A Comprehensive Deep Learning Framework For Real Time Traffic Density Estimation And Distracted Driver Behavior Detection

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ABSTRACT:
This study presents a thorough deep learning framework for detecting distracted driving behavior and estimating traffic density in real time, two essential elements of intelligent transportation systems. Two separately trained modules are included in the suggested method. The first enables effective monitoring of traffic congestion and road usage patterns by identifying and counting vehicles from traffic scene photographs using a YOLOv8 object detection model. The second module classifies driver behaviors into ten categories, such as safe driving, texting, phone use, and other frequent distractions, by analyzing in-car photos using a bespoke Convolutional Neural Network (CNN). To improve the resilience and generalization of the model, extensive preprocessing methods and data augmentation were used. The framework is compatible with automated visual data processing, works in real-time, and may be implemented in driver safety and traffic surveillance systems. This dual-model architecture uses sophisticated vision-based monitoring to help create safer and smarter roads. When traffic congestion and queue clearing are present, the density of traffic is extremely nonlinear. Complex nonlinearities cannot be handled by closed-mathematical versions of standard density estimation techniques, which makes room for data-driven strategies like machine learning techniques. Deep learning algorithms, which identify nonlinear and highly situation-dependent patterns, perform best in data-rich environments.

Keywords: Traffic Density Estimation, Distracted Driver Detection, Deep Learning, Real time monitoring, Driver Behavior analysis, Convolutional neural network (CNN), YOLOv8.

1. INTRODUCTION:

Congestion on the roads is undoubtedly the transportation system's biggest issue. As a result, trips become less dependable and slower than they would be without congestion. Although there are many technological and governmental options to address the negative effects of vehicle emissions and traffic accidents, congestion appears to be a more difficult problem to solve.

Congestion primarily occurs in or close to highly populated areas with high car ownership rates, making it impossible for the roads to handle all possible trips, especially while people are traveling to and from work in the morning and evening. Whether through capacity expansion or demand management, congestion management strategies must consider the potential that road users who were previously discouraged by the prospect of delays may decide to make more and/or longer trips because of faster travel times.

1.1 Role of deep learning in intelligent transportation

Deep Learning (DL) approaches have been used in recent years to construct Intelligent Transportation Systems (ITS) more quickly and efficiently, particularly in problem domains that were previously solved with analytical or statistical methods. Enhancements brought about by DL applications have improved public transportation efficiency, reduced maintenance costs, enhanced safety and security on transit highways, and improved traffic management and planning. And ride-sharing business success, as well as having made significant progress in the development of autonomous vehicles.

1.2 Intelligent Driver Behavior Detection

Automatic Driver Distraction Detection Using Deep Convolutional Neural Networks Deep convolutional neural networks were utilized by Md. Uzzol Hossain and associates (2022) in order to automatically detect driver distraction. Their technique processed visual input from in-car cameras using a number of intricate models. The merit of this study is its large dataset and in-depth neural network analysis, which serve as a reliable standard for our work(Md. Uzzol Hossain, Md. Ataur Rahman, Md. Manowarul Islam, Arnisha Akhter, Md. Ashraf Uddin, 2022).

Detection of Distracted Driver Using Convolution Neural Network The 2022 study by Narayana Carpanini outlines a CNN-based framework or detecting driver distraction that focuses on processing constraints in real-time their methodology is aligned with our work, particularly in their use of a streamlined model for efficient computation. The insights from this study guide our exploration of computational efficiency in model training and real-time detection, providing a comparative perspective that enriches our App (**Narayana Darapaneni, Jai Arora, MoniShankar Hazra, Naman Vig, Simrandeep Singh Gandhi, 2022)**

1.3 Importance of Monitoring Driver Behavior

With the progressive innovation of the Internet of Things (IoT), monitoring and analyzing vehicle behavior has now become a fact, this study develops an Internet of Things-based management system for tracking and observing the activities of the vehicle. An intelligent methodical, inexpensive and efficient system was used in our work, for monitoring driving behavior in order to identify driving style, based on remote, clean and real data (**Mohammed, K., Abdelhafid, M., Kamal, K., Ismail, N., & Ilias, 2023).**

He et al., 2021a, He et al., 2021b examined the influences of package couriers' workload on work emotions, and the effects of these two factors on driving behaviors. The limitation imposed on the study is the ignoration of the road crash risks in the analysis **(He, Y., Sun, C., & Chang, 2023)**.

Driver physiology is a complex field that encompasses various aspects of human health, including alertness, fatigue, stress, and emotions. When an individual takes the car wheel, their physiological state can vary depending on numerous factors such as their level of rest, emotional state, and overall health. Understanding these aspects is essential for predicting dangerous behaviors on the road or studying the variation of injury risks based on their physiological state. Recent studies have emphasized the importance of real-time monitoring of the driver's physiological state, as it directly influences their driving abilities and responsiveness **(Davoli, L.; Mattioli, V.; Gambetta, S.; Belli, L.; Carnevali, L.; Martaló, M.; Sgoifo, A.; Raheli, R.; Ferrari, 2021)**

2. LITERATURE REVIEW:

Monagi h. Alkinani et al. (2022) Distractions make human drivers less competent, which ultimately leads to car crashes when the car loses control and begins to veer out of lanes or abruptly change speed. A motorist may become distracted for one of three reasons: first, when he starts doing something other than driving; second, when someone else starts the distraction; or third, when something unexpected occurs and takes the driver's attention away from the road.

Human driver distractions can take many different forms, depending on their nature and degree. Using a cell phone, making calls, reading or sending messages, staring at other drivers and objects outside the car, smoking, drinking, and eating are all ex
samples of distractions.

Md. Uzzol hossain, et.al (2022) A deep learning study is used to examine multitasking and idea drift. Move learning is a well-liked deep learning technique because of the massive resources needed to train deep learning models or the sizable and difficult datasets utilized to train deep learning models. Profound learning is most beneficial when the initial model highlights are quite large. The learned highlights are first transferred to a base organization that has been produced on a base dataset and task in order to prepare a subsequent objective organization on an objective dataset and task. If the qualities are generic—that is, applicable to both the base and target duties—rather than job-specific, this strategy has a higher chance of succeeding. One helpful technique for resolving issues with predictive modeling is transfer learning. The pre-trained model approach and the build model method are the two most used transfer learning strategies.

Rishabh Jain et. al (2023) Lastly, there has been encouraging progress in improving traffic flow predictions and management through the use of deep learning techniques and intelligent traffic systems. These systems evaluate traffic data in real time, allowing for the optimization of signal timing, the redirection of traffic to less congested routes, and the implementation of congestion pricing. By using real-time vehicle data, intelligent traffic systems may improve their predictive capabilities and provide more accurate and trustworthy traffic flow information, which could result in reduced traffic, quicker travel times, more safety, and less operational expenses. To help address the remaining challenges in using deep learning to predict traffic flows, new deep learning algorithms and data collection techniques are being developed.

M Rifai et. All (2020) As the number of cars on the road continues to climb, traffic congestion and the risk of accidents both worsen. Ignoring a red light is a significant infraction that usually results in collisions. Due to the rapid distribution of green time on comparatively crowded lines, drivers may be more likely to ignore the signals. To track traffic signal compliance and spot violations, like vehicles failing to stop at a zebra crossing when the light is red, this capstone project uses a convolutional neural network technique. The sensor in this case is the camera. Three cameras are used in each row. The microcontroller will get the number of cars detected from the laptop. Data on the number of cars waiting at the light is sent into a convolutional neural network to calculate how long the green light should last. The infraction will be noted if the car stops past the stop line while the red light is on.

Manish Kumar Singh et. All (2021) In this work, we provide a computer vision-based smart traffic control and management system that tracks and identifies vehicles, counts the number of vehicles in a particular lane in real time, and detects vehicle movement. The system will then modify the intensity of the appropriate traffic lights in accordance with this information. There are two things to think about: the lane's priority and density. To cut down on the amount of time vehicles must wait to pass through This proposed method's primary benefit is its real-time ability to recognize all cars on the road, regardless of size. The suggested strategy outperformed even in the presence of obstructions and heavy traffic.

3. Methodology

The methodology adopted in this study involves the design implementation and evaluation of deep learning models for Traffic density estimation and Distracted Driver behavior detection using image data. This research follows a multi-stage pipeline comprising data collection, Data preprocessing, Model architecture, Model training and evaluation.

3.1 Dataset
This study makes use of two publicly accessible datasets designed for two main purposes: driver behavior classification for the identification of distracted driving and vehicle detection for the calculation of traffic density.

Traffic Density Estimation: High-resolution photos of five different vehicle classes—cars, trucks, buses, motorcycles, and ambulances—with labeled bounding boxes make up the Cars Object Detection Dataset. The dataset provides robust item detection tasks and is captured in a variety of real-world circumstances. It is perfect for applications involving autonomous driving, vehicle detection, and traffic monitoring because it is YOLO-formatted with train, valid, and test splits.

Detection of Distracted Driver Behavior: The State Farm Distracted Driver Detection dataset includes more than 22,000 tagged photos of drivers engaging in 10 different kinds of behavior (such as texting, eating, using a phone, and safe driving). To comply with CNN input specifications, photos are scaled to 224×224 pixels and each behavior is grouped into folders c0 through c9.

3.2 Data Preprocessing
Both datasets underwent standard preprocessing procedures to enhance training stability and model performance:

- **Image loading**: All images were loading using openCV.
- **Image resizing:** Traffic images were resized to 640×640 for YOLOv8, while driver images were resized to 224×224 for CNN input compatibility.
- **Label Encoding:** Driver behavior characteristics, such as safe driving, texting, chatting on the phone, etc., are mapped to class labels ranging from c0 to c9.
- **Data augmentation:** To improve generalization, both datasets were enhanced with rotations, brightness shifts, horizontal flips, and scaling.
- **Train-Test Split**

❖ **Traffic Dataset**: 70% training, 10% testing,20%Validation

❖ **Driver Dataset**: 80% training, 20% testing

3.3 Model Architecture
In order to handle real-time traffic density estimation and distracted driver behavior detection, this study combines two specialized deep learning architectures that operate as separate modules within a single system.

YOLOv8 Model

- **Backbone**: Cross Stage Partial Connections, or CSPDarknet
- **Neck:** feature fusion using PANet (Path Aggregation Network)
- **Head:** Detection header for class probabilities, bounding box predictions, and objectness scores

With the settings specified in data.yaml, the model was trained using the YOLO-compatible dataset structure (pictures and.txt labels).

Because of its high accuracy and real-time performance in identifying various vehicle kinds under a range of scenarios, YOLOv8 was chosen.

CNN Model

A custom Convolutional Neural Network (CNN) was constructed using the Tensorflow/keras framework and this architecture include:

- **Input Layer:** 224 x 224 x 3 resized RGB photos are the input layer.
- **Convolution Layers**: MaxPooling and ReLU activation are performed after each of the three convolutional blocks with increasing filters (32, 64, and 128).
- **Flatten Layer**: Produces 1D from 3D feature maps
- **Dense Layer**: 128 neurons with ReLU activation in a fully connected layer
- **Dropout Layer**: Used to avoid overfitting at a rate of 0.5
- **Output Layer:** Ten neurons in the Softmax layer, which represents ten driver behavior types, make up the output layer.

3.4 Training & Evaluation
- **Loss Function**: To increase detection accuracy, the YOLOv8 model combines objectness, categorization, and loss of bounding box regression. The CNN model is appropriate for multi-class classification of driving behaviors because it employs categorical cross-entropy loss.
- **Evaluation Metric**

❖ Mean Average Precision (mAP) and vehicle count accuracy were used to assess the YOLOv8 model.

❖ The primary criterion used to evaluate the CNN model was training and validation accuracy.

- **Configuration for Training:**

❖ Ten to twenty epochs were used to train both models.

❖ In order to balance convergence speed and model performance, learning rate and batch size were adjusted.

- To enhance generalization and lessen overfitting, data augmentation techniques like flipping, rotation, and brightness modulation were used, along with shuffling.

4. Result and Analysis:

This section demonstrates the performance of both models through visuals output and quantitive performance based on actual training dataset.

4.1 Visual result of the framework

The Model has been trained and test on two different datasets:

- Car's detection dataset for traffic density estimation
- State farm distracted driver detection dataset for behavior classification

4.1.1 Detected object in sample image by the pre-trained model

In our sample image, the pre-trained model missed the detectable truck and car that were clearly visible.

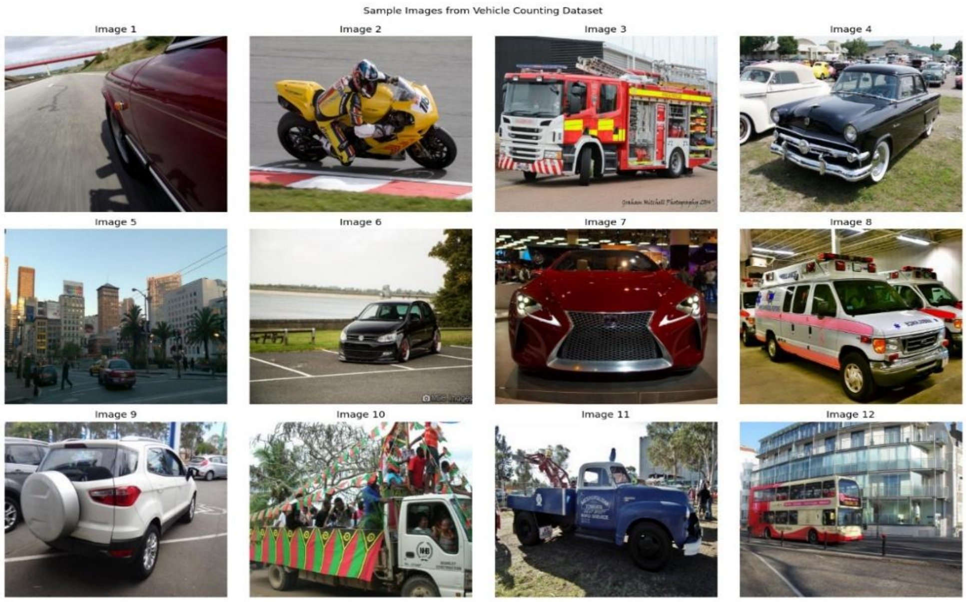

Figure 4.1: Detected object in sample image by the pre-trained model

Model Inference and Detection Results

The Cars Object Detection dataset was used to train the YOLOv8 model and then test photos that had not yet been viewed were used for inference. With a high degree of confidence, the model was able to locate and identify several vehicle classes using bounding boxes.

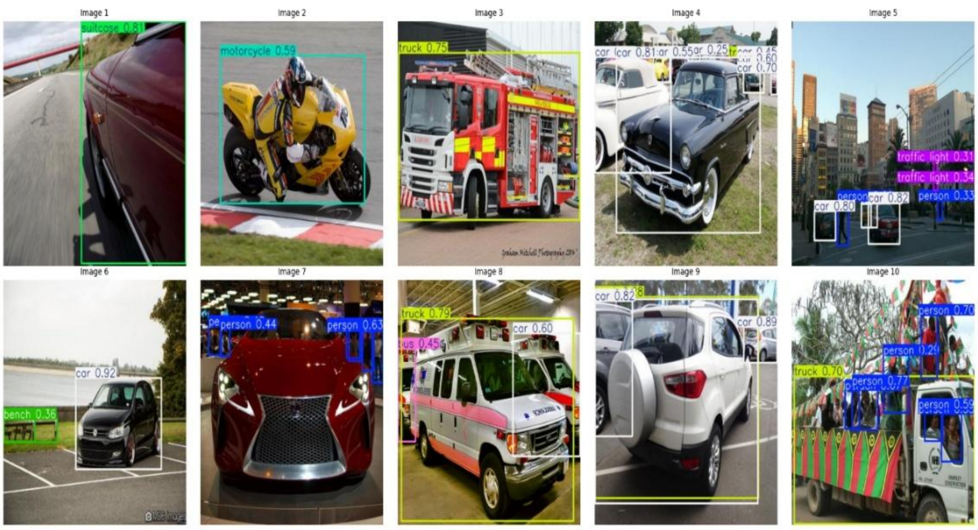

Figure 4.2: Vehicle Detection Output Using Trained YOLOv8 Model

Model Performance Metrics:
The YOLOv8-based vehicle identification and counting model is evaluated both quantitatively and qualitatively in this section. The accuracy of the model's detection and classification is evaluated using several common assessment measures.

Metric	Value
Precision	0.7360
Recall	0.5264
mAP@0.50	0.6170
mAP@0.50:0.95	0.6170

Precision–Recall Curve Analysis of YOLOv8 Model
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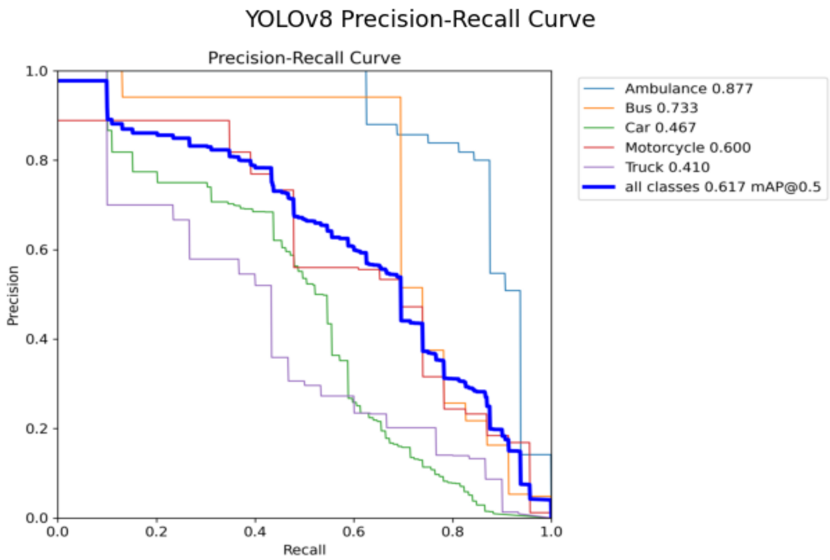

Figure 4.3: Precision–Recall Curve

Evaluation Metrics Visualization
In the meantime, the confusion matrix highlights any patterns in vehicle category misclassification and offers information on class-specific prediction performance.

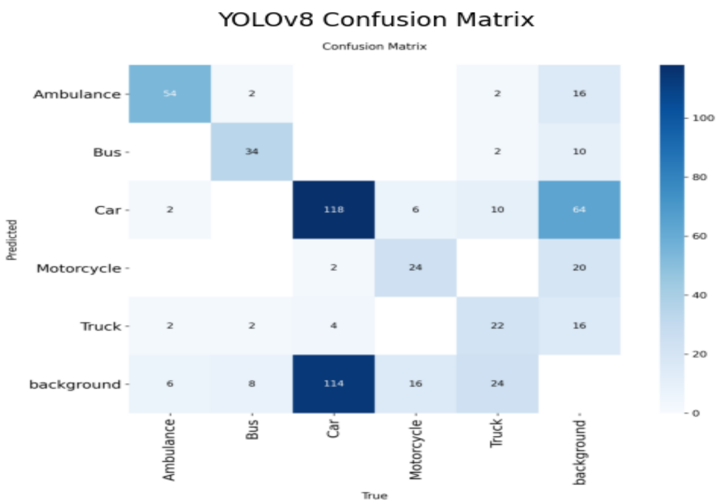

Figure 4.4: Confusion Matrix visualizing

4.1.2 Distracted Driver Behavior Detection

Class Distribution

A bar chart was used to visualize the number of samples available in each class.
The dataset contains a balanced number of images for each class (C0 to C9).
This balance ensures that the models will not be biased towards for any one class.

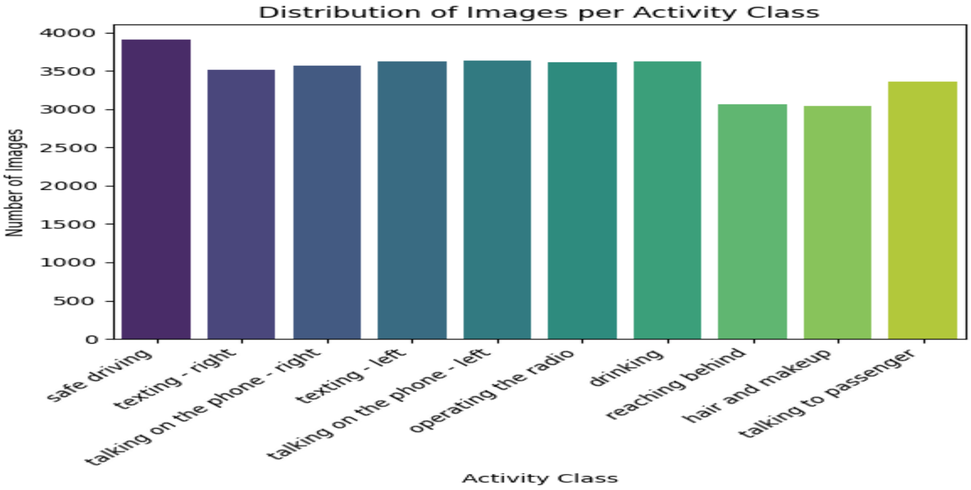

Figure 4.5: Class Distribution of each class

Random Samples of Driver Behavior Classes

A selection of randomly selected training set photographs that show a range of driver behaviors in various subjects and situations are shown in the image below. It provides a visual representation of the dataset's intra- and inter-class variation.

Figure 4.6: Driver behaviors for each class

CNN Training and Validation Metrics Summary

Epoch	Train Accuracy	Train Loss	Val Accuracy	Val Loss
1	0.9408	0.1471	1.0000	0.0001
2	1.0000	~0	1.0000	0.0001
3	1.0000	0.00005	1.0000	0.0002
4	1.0000	~0	1.0000	0.0002
5	1.0000	0.00002	1.0000	0.0002

6	1.0000	~0	1.0000	0.0002
7	1.0000	0.0000007	1.0000	0.0001
8	1.0000	0.0000009	1.0000	0.0001
9	0.9992	0.0055	0.9953	0.0105
10	1.0000	0.0004	0.9944	0.0131

With low loss values, the CNN model demonstrated a high training accuracy of 100% and a validation accuracy of up to 99.5%. This illustrates how well the model generalizes to new data from the validation set. The slight rise in validation loss in subsequent epochs, however, raises the possibility of overfitting, which regularization or augmentation may help to avoid.

Training and Validation Accuracy Curve

This curve illustrates how the model's accuracy improves over the training epochs. The validation accuracy closely follows the training accuracy, indicating good generalization and minimal overfitting.

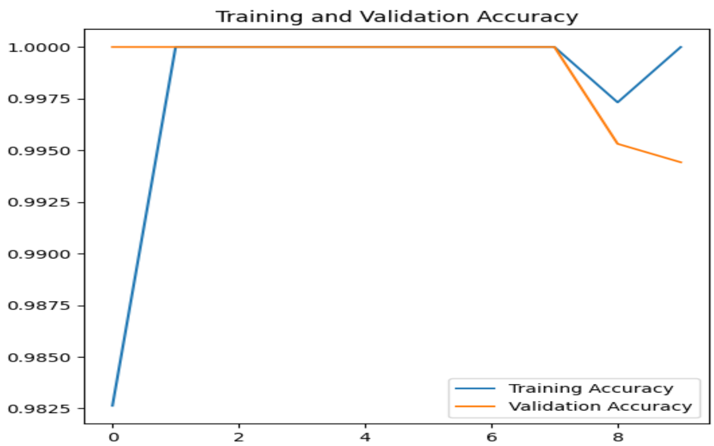

Figure 4.7: Training and Validation Accuracy Curve

Training and Validation Loss Curve

The loss curves demonstrate how the error reduces as the model learns. A sharp drop in training loss during early epochs is evident, and validation loss remains stable, showing convergence without significant overfitting.

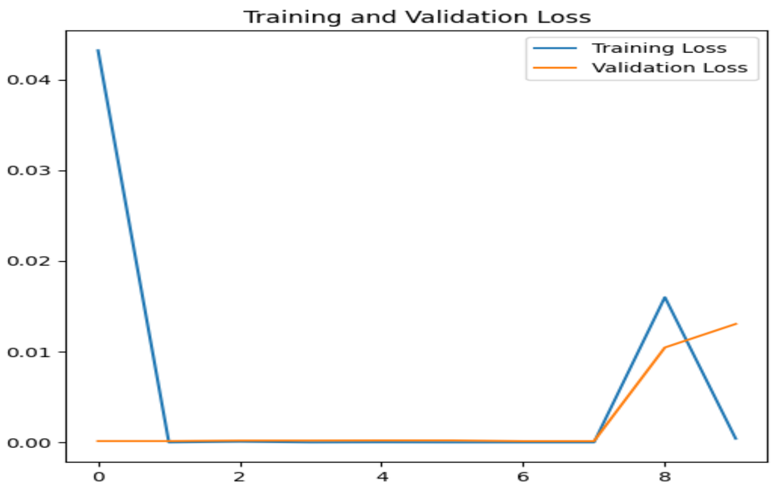

Figure 4.8: Training and Validation Loss Curve

5. Conclusion:

Real-time traffic density prediction and the detection of inattentive driving behavior are two crucial aspects of intelligent transportation systems that this study addressed by proposing and implementing a thorough deep learning architecture.

A proprietary Convolutional Neural Network (CNN) trained on the State Farm Distracted Driver Detection dataset was used in the project's initial phase. The model's ability to recognize various forms of driver distractions from in-car photos was demonstrated by its strong classification performance, which included a final validation accuracy of 99.44%. Techniques for data augmentation were crucial in improving the model's generalizability.

The Cars Object Detection Dataset, which contains excellent annotations for several vehicle classes, was used to train a YOLOv8 object detection model in the second section. With a precision of 0.736, recall of 0.526, and mAP@0.5 of 0.617, the trained model demonstrated its capacity to identify different kinds of cars in actual traffic situations. The dependability of the model for vehicle detection tasks was validated by visualization using bounding boxes, confusion matrices, and PR curves.

Overall, both models performed well in their respective fields, and the experiment shows how deep learning may improve applications for autonomous driving, traffic analysis, and road safety.

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