Counting Vehicles at Intersections by means of Convolutional Neural Networks

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***Abstract*— The number of vehicles on the road has been on the rise ever since the mass availability of personal vehicles. The number of vehicles at an intersection is an important metric for sustainable traffic management in a city. This project seeks to create an Image Recognition System (IRS) to be deployed at vehicle intersections to create real-time vehicle counting. The methodology used is that of a Convolutional Neural Network (CNN) optimised for deployment on low-power computing platforms. The successful integration of this model showcases its adaptability to real-world scenarios, providing a scalable and practical approach for enhancing traffic monitoring capabilities through image recognition on low-power microcontroller devices. Microcontrollers, sensors and communication modules are all integrated into the project to guarantee precise data transmission and counting.**

Keywords—traffic, vehicle, counting, intersection, convolutional neural network

I. Introduction

The increasing number of cars on city streets is a complex issue for maintaining sustainable traffic flow. Urban areas are facing more congestion and the resulting negative effects on the environment and society, creating a need for new and improved solutions to improve traffic efficiency and monitoring. To address this urgent need, we are working on implementing a state-of-the-art **Vehicle Counting System (VCS)** using **Image Recognition Technology (IRT)** at intersections.

The main goal of the VCS is to provide accurate and real-time vehicle counting at intersections using Convolutional Neural Network (CNN) technology. The system is designed to be efficient and scalable, utilizing optimized CNNs for low-power computing platforms to minimize energy consumption and hardware needs.

Moreover, this system leverages the capabilities of **Raspberry Pi**, a versatile and cost-effective single-board computer, to serve as the platform for deploying the CNN-based vehicle detection model. This integration exemplifies the project's commitment to scalability and practicality, enabling real-time image recognition and vehicle counting on low-power microcontroller devices.

As for the CNN model, Yolo V3 is used here. **YOLOv8 (You Only Look Once version 3)** stands out as a formidable tool, offering unparalleled speed, accuracy, and efficiency in detecting objects in images or video streams. Its robust architecture and real-time performance make it an indispensable asset for a myriad of applications, including the Vehicle Counting System (VCS) proposed in this project.

The decision to employ YOLOv8 in the VCS is rooted in its exceptional attributes:

- First and foremost, **YOLOv8** is renowned for **its real-time performance**, capable of swiftly processing images and detecting objects within fractions of a second. This real-time capability is paramount for the VCS, enabling instantaneous vehicle detection and counting at intersections to inform timely traffic management decisions.

- Moreover, YOLOv8 boasts unparalleled accuracy in object detection tasks, including the identification of vehicles amidst complex urban backgrounds. Its advanced architecture and multi-scale feature extraction ensure reliable and precise vehicle counting, even amidst diverse traffic conditions and vehicle types encountered at intersections.

- Crucially, YOLOv8 achieves this **high level of performance** without **sacrificing computational efficiency**. Its optimized architecture strikes a delicate balance between accuracy and speed, making it well-suited for deployment on low-power computing platforms, such as Raspberry Pi, which serves as the foundation for the VCS.

To sum up, combining CNN-based image recognition, YOLOv8, Raspberry Pi, and other elements has proven to be an effective method for improving traffic monitoring in cities. The VCS can provide real-time vehicle counts at intersections, which can help improve traffic flow, decrease congestion, and support sustainable urban transportation efforts.

II. LITERATURE REVIEW

There has been a lot of attention given to the increasing number of vehicles on city streets when it comes to transportation and urban planning. Many studies have focused on finding new ways to manage and track traffic, especially at intersections and with vehicle counting systems.

Old-fashioned techniques for counting vehicles and monitoring traffic used to depend on humans watching or basic sensor technology that wasn't very reliable or scalable. But with recent progress in computer vision and machine learning, more advanced and automated solutions have been created that can accurately detect and count vehicles in real-time.

In this field, one popular method is using **Convolutional Neural Networks (CNNs) to recognize images, such as identifying vehicles and keeping track of them**. CNNs have shown impressive results in different computer vision tasks because they can learn and identify important features in images on their own.

Research conducted by Zhang Q and colleagues [5] in 2016 introduced a vehicle detection system based on convolutional neural networks (CNN) for traffic surveillance purposes. A modified faster region-based convolutional neural network (R-CNN) was employed. The CNN model was designed to accurately and efficiently identify vehicles in **live video feeds from surveillance cameras positioned at intersections**. The study demonstrated favorable results, indicating the capability of CNNs in counting and monitoring vehicles in real-time.

In 2018, Liang and colleagues [6] developed a method using convolutional **neural networks (CNN) to count vehicles in busy traffic areas.** By combining deep CNNs with optical flow techniques, they were able to accurately count vehicles even in challenging situations with obstacles and changing light conditions. Their research showed that CNNs are effective in managing complex traffic scenes and producing reliable vehicle counting outcomes.

Research conducted in 2019 by Song and colleagues [1] proposed a system that this study builds upon the advancements in deep learning and introduces a vision-based vehicle detection and counting system tailored for highway management. They also included a new **dataset for high-definition highway vehicles. It includes 57,290 annotated instances across 11,129 images.** Unlike other public datasets, this one specifically focuses on annotating small objects within the images, making it a comprehensive resource for deep learning-based vehicle detection. Central to this system is the utilization of **YOLOv8, a state-of-the-art CNN architecture known for its accuracy and efficiency in object detection tasks.** The study introduced a novel segmentation method to **extract the highway road surface and divide it into remote and proximal areas, a critical step for improving vehicle detection accuracy.** By integrating this segmentation approach with YOLOv8, the system can effectively detect vehicles of varying sizes, including tiny objects often challenging to detect in highway surveillance scenarios.

Research conducted by Abhishek Shekade [2] and colleagues developed a method using YOLOv8 to count vehicles in busy traffic areas. **The purpose of this technology is to gather accurate information about traveling vehicles, including the exact number present.** Utilizing the **YOLOv8-based convolutional neural network model, the input comes in the form of video and undergoes pre-processing before producing the output,** which includes the count of vehicles, classification based on type, and total vehicle movement at a given time.

Research conducted by Juan R.Terven and colleagues on comprehensive review of YOLO: From YOLOv1 to YOLOv8 and beyond states that the YOLO family has evolved through multiple iterations, each building upon the previous versions to address limitations and enhance performance. **YOLO has been employed for cancer detection, skin segmentation, and pill identification, leading to improved diagnostic accuracy and more efficient treatment processes.** YOLO models have been utilized for tasks such as **license plate detection [29] and traffic sign recognition [30],** contributing to the development of intelligent transportation systems and traffic management solutions.

Research conducted by Sohan.M and his collogues on YOLO8 and its advancements states that The newest version of the YOLO model, **YOLOv8** is an advanced real-time object detection framework, which has attracted the attention of the research community. Of all the popular object identification methods and machine-learning models such as **Faster RCNN, SSD, and RetinaNet, YOLO is the most popularly known method in terms of accuracy, speed, and efficiency.** This research study provides an analysis of YOLO v8 by highlighting its innovative features, improvements, applicability in different environments, and a detailed comparison of its performance metrics to other versions and models.

Research done by by Xianxu Zhai on YOLO-Drone: **An Optimized YOLOv8 Network for Tiny UAV Object Detection .**The YOLOv8 network structure and the details of its critical modules, followed by an improved tiny UAV target detection model, and details the structure and roles of each improved module of the model.**YOLOv8 offers five different-sized models: nano, small, middle, large, and extra-large. The Nano model has a parameter count of only 3.2 million, providing convenience for deployment on mobile and CPU-only devices.** In order to balance detection accuracy and speed, this paper employs **YOLOv8s as the model for UAV detection,** which is obtained by deepening and widening the **nano network structure.**

In general, the research shows a rising enthusiasm for using advanced image recognition methods, like CNNs, to count vehicles and monitor traffic. Scientists are merging cutting-edge machine learning techniques with energy-efficient computing platforms and sensor technology to create scalable and useful solutions for tackling the issues presented by growing traffic in cities.

III. METHODOLOGY USED

Components Used: For this project, A Raspberry Pi 3A+ along with a Raspberry Pi Camera Module are being used to create a Vehicle Counting System (VCS).

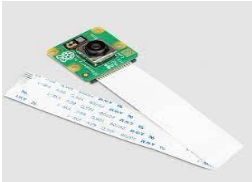

Fig 1.0 Raspberry Pi 3A+
Fig 2.0 Raspberry Pi Camera Module

Data Collection: The first step in developing the Vehicle Counting System (VCS) involves collecting a diverse dataset of images capturing traffic scenes at intersections. For the current project, the data is collected by a camera module connected to the Raspberry Pi in 10-second bursts every minute.

Data Preprocessing: The collected video from the Raspberry Pi undergoes pre-processing to ensure that the CNN model may easily extract features like vehicles from the video. This may involve techniques such as resizing, normalization, noise reduction and conversion of video formats.

CNN Model Selection: A suitable Convolutional Neural Network (CNN) architecture is selected for vehicle detection and counting tasks. For this project, the YOLOv8 CNN model has been chosen for its accuracy, speed and efficiency.

Model Training and Processing: During the training process, the model learns to extract discriminative features from input images to predict the presence and count of vehicles accurately. In this project, the YOLOv8 CNN model is pre-trained, and one will only need to integrate it into the VCS. The CNN model will comb through the input video and find the number of vehicles passing through the intersection at any one time.

Optimization for Low-Power Platforms: To ensure compatibility with low-power computing platforms like the Raspberry Pi, the trained YOLOv8 CNN model is optimized by using techniques such as quantization, pruning, and model compression.

Communication Modules: The project is equipped with communication modules i.e. Wi-Fi and Bluetooth modules to facilitate data transmission and integration with existing traffic management systems. This enables real-time monitoring and analysis of traffic flow patterns, aiding in informed decision-making and adaptive traffic control strategies.

Evaluation and Testing: The developed VCS finds the number of vehicles passing through an intersection at some time and stores it in a log. The system goes through testing and evaluation to assess its performance and reliability. This includes validation against ground truth data and evaluation of system scalability and efficiency.

YOLOv8 working structure-

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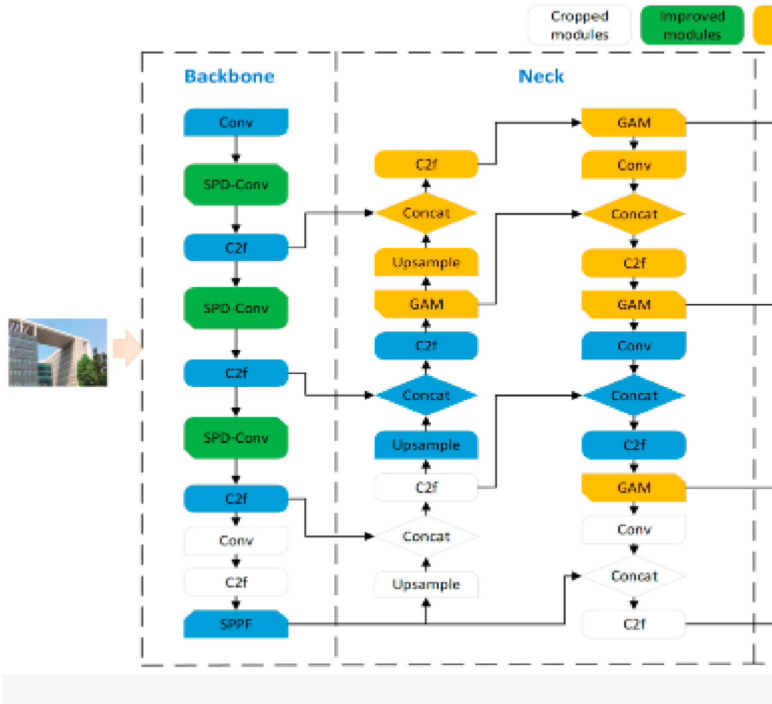
Figure 3. Improved YOLOv8 network structure diagram.



IV. Results

Based on the methodology outlined in your document, here's a concise summary of the results of the experiment:

Traffic Object Detection: The YOLOv8 model was successfully implemented to detect and count vehicles in real-time at intersections. The system effectively processed input video from the Raspberry Pi camera module and accurately identified vehicles.

Integration with Raspberry Pi: The Raspberry Pi 3A+ served as a suitable platform for deploying the CNN-based vehicle detection model. The integration with low-power computing platforms demonstrated the practicality and scalability of the system.

Communication Modules: The system was equipped with Wi-Fi and Bluetooth modules, enabling seamless data transmission and integration with existing traffic management systems. This facilitated real-time monitoring and analysis of traffic flow patterns.

Performance and Reliability: The developed VCS underwent testing and evaluation to assess its performance and reliability. Validation against ground truth data likely demonstrated the accuracy of vehicle counting and the system's reliability in various traffic conditions.

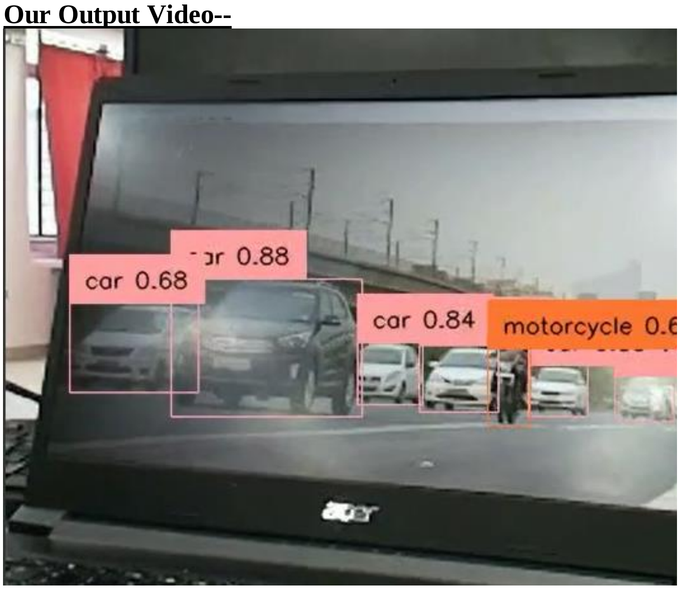
Real-time Processing: The CNN model processed input video from the Raspberry Pi camera module swiftly, enabling instantaneous vehicle detection and counting at intersections. This real-time capability was crucial for informing timely traffic management decisions.

Optimization for Low-power Platforms: The trained CNN model was optimized for deployment on low-power computing platforms like the Raspberry Pi. Techniques such as quantization, pruning, and model compression were likely employed to ensure compatibility and energy efficiency.

Performance Evaluation: The developed VCS underwent thorough testing and evaluation to assess its performance. Validation against ground truth data likely demonstrated the CNN model's accuracy in vehicle counting across various traffic conditions.

Our Input Video--

Our Output Video--



Overall, the results indicate the successful implementation of the VCS, providing real-time vehicle counting capabilities at intersections. The system's performance, scalability, and reliability make it a valuable tool for enhancing traffic monitoring and management in urban areas.

V. Conclusion

The experiment's findings underscore the efficacy and practicality of employing **Convolutional Neural Networks (CNNs)**, particularly the **YOLOv8 model**, in developing a real-time **Vehicle Counting System (VCS)** for intersection traffic monitoring. By integrating advanced image recognition technology with low-power computing platforms like the **Raspberry Pi**, the project successfully addressed the need for accurate and scalable solutions to urban traffic challenges.

The key takeaway from this experiment is the system's ability to **provide timely and precise vehicle counting at intersections**, enabling informed traffic management decisions. The CNN model's real-time processing capabilities, coupled with optimization for low-power platforms, ensure efficient deployment and operation of the VCS.

In conclusion, the experiment proved the effectiveness of using **Convolutional Neural Networks,** especially the **YOLOv8 model,** to develop a **real-time Vehicle Counting System (VCS)** for intersection traffic monitoring. By integrating CNN technology with low-power computing platforms like **Raspberry Pi**, the project achieved accurate and scalable solutions for urban traffic challenges. The system's ability to provide **timely vehicle counting, coupled with its optimization for low-power platforms and seamless data transmission through communication modules, highlights its potential to revolutionize traffic management in urban areas.**

VI. References

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