestrian safety.
- Emergency Response: Detecting anomalies in movement for quicker emergency intervention and accident prevention.

b. Methodology:

The methodology involved designing and evaluating an edge-computing device for real-time traffic monitoring in a smart city environment. They adopted a community-centered approach, using feedback from urban planners and residents through workshops to define key requirements. The sensors were designed to detect and track multiple modes of transportation, including pedestrians, vehicles, and cyclists while ensuring privacy compliance by processing data at the edge before transmission. The system leveraged existing CCTV infrastructure to minimize costs and improve scalability. The hardware consisted of an NVIDIA Jetson TX2 integrated with a LoRaWAN communication module. The software stack combined the YOLO V3 deep learning model with the SORT algorithm ensuring efficient processing on low-power devices.

During the development of the sensor, several constraints and requirements were considered. Privacy was a primary concern, leading to the decision to process video data locally and only transmit denatured data. The sensor also needed to operate efficiently with limited network bandwidth, making edge computing a critical design choice. Scalability and interoperability were ensured through the Agnosticity framework, which allowed seamless data collection and integration from multiple sensors using open-source standards. The evaluation involved real-world deployment in Liverpool where 20 sensors were installed to monitor traffic patterns. The system's performance was validated using datasets and live field tests, demonstrating its ability to provide accurate traffic flow insights while maintaining operational efficiency in an urban setting.

c. Technology and Implementation:

Hardware: The NVIDIA Jetson TX2 was used as an embedded computing platform due to its balance of performance, power efficiency, and cost. It features a quad-core ARM Cortex-A57 CPU, a 256-core Pascal GPU, and 8GB of LPDDR4 memory, making it suitable for deep learning inference. The Jetson TX2 efficiently runs neural networks while operating under low power consumption, an important factor for outdoor deployment in smart city applications. Additionally, its GPU acceleration optimizes real-time object detection tasks while handling multiple sensor inputs. The sensor system also integrates a LoRaWAN module for low-power, long-range communication, enabling efficient data transmission in smart city environments.

Software: YOLO V3 (You Only Look Once) was used as the deep learning object detection model because of its real-time processing speed and multi-scale object detection capabilities. Unlike traditional object detection methods that process an image in multiple steps, YOLO V3 processes an entire frame in a single pass, making it highly efficient. The model was trained to detect pedestrians, vehicles, bicycles, buses, trucks, and motorbikes, ensuring comprehensive traffic monitoring. To complement YOLO V3, the SORT (Simple Online and Real-time Tracking) algorithm was implemented for object tracking, maintaining the identities of detected objects across frames.

Edge-Computing Paradigm refers to processing data at the sensor level (edge) rather than transmitting raw data to a central server. This approach offers several benefits:

Reduced Network Bandwidth Usage: The strain on network infrastructure is reduced and it allows seamless integration with low-bandwidth networks like LoRaWAN because the raw video feed is processed locally, transmitting only object counts and trajectories.

Privacy Preservation: The system complies with strict privacy regulations by ensuring that only processed, anonymized data is shared, and no personal information leaves the sensor.

Low Latency for Real-Time Monitoring: The data analysis and insights are generated instantly at the edge allowing real-time decision-making that is important for traffic control and smart city planning.

Scalability and Cost Efficiency: Cities can deploy multiple sensors without overloading centralized cloud servers leveraging existing CCTV infrastructure and reducing deployment costs.

Improved System Resilience: Edge-computing ensures uninterrupted operations even in connectivity outages unlike cloud-based approaches, where network failures can disrupt processing.

d. Validation and Performance:

Accuracy and Performance Assessment: The sensor's accuracy was tested using the Oxford Town Center Dataset, a high-resolution CCTV video sequence with 230 manually annotated pedestrians. The system's object detection accuracy and speed were analyzed by comparing detected objects to the ground truth annotations.

- Key Accuracy Metrics:

Mean Accuracy: 69%

Relative Error: 33% median error rate

Detection Tendency: The system underestimated pedestrian counts, leading to false negatives rather than false positives.

Crowd Handling: The accuracy dropped in high-density areas due to occlusion, as the YOLO V3 object detector's non-maximum suppression (NMS) occasionally discarded overlapping bounding boxes.

Detection Trends: Despite underestimation, the system maintained a consistent relationship between actual and detected objects, making it useful for traffic trend analysis.

- Speed and Processing Metrics:

Average FPS (Frames Per Second): 19.57 FPS

Variation: FPS decreased when more objects were present due to increased computational load.

Processing Bottleneck: The SORT tracking algorithm was CPU-dependent and did not utilize the GPU, causing slowdowns.

The sensor reliably tracked overall traffic trends despite some underestimation in crowded environments.

System and Network Utilization: The real-world deployment tested the sensor's ability to handle long-term operations in an urban setting. The system resource utilization, thermal stability, and network efficiency were monitored.

- Key Utilization Metrics:

CPU Utilization: Fluctuated, peaking during heavy tracking tasks.

GPU Utilization: Occasionally dropped due to CPU-based SORT tracking, leading to inefficiencies.

Memory & Disk Usage: Remained stable throughout the test.

Temperature: Maintained operational stability over extended periods.

- Network Performance:

Data Transmission Efficiency: Incoming data were live video frames from CCTV.

Outgoing data were only metadata (counts, trajectories), significantly reducing bandwidth usage.

Bandwidth Reduction: The sensor transmitted only processed metadata, making it suitable for low-bandwidth networks like LoRaWAN. Data transmission peaks occurred every one minute, maintaining network efficiency.

The system effectively minimized bandwidth usage, making it feasible for deployment in locations with limited connectivity. Privacy compliance was achieved, as no raw images were transmitted.

e. Real-World Applications:

The edge-computing traffic monitoring sensor was deployed in two real-world scenarios to evaluate its effectiveness in indoor and outdoor environments:

Indoor Deployment: Emergency Evacuation Monitoring occurred inside a university building at the SMART Infrastructure Facility, University of Wollongong. The sensor was positioned in front of a stairway, monitoring pedestrian movement for an hour.

- Key Findings:

The system successfully detected 631 unique individuals, tracking their movement patterns.

A false fire alarm during the experiment provided an unexpected real-world evacuation test.

The sensor detected no individuals during the alarm, confirming that people evacuated the building efficiently. After clearance, the number of individuals who returned was lower than those who evacuated, indicating real-world behavioral patterns during emergencies.

- Effectiveness and Urban Planning Impact:

Emergency Response Planning: The system validated that the building was effectively evacuated.

Crowd Movement Analysis: Authorities can use the data to identify bottlenecks and optimize evacuation routes.

Anomaly Detection: Technology can be used to monitor unauthorized movements or detect congestion in real-time.

Outdoor Deployment: Traffic Monitoring in Liverpool, Australia involved installing 20 visual sensors across Liverpool's city center, focusing on pedestrian and vehicular traffic flow at a busy intersection.

- Key Findings:

The system tracked daily pedestrian, vehicle, and bicycle movements. Peak pedestrian activity occurred around noon. Vehicle traffic showed two daily peaks: one around 9:00 AM (morning rush) and another around 4:00 PM (evening rush).

The system captured pedestrian movement at crosswalks, detecting cases where people crossed outside designated areas. It also identified two major pedestrian movement paths, highlighting critical mobility patterns in the city.

- Effectiveness and Urban Planning Impact:

Traffic Optimization: Data can help redesign intersections, optimize traffic signals, and improve pedestrian pathways.

Smart City Development: The continuous real-time monitoring supports data-driven urban planning.

Bicycle & Pedestrian Safety: The system detected mixed pedestrian and bicycle traffic, helping authorities improve shared road spaces.

Role of Sensor Technologies and Edge Gateways in Urban Planning: Both deployments demonstrated the advantages of using edge-computing sensors for urban monitoring:

Real-Time Data Processing: The edge-computing paradigm ensured fast analysis without relying on cloud computing.

Privacy Compliance: The system processed video locally and transmitted only metadata to maintain privacy.

Network Efficiency: By minimizing bandwidth use, the sensors remained efficient and scalable.

Scalability & Integration: The Agnosticity framework allowed seamless integration of multiple sensors, supporting smart city expansion.

The indoor and outdoor deployments showcased the sensor's ability to enhance urban planning by providing real-time, privacy-compliant traffic insights. The system's accuracy, speed, and scalability make it a powerful tool for smart city infrastructure, enabling efficient mobility planning, emergency response improvements, and pedestrian safety enhancements.

f. Challenges and Future Work:

Main Challenges Encountered and Proposed Solutions:

Detection Accuracy Issues: The sensor underestimated pedestrian counts, especially in crowded environments, due to occlusion and non-maximum suppression (NMS) in YOLO V3.

Solution: Future models should incorporate advanced occlusion handling techniques, such as transformer-based detection models (e.g., DETR or YOLOv8) and improved tracking algorithms using Re-Identification (ReID) to maintain identities across frames.

Computational Bottlenecks: The SORT tracking algorithm ran on the CPU instead of the GPU, causing frame rate drops in high-density traffic conditions.

Solution: Optimize SORT to run on the GPU and explore deep learning-based tracking (e.g., DeepSORT, ByteTrack) to improve real-time efficiency.

Network and Bandwidth Constraints: The LoRaWAN protocol used for data transmission had limited bandwidth, restricting data transmission rates.

Solution: Consider 5G and LPWAN (Low-Power Wide-Area Network) technologies for higher transmission efficiency, enabling real-time analytics with minimal latency.

Privacy and Data Compliance: Legal restrictions prevented the storage and transmission of raw video data, limiting the ability to validate model performance effectively.

Solution: Implement on-device federated learning to improve model performance without transmitting sensitive data.

Hardware Constraints: The NVIDIA Jetson TX2 had limited processing power and memory for handling larger datasets and multiple video streams.

Solution: Upgrade to NVIDIA Jetson Xavier NX or Orin, which have more CUDA cores and Tensor cores for accelerated AI inference.

Future Work and Suggested Improvements:

The authors proposed several improvements to enhance sensor performance, accuracy, and efficiency:

Hardware Upgrades: Shift from Jetson TX2 to Jetson Xavier or Orin for faster neural network processing. Integrate more power-efficient AI accelerators like Google Edge TPU or Intel Movidius VPU.

Software and AI Model Enhancements: Implement more advanced tracking algorithms (e.g., DeepSORT, FairMOT) for better object re-identification. Explore self-supervised learning to reduce dependency on labeled datasets.

Improved Data Collection & Processing: Upgrade from PyTorch 1.0 to TensorFlow with TensorRT optimization, enhancing real-time inference speed. Integrate automated anomaly detection to flag unusual pedestrian or vehicle behavior.

Scalability and Interoperability: Expand the Agnosticity framework to support real-time urban mobility analytics. Deploy multi-sensor fusion, integrating LiDAR, thermal imaging, and radar sensors to enhance object detection reliability.

Technological Developments Since 2019 Impacting the Project:

Since the publication, several advancements in edge computing, AI, sensor technology, and communication protocols could significantly improve the implementation of similar projects.

- Advancements in Edge Computing:

NVIDIA Jetson Orin (2022): Provides 8x more AI performance than Jetson TX2, improving deep learning efficiency.

Google Edge TPU & Coral Dev Board: Low-power AI acceleration for real-time inference on edge devices.

Federated Learning: Allows training models directly on edge devices without sharing raw data, enhancing privacy.

- AI and Deep Learning Enhancements:

YOLOv8 (2023): Improved object detection with faster inference speed and higher accuracy than YOLO V3.

DETR (End-to-End Object Detection Transformer): Better at handling occlusion in crowded environments.

Vision Transformers (ViTs): More robust than CNNs for real-world traffic surveillance applications.

- Advancements in Sensor Technology:

Multi-Modal Sensors: Combining LiDAR, thermal, and RGB cameras can improve detection in low-light and crowded scenarios.

Event-Based Cameras (Neuromorphic Sensors): Capture movement more efficiently than traditional video sensors, reducing power consumption.

mmWave Radar Sensors: Enhance pedestrian and vehicle detection in poor visibility conditions.

- Improved Communication Protocols:

5G Networks: Faster data transmission for real-time smart city applications.

LPWAN (Low-Power Wide-Area Networks): Lower power requirements than LoRaWAN, increasing device battery life.

Wi-Fi 6 and Edge Mesh Networks: Provide better bandwidth efficiency for sensor communication in dense urban environments.

g. Personal Evaluation:

The Liverpool Smart Traffic Monitoring Project is an example of how edge computing and AI-driven sensors can improve urban mobility management. By processing video locally and transmitting only metadata, the system ensures privacy compliance, reduces network load, and enables real-time analytics for urban planning. Unlike traditional surveillance, which often lacks automated intelligence, this project transformed passive CCTV infrastructure into an active traffic monitoring tool, maximizing the utility of existing systems without requiring significant new investments. This cost-effective and scalable approach positions it as a practical model for other smart cities.

A key strength of the project is its contribution to data-driven decision-making. By capturing real-time pedestrian and vehicle movement, urban planners can make evidence-based improvements to infrastructure, enhancing traffic flow and safety. The system's ability to adapt to changing conditions makes it a valuable tool for future urban development, especially as cities prioritize sustainability and efficient transportation networks. However, integrating self-learning AI models, federated learning, and multimodal sensors would enhance detection accuracy and adaptability, further refining urban traffic management.

Since the project's launch, advancements in AI, edge computing, and communication networks have provided new opportunities. 5G connectivity, improved edge hardware, and low-power IoT networks now allow for faster, more efficient real-time processing, making such systems even more viable for large-scale deployment. Future enhancements should focus on leveraging these technologies to expand sensor capabilities, improve real-time anomaly detection, and integrate AI-assisted urban design. Overall, this project sets a strong foundation for the future of smart city infrastructure, demonstrating how technology-driven urban planning can improve mobility, safety, and quality of life.

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