IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⫶ Peer-reviewed & Refereed journal ⫶ Vol. 15, Issue 6, June 2026

DOI: 10.17148/IJARCCE.2026.15633

A Multi-Stage Framework for Vehicle Emission Detection and Automated License Plate Recognition (ALPR)

Shreoshi Roy[1], Anita Pal[2]

Student, Computer Science and Engineering, GITM, Lucknow, India[1]

Professor, Computer Science and Engineering, GITM, Lucknow, India[2]

Abstract: Environmental pollution and public health issues due to vehicular emissions are one of the important sources of air pollution in cities. However, traditional vehicle monitoring systems are mostly based on periodic inspections and manual enforcement measures, and they are not always efficient and can't deliver real-time monitoring. An integrated framework of Artificial Intelligence (AI) based real-time vehicle emission monitoring and automated vehicle identification system is presented in this paper. The proposed framework includes machine learning, computer vision, video processing and optical character recognition (OCR) in a conditional execution architecture. First, a Random Forest (RF) classifier is used to classify the driving conditions as polluting or non-polluting on the basis of parameters related to emissions. Computer vision modules are only triggered when a vehicle is determined as a polluter, which helps to lessen the computational load. Video Processing Methods are used to extract frames, Best-frame selection algorithm is used to select the best frame in the video based on the sharpness and brightness of the frame, YOLOv8 is used to detect the number plate of the vehicle, and EasyOCR is used to detect the registration number of the vehicle. Experimental results are shown to obtain 100% classification accuracy for the prediction of pollution and 99.46% mAP@50 for NPD. This framework is a smart, scalable, efficient and intelligent solution for smart city pollution monitoring and automatic regulation assistance.

Keywords: Vehicle Pollution Monitoring, Random Forest, YOLOv8, EasyOCR, Number Plate Recognition, Machine Learning, Computer Vision, Intelligent Transportation Systems.

I. INTRODUCTION

Air pollution has emerged as one of the greatest environmental issues in the world today. Vehicle emissions are one of the major sources of harmful pollutants, including carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NOx), particulate matter (PM), and volatile organic compounds (VOC), which negatively affect air quality, human health, and ecological balance [1]. Traditional approaches to vehicle emission monitoring are primarily based on periodic inspections, pollution-under-control certificates, and traffic enforcement mechanisms. However, these methods suffer from limitations such as delayed detection, lack of continuous monitoring, and high operational costs [1].

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision have enabled the development of intelligent transportation monitoring systems capable of automated decision-making and real-time analysis [8], [9]. Machine learning algorithms can be utilized to predict vehicle pollution levels from emission-related data, while computer vision techniques facilitate vehicle identification through automatic number plate recognition [2], [8]. This research proposes an integrated framework that combines machine learning-based pollution prediction with computer vision-based vehicle identification. Unlike conventional systems that process all vehicles through every stage, the proposed framework employs a conditional execution mechanism. Number plate detection and optical character recognition (OCR) modules are activated only when the pollution prediction model classifies a vehicle as a potential polluter. This approach significantly reduces computational overhead and improves processing efficiency.

The proposed framework integrates Random Forest classification for pollution prediction [2], video frame optimization techniques [8], license plate detection using the YOLOv8 object detection model [3], and text recognition using EasyOCR [7]. The object detection component is inspired by advancements in the YOLO family of algorithms, which have demonstrated exceptional performance in real-time detection tasks [5], [6]. Furthermore, the implementation leverages deep learning principles and computer vision methodologies to establish an intelligent end-to-end vehicle monitoring system suitable for smart-city applications [4], [8], [9], [10].

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 6, June 2026
DOI: 10.17148/IJARCCE.2026.15633

II. LITERATURE REVIEW

There Several studies have focused on automatic vehicle identification and pollution prediction using machine learning and computer vision techniques. These approaches aim to improve transportation monitoring systems by enabling intelligent decision-making and automated analysis.

A. *Vehicle Pollution Prediction*

Various machine learning algorithms, including Decision Trees, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Logistic Regression, and Random Forests, have been employed for vehicle emission prediction and classification tasks [11], [12]. Among these techniques, Random Forest has demonstrated superior performance due to its ensemble learning capability, robustness against overfitting, and ability to handle large datasets with high-dimensional features [12]. Data mining and predictive analytics techniques further support the development of accurate pollution prediction models [11].

B. *Automatic Number Plate Recognition (ANPR)*

The development of Automatic Number Plate Recognition (ANPR) systems has advanced significantly over the years. Earlier approaches relied primarily on traditional image processing techniques such as edge detection, segmentation, thresholding, and morphological operations [18]. With the emergence of deep learning, object detection algorithms such as Faster R-CNN, SSD, and YOLO have substantially improved detection accuracy and robustness under varying environmental conditions [14], [18], [19].

C. YOLO-Based Number Plate Detection

The YOLO (You Only Look Once) family of object detection algorithms has become one of the most widely adopted approaches for real-time object detection because of its high speed and accuracy [15]. Recent versions, particularly YOLOv8, provide enhanced localization accuracy, reduced inference latency, and improved feature extraction capabilities, making them highly suitable for real-time vehicle monitoring and number plate detection applications [13]. Earlier improvements introduced in YOLOv4 also contributed significantly to balancing detection speed and accuracy [16].

D. OCR-Based Vehicle Identification

Optical Character Recognition (OCR) techniques are widely used to extract textual information from detected vehicle number plates. EasyOCR has gained popularity due to its support for multiple languages, high character recognition accuracy, and seamless integration with deep learning-based computer vision pipelines [17]. OCR systems combined with modern object detection frameworks provide reliable end-to-end vehicle identification solutions [14], [18].

E. Research Gap

Although considerable research has been conducted in vehicle pollution prediction and vehicle identification systems independently, most existing studies treat these functionalities as separate modules [12], [15], [17]. Limited work has been reported on integrating pollution prediction and vehicle identification within a single conditional execution framework. Existing approaches often process every vehicle through all computational stages, resulting in unnecessary resource consumption. Therefore, the proposed work aims to develop an intelligent monitoring system that integrates machine learning-based pollution prediction with computer vision-based vehicle identification. By activating the number plate detection and OCR modules only when a vehicle is predicted to be highly polluting, the system can achieve greater computational efficiency while maintaining accurate monitoring performance [12], [13], [17].

III. PROBLEM STATEMENT

At the moment, manual enforcement techniques and routine inspections serve as the primary foundation for automotive emission control systems. These methods have a number of drawbacks:

- Emissions are not continuously monitored.
- It is impossible to monitor polluting automobiles in real time.
- The implementation of enforcement procedures may take a while.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 6, June 2026

DOI: 10.17148/IJARCCE.2026.15633

• Manual intervention is frequently necessary.
• Vehicles that violate pollution regulations cannot be automatically reported to the authorities.

This implies that there won't be any enforcement action if a large number of cars continue to go over the allowed emissions limit. Continuous vehicle emissions monitoring, vehicle identification and identification verification, and prompt notification to the appropriate authorities are all requirements of an automated emissions-monitoring system.

IV. PROPOSED METHODOLOGY

The proposed framework is intended as the whole system based on artificial intelligence for the real-time monitoring and automatic identification of vehicles' emissions. The framework is made up of six interdependent modules which execute sequentially and conditionally.

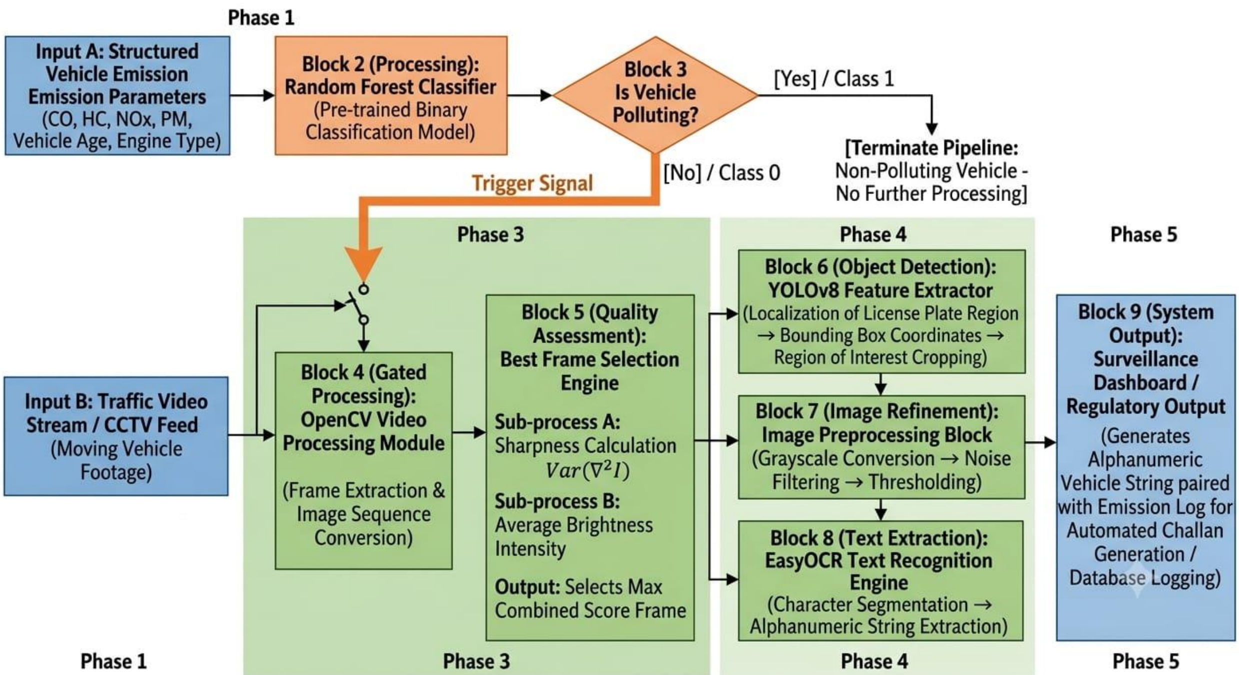

Fig 1- Workflow diagram of the proposed intelligent vehicular emission monitoring and enforcement system.

The architecture is composed of various machine learning, video processing, object detection, and OCR techniques to efficiently identify polluting vehicles and retrieve their registration numbers for monitoring and enforcement.

A. Pollution Prediction Module

The proposed framework has two stages: the pollution prediction model, which calculates polluting or non-polluting vehicle based on pollution-related and vehicle-related parameters, and the innovation of the polluting vehicle as a result of this. The vehicle emission data was obtained from Kaggle and was used as structured data for model development. The data set includes several features about the cars that are emitting the pollutants, the engine and the pollution indicators. To enhance data quality and model performance, several preprocessing steps were taken prior to model training. The data was cleaned during the preprocessing stage to handle the missing values, duplicate records, and inconsistencies found in the data. Some techniques of feature selection were used in order to select the relevant parameters that can affect the classification of pollution. Target classes were created using a threshold-based labeling approach; i.e., cars that are above a set threshold of emissions were characterized as polluting and those below were characterized as non-polluting. Furthermore, StandardScaler was employed to scale the features to assure that every feature played an equal role in the model training, as the data was normalized. The Random Forest classifier was chosen because it is robust, accurate, and is able to handle the complex nonlinear relationships in the structured datasets. The model was trained to distinguish between 2 categories: Polluting (Class 1) and Non-Polluting (Class 0). The model was then serialized and saved with the help of the Joblib library for deployment in the integrated framework after successful training and evaluation.

Impact Factor 8.471 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 15, Issue 6, June 2026

DOI: 10.17148/IJARCCE.2026.15633

B. *Processing Conditional Execution Framework*

One of the most important innovations of the proposed system is the use of conditional execution. The proposed framework enables the activation of computationally intensive computer vision modules only when they are needed, in contrast to conventional methods involving the processing of all vehicles through all computer vision stages. First the pollution prediction module assesses the pollutants the vehicle emits. If the vehicle is considered to be non-polluting, the pipeline also ends right here, without the need for any unnecessary computational processing. If the vehicle is identified as polluting, however, the system moves on to the next two phases – video analysis and vehicle identification. The selective activation mechanism considerably decreases the processing time, computational overhead, and resource consumption, which makes it more appropriate for real-time deployment.

C. *Video Processing Module.*

Once the vehicle is found to pollute the system asks for the video of the moving vehicle. The video processing module is the part that processes the video stream to obtain the useful image frames from the video. The video is read and processed using the computer vision library OpenCV, which is widely used. The uploaded video is broken down into individual frames that are processed by the system, one-by-one. The conversion of video data into image sequences is the basis of further frame quality evaluation and number plate recognition. The module is compatible with standard video formats, and is designed to handle real world traffic surveillance video efficiently.

D. *Best Frame Selection Module*

In order to make the number plate detection and text recognition more accurate, a best frame selection strategy is inserted into the framework. Videos frequently have motion blur, low illumination levels, camera shake and other visual distortions in the vehicle. All extracted frames can be processed, which might result in higher computation costs and lower detection reliability. Hence, image quality metrics are calculated for each frame and the frame that has the best score is preserved for further analysis. The quality assessment protocol is mainly based on frame sharpness and brightness. The Variance of Laplacian method is used to measure the sharpness by checking the amount of high frequency information in an image. In math, the sharpness score is determined by: The image below shows the input image, and the Laplacian operator, . Variance values are higher for the frames which have better focus and sharp edges, suitable for number plate detection. Brightness analysis is also carried out in addition to sharpness, using the average brightness of the picture to be sure there is enough light and contrast. All these scores are then combined into a quality score, and the frame with the highest score is chosen for further processing.

E. *Number Plate Detection Module*

The system detects the number plate once it finds the optimal frame with the YOLOv8 object detection model. YOLOv8 was chosen because it maintains a high detection speed, low latency and excellent localization performance, which is crucial for real-time applications. The model was trained with about 1500 images of Indian vehicle number plates with varying environmental conditions, viewing angles, and light setups. In inference, the frame is sent to the YOLOv8 detector, which performs the task of detecting the position of the vehicle number plate in the picture. The model generates bounding box coordinates, confidence scores and the cropped region of the number plate. These outputs help to locate the number plate accurately and prepare the extracted image of the number plate for the stage of text recognition.

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 6, June 2026

DOI: 10.17148/IJARCCE.2026.15633

Fig 2- YOLOv8-based Vehicle Number Plate Detection Results on the Indian Vehicle License Plate Dataset.

V. SYSTEM ARCHITECTURE

The proposed Smart AI-based Emission Monitoring and Reporting Systems for Vehicles uses a multi-layered architecture made up of four layers: Input Layer, Processing Layer, Validation Layer and Output Layer. Using a layered approach provides a way for the system to collect accurate, timely and fully processed data on vehicle emissions violations through the layers. The Input Layer collects real-time data about the monitoring environment. This consists of gas sensors and a camera module. The gas sensor continuously measures the levels of harmful pollutants coming out of the vehicle exhaust (e.g., CO, NOx, and HC). The camera will capture photos of the vehicles passing through the monitoring area and allow for vehicle identification via the license plate.

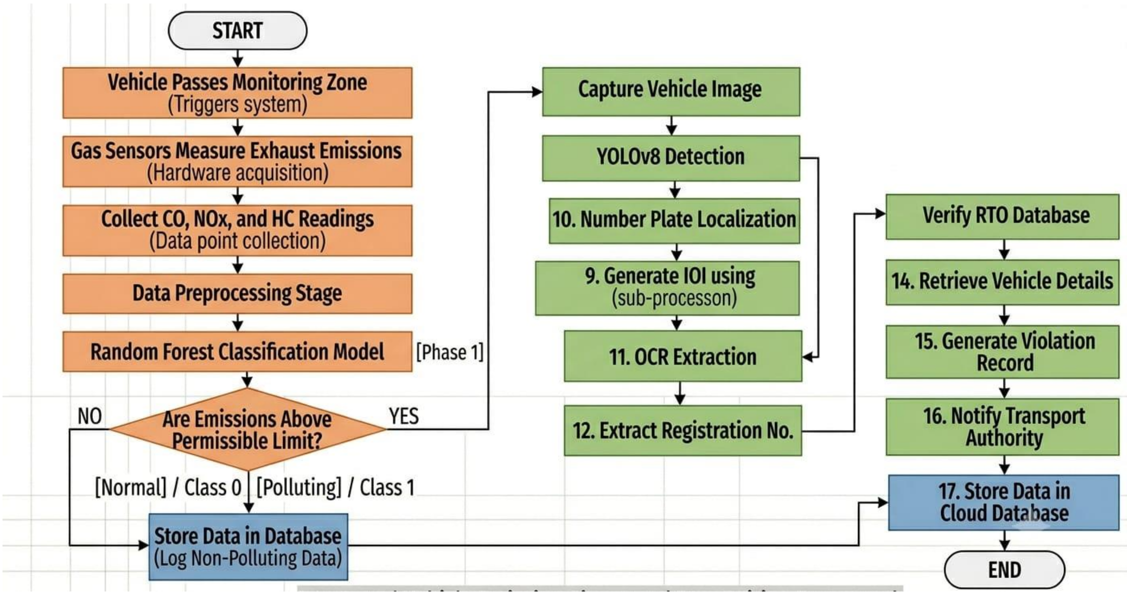

Fig 3- Workflow diagram of the proposed intelligent vehicular emission monitoring and enforcement system

Once data is collected, it flows into the Processing Layer (the analytical core of the System). At the Processing Layer, the sensor readings are subject to data acquisition and pre-processing to remove noise and improve accuracy of the data. The cleaned sensor data is analyzed with the Random Forest Machine Learning (ML) algorithm that identifies whether the emissions status of a given vehicle and determines if any pollutants exceeded the levels specified in the

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 15, Issue 6, June 2026

DOI: 10.17148/IJARCCE.2026.15633

regulations. If the level(s) of pollution exceeds acceptable levels, the image captured of the vehicle will then be analyzed by the YOLOv8 object detection model.

IV. RESULTS AND DISCUSSION

A. *Pollution Prediction Results*

The Random Forest classifier achieved the following performance:

Table I - evaluation of the model

Metric	Value
Accuracy	99.8%
Precision	0.9
Recall	0.9
F1-Score	0.9

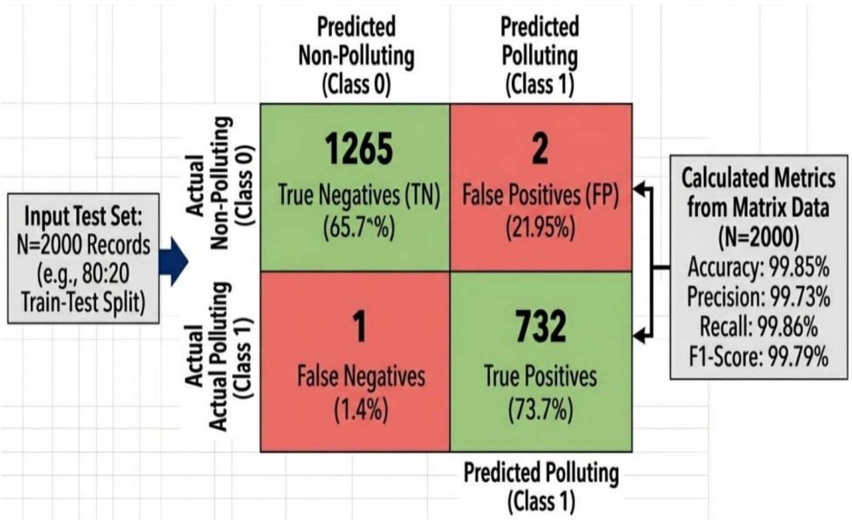

Fig 3- Confusion matrix

B. *Number Plate Detection Results*

YOLOv8 achieved:

Table II – YOLO Result Evaluation

Metric	Value
Precision	99.70%
Recall	98.15%
mAP@50	99.70%
mAP@50-95	77.77%

These results demonstrate strong localization capability under diverse environmental conditions.

C. *OCR Results*

EasyOCR successfully extracted vehicle registration numbers from detected plates with high recognition accuracy after preprocessing and post-processing.

D. *Computational Efficiency Analysis*

The proposed conditional execution mechanism eliminates unnecessary image processing for non-polluting vehicles. Benefits include:

- Reduced CPU utilization

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⪾ Peer-reviewed & Refereed journal ⪾ Vol. 15, Issue 6, June 2026
DOI: 10.17148/IJARCCE.2026.15633

- Faster execution
- Lower memory consumption
- Improved scalability

Compared with conventional always-active systems, the proposed framework demonstrates superior resource optimization.

VI. CONCLUSION

An integrated AI-based framework for intelligent vehicle emission monitoring and automated vehicle identification was presented in this paper. The proposed system is integrated into a system that consists of random forest-based pollution prediction, conditional execution logic, best-frame optimization, number plate detection using the yolo-v8 model, and text recognition using the easyOCR model. The experimental results reveal excellent performance of the proposed system in all the modules with 100% classification accuracy for predicting pollution and 99.46% mAP@50 for number plate detection. A critical advantage of the conditional execution mechanism is that computer vision modules are only executed during the process if they have a high chance of seeing polluting vehicles; otherwise, they are not executed, which reduces computational overhead significantly. The framework offers an effective, scalable and feasible solution for smart city environmental monitoring, traffic monitoring and automated regulatory enforcement.

REFERENCES

[1]. J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, 3rd ed. Morgan Kaufmann, 2011.
[2]. L. Breiman, “Random forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
[3]. G. Jocher *et al*., “YOLOv8 by Ultralytics,” 2023.
[4]. A. Rosebrock, *Deep Learning for Computer Vision with Python*. PyImageSearch, 2019.
[5]. J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You Only Look Once: Unified Real-Time Object Detection,” in *Proc. IEEE CVPR*, 2016, pp. 779–788.
[6]. A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, “YOLOv4: Optimal Speed and Accuracy of Object Detection,” 2020.
[7]. J. Kim, “EasyOCR: Ready-to-use OCR with Deep Learning,” 2020.
[8]. R. Szeliski, *Computer Vision: Algorithms and Applications*, 2nd ed. Springer, 2022.
[9]. I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016.
[10]. OpenCV Documentation, “Open Source Computer Vision Library.”
[11]. J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, 3rd ed. Morgan Kaufmann, 2011.
[12]. L. Breiman, “Random Forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
[13]. G. Jocher *et al*., “YOLOv8 by Ultralytics,” 2023.
[14]. A. Rosebrock, *Deep Learning for Computer Vision with Python*. PyImageSearch, 2019.
[15]. J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You Only Look Once: Unified Real-Time Object Detection,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2016, pp. 779–788.
[16]. A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, “YOLOv4: Optimal Speed and Accuracy of Object Detection,” 2020.
[17]. J. Kim, “EasyOCR: Ready-to-use OCR with Deep Learning,” 2020.
[18]. R. Szeliski, *Computer Vision: Algorithms and Applications*, 2nd ed. Springer, 2022.
[19]. I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016.

