A Machine Learning Framework for Traffic Forecasting Using Air Pollution Data from Cost-Effective Sensors

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Abstract— **Air pollution, particularly PM2.5 and NO_2, is the cause of approximately 6.7 million premature deaths globally per year, with a significant contributor being road traffic emissions, resulting in costs of £20 billion/year through healthcare expenditure and lost productivity. While past measures have helped to alleviate pollution, the static nature of such schemes limits them in addressing real-time variations in pollution levels. Past efforts have effectively improved traffic detection and air quality monitoring separately, but they do not go far in achieving full integration with real-time traffic forecasting, pollution monitoring, and adaptive systems that dynamically respond to changing urban traffic and pollution levels.**

This research integrates low-cost pollution sensors and real-time traffic with time series forecasting. The real-time traffic information was collected by using a camera placed on a busy London intersection, coupled with sensors measuring PM2.5, CO_2, CO, methane, temperature-humidity, volatile organic compounds, and noise. The YOLOv8 object detection algorithm was used to detect vehicles from the camera sensor, with a mAP50 value of 0.865. ARIMA and LSTM models were used for traffic-forecasting, with LSTM performing best with a RMSE of 0.0203 for traffic forecasting. The results show that while the LSTM model is the most effective in predicting traffic patterns, there is a weak observed correlation between number of vehicles on the road and pollution levels. This research proposes a system that will integrate sensor and camera units to assess traffic and atmospheric data at congested junctions. By combining pollution sensor data with an LSTM model, the system will forecast traffic and its potential impact on air quality. The data will feed into algorithms to optimize traffic management by adjusting flows and rerouting vehicles to reduce congestion and improve air quality. The system is envisioned for future use in smart city infrastructures, contributing to more sustainable urban environments through data-driven traffic and pollution control.

Keywords— PM2.5, air pollution, LSTM, YOLOv8, mAP50, RMSE

I. Introduction

Air pollution is one of the most pressing issues of the 21st Century, especially within an urban environment where traffic-related emissions contribute to poor air quality and negative health effects. According to estimates by the World Health Organization, almost 6.7 million people die prematurely each year due to exposure to fine pollutants such as PM2.5 [1], causing a loss of £20 billion/year through healthcare expenditure and lost productivity [2]. These particulates, with a diameter of less than 2.5 micrometers, are especially dangerous because they penetrate deep into the lungs and reach the bloodstream, thereby causing various respiratory diseases like asthma and chronic obstructive pulmonary disease, among all other cardiovascular diseases [3]. Emissions from traffic in the city are considered one of the biggest contributors to PM2.5, CO_2, methane, and VOCs [4]. For example, despite measures like the Ultra Low Emission Zone, which have led to a reduction of other pollutants, such as NOx emissions by 54%, London registered 2.2 megatons of CO_2 emissions in 2022 from traffic [5]. However, static systems like ULEZ cannot adapt to real-time changes in traffic patterns; hence, they have limited capabilities when it comes to dealing with localized pollution spikes [6].

While there has been much progress, previous attempts to address traffic-related pollution have notable limitations. Ground-based systems lack spatial coverage, mobile sensors are reactive and lack prediction, and low-cost sensors often struggle with data quality. Hybrid models improve estimates but require extensive calibration and face data gaps. These issues limit real-time traffic-related pollution management.

This paper introduces a dynamic, real-time traffic and pollution management system that integrates real-time pollution monitoring, advanced traffic detection, and predictive modeling into a single adaptive framework. A low-cost, high-precision sensor is employed to measure PM2.5, CO_2, CO, NO_2, methane, temperature-humidity and VOCs to obtain localized continuous pollution data, while a YOLOv8 object detection model is used for vehicle detection with both aerial imagery for real-time traffic monitoring. Predictive modeling of traffic and pollution is achieved using a Long Short-Term Memory (LSTM) model and an Autoregressive integrated moving average (ARIMA) model, trained on a dataset of historical traffic and pollution readings in Virginia, enabling the traffic forecasting and its impact on air quality up to two hours ahead. Combining these three modalities together helps the system overcome the limitations of previous approaches in offering a holistic proactive solution that adapts to both present and future pollution challenges.

This study makes three major contributions: the development of an integrated real-time framework that dynamically combines pollution data, traffic detection, and predictive modeling; achieving enhanced spatial and temporal granularity through correlation of data across modalities; and introducing proactive mitigation capabilities, enabling actionable responses to predicted pollution spikes for enhanced urban sustainability.

II. Related Work

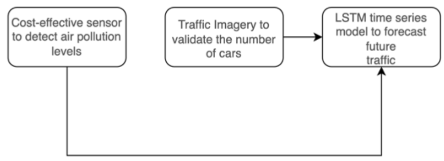
Recent development in intelligent traffic management and vehicle detection has focused on accuracy and efficiency using various techniques. Chaudhuri (2018) developed a vehicle management system for different weather conditions in New Delhi using a benchmark dataset, which contributed substantially to the accuracy of traffic monitoring [7]. Xiaohong et al. (2021) applied YOLOv2 for real-time object detection with particular emphasis on small vehicles to improve the detection rate in urban traffic management [8]. Tajar et al. (2021) introduced Tiny-YOLOv3, a lightweight vehicle detection technique that is suitable for real-time applications and emphasizes fast processing and high-accuracy detection [9]. In the task of classification, Jung et al. (2017) utilized ResNet50 in vehicle localization and classification, and presented an effective deep learning model in traffic surveillance systems [10]. Bakirci (2024) applied YOLOv8 for traffic monitoring in intelligent transportation systems, which showed high accuracy in the vehicle detection and tracking task due to its real-time processing [11]. The study showed that YOLOv8 is effective in dealing with complicated traffic surroundings where vehicle density differs, hence it is applicable to real-time ITS applications. Ojha et al. (2021) combined the Mask R-CNN for instance segmentation to realize high-accuracy intelligent vehicle systems [12]; Hbaieb et al. (2019) introduced a way for vehicle detection using support vector machine (SVM) with Gaussian mixture models, aiming at better performance of detection in aerial images [13]. Tayara et al. (2018) worked on vehicles detection in high-resolution aerial imagery using convolutional regression neural nets to cope with problems in identifying vehicles from tough angles [14].

Several studies have investigated air pollution monitoring, although they usually focus either on pollution tracking or predictive modeling without fully integrating traffic data. Castell et al. (2017) investigated the feasibility of using low-cost commercial sensor platforms for air quality monitoring and exposure estimation [15]. This study evaluated the performance of such sensors in urban environments and proved that, although low-cost sensors can complement traditional air quality monitoring stations by increasing spatial resolution, they suffer from lack of data accuracy and reliability. On the predictive modeling side, Bui et al. (2018) used LSTM networks to forecast pollution based on traffic and meteorological data [16]. Chaudhuri et al. (2024) put forward a proposal for a smart traffic management system using Faster R-CNN in vehicle detection and tracking, not to mention estimation of traffic density in challenging environments with occlusion and different densities of traffic flow [17]. Their four-step framework shows high accuracy in segmentation, especially in scenarios of heavy congestion and low visibility.

While existing literature has made attempts to improve air pollution monitoring and traffic detection, there remains a large gap in integrating these systems to achieve fully dynamic urban air quality management in real time. Most studies have focused on either monitoring pollution independently or forecasting traffic independently without considering how changing traffic flows impact pollution concentrations. This research fills that gap by integrating real-time traffic detection and air quality monitoring with predictive modeling into one system, hence providing the solution that can dynamically respond to changing traffic conditions, offering greater potential to mitigate impacts of urban pollution.

III. Methodology

Fig. 1 Solution Architecture



To create this solution, we needed to develop several technologies. As seen in Fig. 1., the first was low-cost integrated sensors. Second was detecting and tracking live traffic. Finally, the last technology was predicting future pollution patterns. The following sections provide detailed explanations of the experiments conducted for each of these components: sensor design, traffic detection, and air quality forecasting.

A. Sensors

The air quality monitoring system was designed to measure various pollutants and environmental factors, including PM2.5, CO_2, CO, volatile gases, NO_2, methane, and temperature-humidity. These pollutants have been selected because they are known to produce several adverse effects to human health and the environment. Particularly, PM2.5 and NO_2 are associated with respiratory and cardiovascular diseases [18], while CO_2 and methane contribute to greenhouse gas emissions and climate change [19]. The sensors were assembled using an ESP-32 microcontroller coupled with different sensor modules sensing specific pollutants. The ESP-32 was chosen because of its low price, low power consumption, and built-in Wi-Fi capabilities; hence, it is suitable for real-time data transmission in sensor networks [20]. It also features a dual core that allows fast processing of signals coming simultaneously from multiple sensors, thus showing great potential and becoming a solid solution for an environmental monitoring system.

1) Design and Construction

The sensor network was constructed using Arduino-compatible hardware programmed with Micro Python. Each of the sensors was mounted on an ESP-32 board that served as a central controller, transmitting data to the central server via an MQTT client [21]. The system was set to provide real-time data at every 15 minutes to ensure that traffic and pollution level variations remain meaningful without causing an overload of the sensor system.

The time interval of 15 minutes is selected because it would give a good balance between detailed monitoring and system efficiency, considering traffic patterns usually fluctuate over short periods. The ESP-32 also goes into sleep mode to consume minimum power, increasing the efficiency of the system. It was set to sleep for 15 minutes and wake for a few seconds to record the data to ensure long battery life with continuous monitoring.

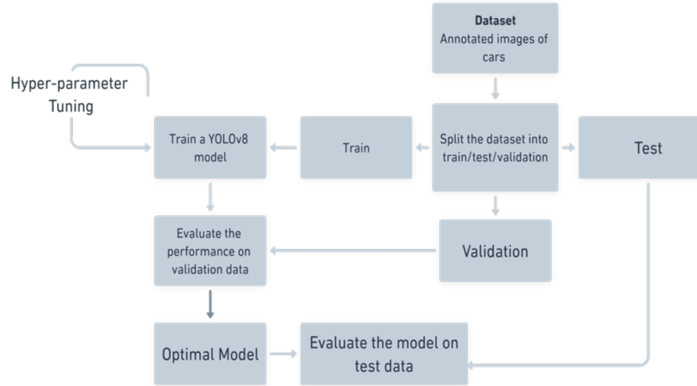
These sensors were installed in the congested road intersection at Kingston upon Thames in London. This information contained time-stamps that were synchronized with the camera recording traffic flow at the same location, such that direct comparison of the state of traffic congestion and air quality at the time would be made easier.

B. Traffic Dectection

1) Dataset

A dataset consisting of 263 vehicular traffic images was collected using a camera placed at the junction in London, where the sensors were deployed locally. The dataset was manually annotated, labeling vehicles as cars, buses, or trucks. It was then split into training (70.3%), validation (19.8%), and test (9.9%) sets. This annotated dataset served as the foundation for training the traffic detection model. This is explained in Fig. 2.

Fig. 2. Methodology for Traffic Detection



2) Algorithm: YOLOv8

The YOLO (You Only Look Once) algorithm is a state-of-the-art object detection model designed for real-time applications [23]. YOLOv8 was chosen due to its superior speed and accuracy compared to earlier versions, such as YOLOv3 and YOLOv4. YOLOv8 performs object detection in a single forward pass of the network, making it highly efficient for real-time traffic monitoring. The architecture of YOLOv8 includes three key stages: feature extraction using a backbone network, feature aggregation through path aggregation networks, and prediction using detection heads that predict bounding boxes, class probabilities, and objectness scores.

As seen in Fig. 2., the training pipeline involved preprocessing the images by resizing them to a 640x640 resolution to match the input requirements of YOLOv8. The model was then trained using the annotated dataset, with the following key hyperparameters:

TABLE I. HYPERPARAMETER TUNING VALUES USED FOR TRAINING THE YOLOV8 MODEL.

Hyperparameters	Values
Learning Rates	0.00001, 0.0005, 0.005, 0.01
Epochs	100, 150, 250, 300

Hyperparameter tuning is important to maximize the performance of the YOLOv8 model, which balances training efficiency and accuracy. The values chosen for the learning rates and epochs are selected since they are widely accepted by the deep learning community as the best choices for object detection tasks [24]. The hyperparameter tuning for YOLOv8 is performed in a grid search manner by trying different configurations of the learning rate and number of epochs, as indicated in Table 1. The best configuration is determined based on the highest Mean Average Precision (mAP50) score on the validation set. Early stopping was utilized in training to prevent overfitting, where training would stop if there was no improvement in validation loss for 10 consecutive epochs. The final model is the one that performed best mAP50 on the test set with an Intersection over Union IoU threshold of 0.5—meaning that predictions are considered correct if the overlap between predicted and ground truth bounding boxes is at least 50%.

Fig. 3. YOLOv8 Object Detection counting vehicles from local camera images and forecasting traffic with a confidence rating.

C. Air Quality Forecasting

The air quality forecasting component of this study involves the prediction of future pollution levels based on current sensor data and historical traffic data. Two models were evaluated: LSTM [25] and ARIMA [26].

1) Dataset

This traffic forecasting dataset was chosen was due to its accurate temporal and spatial characteristics, which are ideal for modeling traffic patterns accurately. With data collected at 36 sensor locations along two major highways in Northern Virginia/Washington D.C., the dataset provides a comprehensive representation of real-world traffic conditions. Traffic volume was recorded every 15 minutes, ensuring sufficient temporal granularity to capture fluctuations in traffic flow, while the inclusion of 47 features—such as historical traffic volume, weekday, hour of the day, road direction, number of lanes, and road names—allowed for a detailed analysis of traffic dynamics. The dataset was then divided into training and testing datasets: 1261 quarter-hours for training and 840 quarter-hours for testing [27]. The diversity of features, combined with the spatial distribution of sensors, allowed the model to consider both local and regional traffic patterns, which made this dataset especially suitable for long-term forecasting. Moreover, its application in previous studies [27] confirms its reliability and applicability in traffic prediction research.

2) Algoritm: LSTM

The LSTM model was trained on historical data and is developed to forecast traffic up to two hours in advance, allowing pollution data to serve as a proxy for predicting traffic. LSTM is a type of recurrent neural network (RNN) designed to capture long-term dependencies in time-series data [25]. To achieve the best possible performance, a piece of code was written to automatically cycle through various hyperparameter combinations (such as different learning rates and epochs) and test each configuration. The goal was to minimize the RMSE as much as possible.

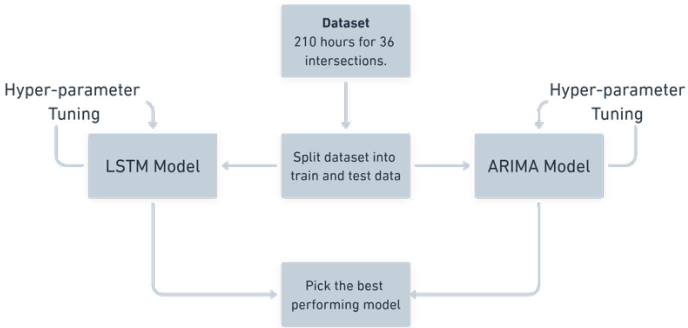
TABLE II. HYPERPARAMETER TUNING VALUES USED FOR TRAINING THE LSTM MODEL.

Hyperparameters	Values
Learning Rates	0.00001, 0.0005, 0.0001, 0.005, 0.001, 0.01
Epochs	50, 100, 150, 200

Hyperparameter tuning is very important for LSTM models to enhance their performance and to allow them to capture temporal patterns in data efficiently. As seen in Table 2, the selected learning rates and epoch values are widely recognized as optimal choices for training LSTM networks in various applications [28]. LSTMs are particularly efficient for Time-Series Forecasting because, using memory cells, information can be preserved over longer sequences, ensuring the model can learn patterns over long periods.

The length of a sequence was set to 10, meaning that the model used the last 10-time steps—equivalent to 150 minutes of historical data—to make predictions about future traffic. This sequence length was chosen to balance the need for enough historical data with not making the computation too complex.

Fig. 4. Methodology for LSTM Evaluation



After hyperparameter tuning, a learning rate of 0.001 was selected, optimized using the Adam optimizer, which is widely used for its ability to handle noisy gradients. A lower learning rate ensures that the model converges steadily without large fluctuations in the gradient updates.

3) Algorithm: ARIMA

ARIMA is a statistical model used for time-series forecasting. ARIMA predicts the variable of interest using a linear combination of past values, differencing the data to make it stationary [29]. ARIMA then models the error as a linear combination of past errors. The ARIMA model was structured with the following parameters: p (lag order), d (degree of differencing), and q (order of the moving average). Due to lack of time, well-established parameters were tested for hyper-parameter tuning for p,d, and q values.

D. Testing and Metrics

The performance of the LSTM and ARIMA models is evaluated using RMSE. Both are tested on unseen data, so they can generalize to datasets that are not in the training set. The best-performing model was LSTM; hence, it has been integrated into the final system for real-time traffic flow and pollution level forecasting. The YOLOv8 model is tested using the Mean Average Precision 50 (mAP50) values. mAP50 values are at an intersection over union threshold of 0.50. It is a measure of the model's accuracy considering only the "easy" detections. The higher the mAP50 values, the more accurate the object detection [30].

IV. Results

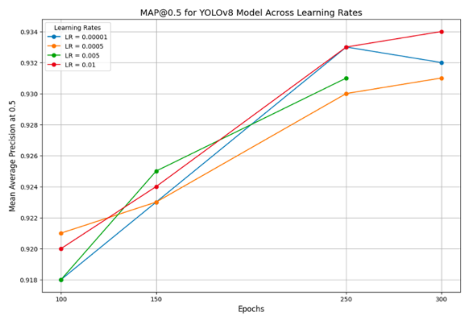
The results from both traffic detection and air quality forecasting experiments are presented below, following the sequence outlined in the methodology. Each model's performance was evaluated using appropriate metrics, and the best-performing models and hyperparameter values were identified for both tasks.

A. Traffic Detection

Traffic detection was performed using the YOLOv8 object detection model, with the performance evaluated based on mAP50 at different hyperparameter settings. The model was fine-tuned by varying the learning rate and number of epochs, as illustrated in Fig. 5.

The YOLOv8 model, trained for 300 epochs with a learning rate of 0.01, achieved a mAP50 of 0.865 on the locally collected traffic data, confirming these values as the optimal hyperparameters for YOLOv8. This means that the model was highly effective at accurately detecting vehicles. This reached high accuracy in vehicle detection for different traffic scenarios. Furthermore, as shown in Fig. 5., no data was collected for 300 epochs with a learning rate of 0.005 due to a lack of capacity to test additional models.

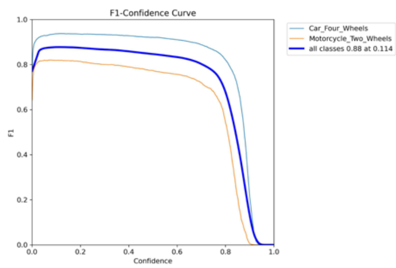
Fig. 5. MAP50 values for all the learning rates for the YOLOv8 model on secondary data.



The YOLOv8 model, trained for 300 epochs with a learning rate of 0.01, achieved a mAP50 of 0.865 on the locally collected primary traffic data, confirming these values as the optimal hyperparameters for YOLOv8. Furthermore, as shown in Fig. 5., no data was collected for 300 epochs with a learning rate of 0.005 due to a lack of capacity to test additional models.

Fig. 6. is an F1-Confidence Curve for the best performing YOLOv8 model, trained for 300 epochs with a learning rate of 0.01. The curve shows how the model's confidence threshold affects its F1 score, which balances precision (correct detections) and recall (detecting all vehicles).

Fig. 6. F1-Confidence Curve for best performing YOLOv8 model with 300 epochs and a learning rate of 0.01



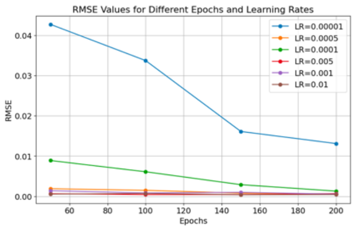
The x-axis represents the confidence threshold, and the y-axis shows the F1 score. At lower thresholds, the model detects more vehicles; that is, it has a high recall but low precision. As the threshold increases, precision becomes higher, while recall decreases; hence, the peak of the curve represents the optimal balance between precision and recall for the model, which has the highest F1 score at this point.

B. Air Quality Forecasting

For air quality forecasting, both LSTM and ARIMA models were used to predict traffic-related pollution levels, with their performances compared. The results of hyperparameter tuning and model evaluations for both LSTM and ARIMA are presented below.

The LSTM model underwent extensive tuning, with different learning rates and epoch counts evaluated. The best result was achieved with 150 epochs and a learning rate of 0.01, yielding a RMSE of 0.0203. This low RMSE indicates that the LSTM model was highly effective in long-term traffic and pollution forecasting, capturing complex temporal dependencies in the data, and fit the data well. Fig. 7. outlines the trend in LSTM hyperparameter tuning results; the error reported is for the time series forecast of traffic 2 hours into the future.

Fig. 7. Root Mean Squared Errors in predicting traffic for different hypermeter values in training the LSTM model.



The best result for ARIMA was achieved with p=2 and q=2, yielding a RMSE of 0.0835. As seen in Table 3, no data was collected for p=10, q=10 or p=15, q=10 due to a lack of capacity to test additional models.

TABLE III. Hyperparameter tuning results for ARIMA model reported in Root Mean Squared Error.

p/q	2	5	10	15
2	**0.0835**	0.0865	0.0890	0.0913
5	0.0880	0.0896	0.0899	0.0849
10	0.0902	0.0908	-	-

LSTM, with its ability to capture long-term dependencies in the data, outperformed ARIMA in long-term forecasting tasks. The LSTM model's ability to predict long-term traffic patterns resulted in a lower RMSE of 0.0203 compared to ARIMA's RMSE of 0.0835. These results validate the use of advanced machine learning models for effective traffic management and pollution mitigation in real-world scenarios.

The analysis of the acquired traffic and pollution data revealed several interesting findings.

Fig. 8. Confusion Matrix for air pollution elements against traffic count to visualize the correlation between traffic and air pollution

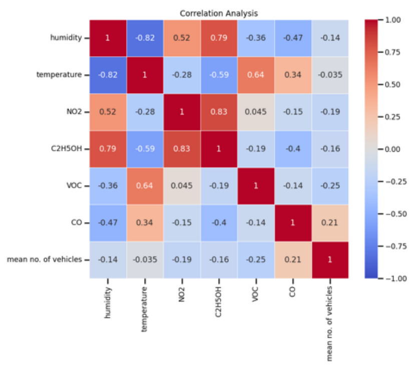


Fig. 9. Time Series Analysis of air pollution at different times of the day in the LSTM model

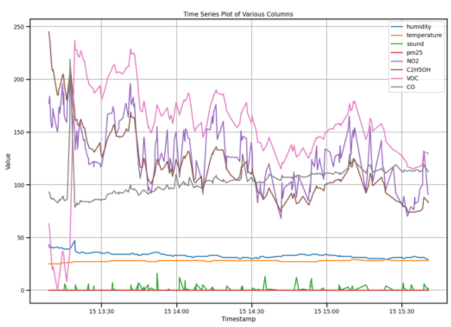


Fig. 8. is a confusion matrix to illustrate the correlation among air pollution elements and traffic counts. The pollution metrics—PM2.5, CO_2, and NO_2—showed high correlation with one and other, which was expected because pollutants rise together since they are all emitted from vehicles. However, the most striking finding was that pollution metrics seemed to be largely uncorrelated with traffic volume; one would naturally expect greater volumes of traffic to equate to greater volumes of pollutants in the air, but there was no strong, consistent correlation between the two. The variability of pollution over timescales as short as a few days suggests that factors other than traffic volume are at play. This is somewhat unexpected and forms the focus of some further investigation in the discussion section.

Additionally, Fig. 9. displays a time series analysis from the LSTM model, highlighting the daily fluctuations in air pollution. This figure demonstrates the LSTM model's ability to track and predict pollution patterns, revealing significant variability in pollution levels throughout the day, which could further explain the weak correlation with traffic volume observed in the confusion matrix.

V. Discussion

This study has successfully proved the feasibility of using low-cost sensors coupled with machine learning models to perform traffic detection and air quality forecasting. Our YOLOv8 results are like those reported by [11], in that both studies demonstrate high accuracy in vehicle detection, particularly in real-time traffic monitoring. Results align with related works in smart traffic management, where machine learning techniques are effectively applied to traffic detection and forecasting. This consistency further validates the robustness and applicability of YOLOv8 for intelligent traffic management systems. However, integrating air quality sensors with traffic detection and the forecasting of both traffic and pollution levels extends the scope of previous work to provide a holistic solution aimed at traffic management and environmental impact.

The positive results from this research underline the possibility of these methods being applied in real-world scenarios, especially the YOLOv8 model for detecting vehicles with high accuracy (mAP50 of 0.865) and the strong predictive performance of the LSTM model (RMSE of 0.0203). These results show that low-cost aerial sensors and object detection models can successfully be applied in monitoring traffic, and machine learning models like LSTM predict the traffic flow with high accuracy. More specifically, the possibility of predicting the flow of traffic holds a lot of promise for future smart city applications, where adaptive traffic control systems can aid in reducing congestion and lowering environmental impact.

Yet, from the confusion matrix between vehicular traffic and pollution levels shown in Fig. 8., it was surprising to find minimal correlation between the two variables. There are several possible explanations for this. One reason lies in seasonal variation: on different days or months, environmental conditions—like the wind or temperature—have a more profound effect on pollution dispersion than traffic density. It is also possible that the volume of traffic at the junction in Kingston upon Thames, a town in London, was never high enough to generate a large increase in pollution levels. Besides, the prevalence of low-emission or electric vehicles in the area may have reduced the expected correlation between traffic and pollution. Such findings only mean that the data collection should be done for much longer periods, during different seasons, and in higher traffic density areas, such as metropolises like London or Mumbai. There is an opportunity to integrate more accurate and sensitive pollution sensors to capture the more subtle variations of the pollution level due to traffic.

This research has demonstrated that economic sensors can effectively measure both pollution levels and traffic volume, offering an affordable and scalable solution for monitoring urban environments. The time-series forecasting models used in this study showed that it is possible to predict future traffic and pollution levels, which can inform decisions about urban planning and traffic management. The integration of such systems into navigation tools like Google Maps could enable users to make informed decisions about their routes, balancing time efficiency with environmental impact. This approach could also help mitigate the need for stringent traffic regulations, such as ULEZ [31], by providing users with alternative routes that minimize their contribution to pollution.

VI. Conclusion

This research developed a low-cost air pollution and traffic monitoring system using low-cost sensors and advanced machine learning models. This study showed that the YOLOv8 model can detect vehicles in real time with high accuracy and that the LSTM model performs very strongly in predicting future traffic and pollution levels. While effective, the system exhibited a rather weak relationship between the amount of traffic and pollution, indicating the possibility of other influences of pollution. The results give important insights into future urban traffic and pollution management, with a potential for improvement by increasing data collection and further refinement of sensors. This study lays the groundwork for more integrated, adaptive traffic systems to decrease the ecological footprint.

Improvements that will be relevant moving forward include those related to sensor accuracy in pollutant detection and noise pollution. Enhancing the accuracy of the sensors, particularly for noise pollution and pollutant detection, will be crucial. Additionally, expanding data collection to other regions and countries will provide more comprehensive insights into how traffic and pollution interact in different environments. The solution can be scaled up by engaging with local councils and integrating the object detection model into existing traffic camera systems. This research might evolve into a robust solution for sustainable traffic management, which might have far-reaching implications for public health, urban planning, and environmental sustainability. Ultimately, this research promises to provide a pathway toward smarter and sustainable cities by empowering communities with the capability of monitoring and mitigating the impact that traffic has on air quality.

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