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A FREQUENCY-AWARE TRANSFORMER FRAMEWORK FOR VEHICLE SPEED VIOLATION DETECTION WITH ROBUST LICENCE PLATE RECOGNITION

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ABSTRACT

This paper presents a frequency-aware transformer-based framework for vehicle speed violation detection and automatic licence plate recognition using traffic surveillance video. The proposed framework integrates vehicle detection, multi-object tracking, speed estimation, violation classification, and licence plate recognition into a unified pipeline. Spatial and frequency-domain feature representations are intended to improve vehicle detection under challenging illumination and image-quality conditions, while transformer-based feature fusion models contextual relationships in traffic scenes. Vehicle speed is estimated from tracked trajectories using camera calibration and temporal displacement, and vehicles exceeding the applicable speed limit are processed by a deep learning-based licence plate recognition module. The manuscript reports an experimental evaluation using traffic surveillance videos, vehicle image frames, and licence plate images. The reported results include 97% vehicle detection accuracy, 95% speed-estimation accuracy, 96% licence plate recognition accuracy, and a 3% false-violation rate. The reported classification results also include a precision of 96.8%, recall of 97.8%, and F1-score of 97.3%. These findings indicate the potential of integrating vehicle detection, trajectory-based speed estimation, and licence plate recognition into a unified traffic-monitoring system. Further validation using clearly documented datasets, calibrated speed measurements, and reproducible comparative experiments is necessary to establish the framework's generalizability and real-world effectiveness.

Keywords: *Vehicle Speed Violation Detection, Frequency-Aware Deep Learning, Transformer-Based Computer Vision, Automatic License Plate Recognition, Intelligent Transportation Systems.*

1. INTRODUCTION

Road traffic accidents remain a major public safety concern worldwide, with *over-speeding identified as one of the leading causes of fatalities and severe injuries* [17][18]. Rapid urbanization and the increasing number of

vehicles on roads have significantly intensified traffic congestion and road safety challenges. According to global road safety reports, a substantial proportion of accidents occur due to drivers exceeding permissible speed limits. Effective monitoring and enforcement of speed regulations are therefore essential to ensure road safety and reduce accident rates. Traditional traffic enforcement methods, such as radar guns and manual monitoring by traffic authorities, have been widely used for detecting speed violations [10\[11]. However, these approaches often require expensive hardware infrastructure, continuous human supervision, and limited coverage, making them difficult to deploy at large scale in modern smart city environments.

Recent advancements in *computer vision and deep learning* have enabled the development of intelligent traffic surveillance systems [19][27] capable of automatically monitoring road activities using video cameras. Vision-based approaches provide a cost-effective alternative to radar-based systems by utilizing existing surveillance infrastructure. Modern object detection algorithms, such as convolutional neural networks (CNNs) and real-time detection frameworks, have demonstrated significant improvements in vehicle detection and tracking performance [1] [2] [3] [4]. These techniques enable automatic identification of vehicles in traffic videos, facilitating tasks such as traffic flow analysis, violation detection, and incident monitoring. In addition, *automatic license plate recognition (ALPR)* systems allow authorities to identify offending vehicles [14] [15] [16] by extracting registration information from captured images, further enhancing the automation of traffic enforcement systems.

Despite these advancements, several challenges still limit the reliability of existing vision-based traffic monitoring systems. First, most current methods rely solely on spatial features extracted from image frames [20] [21] [24], which often leads to reduced performance under challenging environmental conditions such as low illumination, rain, fog, motion blur, and dense traffic scenarios. Second, many existing studies treat *vehicle speed estimation and license plate recognition as independent modules*, resulting in fragmented systems that lack a unified architecture for real-time traffic violation detection. Third, traditional convolution-based approaches have limited capability in modeling long-range contextual relationships between frames [5] [6] [7], which is essential for accurate vehicle tracking and motion analysis in complex traffic environments.

To address these limitations, recent research has explored advanced deep learning architectures that combine multiple feature representations and attention mechanisms to improve system robustness. In particular, *transformer-based models* have shown remarkable performance in computer vision tasks [5] [6] [7] due to their ability to capture global contextual information and long-range dependencies within visual data. Furthermore, integrating *frequency-domain information* with spatial features can significantly enhance the robustness [20] [21] of vision models, as frequency features capture structural patterns that remain stable under lighting variations, noise, and motion distortions. However, the integration of frequency-aware learning with transformer-based architectures for traffic monitoring and violation detection remains relatively unexplored.

Motivated by these challenges, this paper proposes a *Frequency-Aware Transformer-Based framework for vehicle speed violation detection integrated with robust multi-condition license plate recognition*. The proposed system introduces a novel feature extraction strategy that combines spatial and frequency-domain representations to improve vehicle detection performance under diverse environmental conditions. A transformer-based attention mechanism is employed to fuse these complementary features and enhance vehicle tracking across video frames. Based on the tracked vehicle trajectories, a motion analysis module estimates vehicle speed and identifies speed violations in real time. Additionally, a deep learning–based license plate recognition module is integrated to accurately identify violating vehicles under varying lighting conditions, viewing angles, and occlusions.

The key contributions of this work can be summarized as follows:

1. *A frequency-aware feature extraction framework* that combines spatial and frequency-domain representations to enhance vehicle detection robustness under challenging environmental conditions.
2. *A transformer-based feature fusion architecture* that captures long-range dependencies in traffic video sequences for improved vehicle tracking and motion analysis.
3. *An integrated end-to-end framework* that simultaneously performs vehicle detection, speed

violation identification, and automatic license plate recognition.

4. *A robust multi-condition license plate recognition model* capable of recognizing vehicle plates under varying illumination, noise, and partial occlusion scenarios.

5. *A scalable and cost-effective traffic monitoring solution* that can be deployed using existing surveillance camera infrastructure for smart city applications.

2. RELATED WORK

Automated traffic monitoring has become an important research area within *intelligent transportation systems (ITS)*, particularly for detecting traffic violations and improving road safety. With the rapid development of computer vision and deep learning techniques, several approaches have been proposed for vehicle detection, speed estimation, and automatic license plate recognition. This section reviews the major research contributions in these areas and highlights the limitations that motivate the proposed work.

2.1 Radar-Based and Sensor-Based Speed Detection

Traditional speed monitoring systems primarily rely on radar guns, loop detectors, and laser-based sensors [10] [11] to measure vehicle speed. These systems are widely used by traffic enforcement agencies due to their relatively high accuracy in measuring vehicle velocity. However, such sensor-based approaches require dedicated hardware installation and periodic maintenance, which significantly increases deployment cost. Moreover, these systems typically monitor only a single lane or limited road segment, making them unsuitable for large-scale traffic surveillance. Due to these limitations, researchers have increasingly focused on camera-based approaches that can utilize existing surveillance infrastructure for automated traffic monitoring.

2.2 Vision-Based Vehicle Detection and Tracking

With the availability of high-resolution surveillance cameras, vision-based vehicle detection has emerged as an effective alternative for traffic monitoring. Early approaches relied on traditional image processing techniques such as background subtraction, edge detection, and feature-based descriptors [13]. Histogram of Oriented Gradients (HOG) and Support Vector Machines (SVM) were commonly used for object detection [13] in early traffic surveillance systems. Although these methods provided reasonable performance in controlled environments, they were highly sensitive to illumination changes, occlusions, and complex backgrounds.

The emergence of deep learning significantly improved the performance of object detection models. Convolutional neural networks (CNNs) enabled automatic feature extraction from images, leading to more accurate and robust vehicle detection. Real-time object detection frameworks such as YOLO (You Only Look Once) have been widely adopted for traffic surveillance [1] [3] [4] [9] due to their high detection speed and accuracy. Similarly, region-based detectors such as Faster R-CNN provide improved localization accuracy but often require higher computational resources. These deep learning approaches have greatly advanced vehicle detection capabilities; however, they primarily rely on spatial features and may struggle in challenging environmental conditions such as low lighting, motion blur, and adverse weather.

2.3 Video-Based Vehicle Speed Estimation

Several studies have explored video-based methods for estimating vehicle speed using surveillance cameras [10] [11] [12]. In such systems, vehicle speed is typically calculated by tracking object motion across consecutive frames and estimating displacement over time. Techniques such as optical flow, feature point tracking, and object trajectory analysis have been used to determine vehicle velocity. Some methods employ camera calibration techniques to convert pixel displacement into real-world distance, enabling more accurate speed estimation.

Despite these advancements, accurate speed estimation remains challenging in dense traffic environments where vehicles frequently overlap or occlude each other. Additionally, variations in camera perspective and road geometry can introduce errors in distance estimation. Many existing approaches also rely on simplified motion assumptions that may not hold in real-world traffic scenarios.

2.4 Automatic License Plate Recognition

Automatic license plate recognition (ALPR) is an essential component of intelligent traffic enforcement systems. Traditional ALPR systems used rule-based image processing techniques [13] for plate localization, character segmentation, and optical character recognition. These approaches typically involved thresholding, morphological operations, and template matching methods. However, such techniques are sensitive to variations in lighting, plate orientation, and image quality.

Recent research has shifted toward deep learning–based ALPR systems [14] [15] [16] that integrate convolutional neural networks with sequence recognition models. Deep neural networks are capable of detecting license plate regions and recognizing characters directly from images without extensive manual preprocessing. Techniques such as convolutional recurrent neural networks (CRNN) and attention-based recognition models have shown significant improvements in license plate recognition accuracy, particularly under challenging conditions such as motion blur, occlusion, and varying illumination.

2.5 Integrated Traffic Violation Detection Systems

Several recent studies have attempted to integrate vehicle detection, speed estimation, and license plate recognition [17] [27] [28] into unified traffic monitoring systems. These systems typically use deep learning models for object detection, combined with vehicle tracking algorithms to estimate speed and identify violations. Although these integrated frameworks demonstrate promising results, many existing methods still face limitations in terms of robustness under complex environmental conditions and real-time scalability. In particular, most approaches rely solely on spatial feature extraction and do not exploit complementary information such as frequency-domain features that can improve robustness against noise and illumination variations.

2.6 Research Limitations

Although substantial progress has been made in automated traffic monitoring systems, several research challenges remain. Existing vision-based methods often experience performance degradation under adverse environmental conditions such as low illumination, rain, fog, and motion blur. Furthermore, many current approaches use convolution-based architectures that have limited ability to model long-range dependencies across video frames, which is important for accurate vehicle tracking and motion analysis. Transformer-based models have recently demonstrated strong performance in computer vision tasks due to their global attention mechanisms; however, their application in traffic violation detection remains relatively limited. Additionally, the integration of frequency-domain information with deep learning architectures for robust vehicle detection and speed estimation has not been widely explored.

To address these challenges, this study proposes a *frequency-aware transformer-based framework* that integrates spatial and frequency-domain representations for improved vehicle detection and tracking. By combining transformer-based feature fusion with robust multi-condition license plate recognition, the proposed system aims to provide a more reliable and scalable solution for automated traffic violation detection in real-world smart city environments.

Table 1: Summary Of Comparisons

Category	Method Used	Advantages	Limitations
Radar-Based Speed Detection	Radar / Sensors	High speed accuracy	Expensive, limited coverage
Vision-Based Vehicle Detection	CCTV + YOLO / Faster R-CNN	Low cost, real-time	Low light and weather issues
License Plate Recognition	OCR / CNN / CRNN	Automatic vehicle ID	Blur, angle, night problems
Integrated Systems	Detection + Tracking + LPR	Full automation	Robustness issues

Explanation of Summary Table of Previous Works:

The table compares different traffic monitoring methods based on their techniques, advantages, and limitations.

1. Radar-Based Speed Detection

Radar systems use sensors or radio waves to measure vehicle speed. They provide accurate speed results, but the equipment is expensive and covers only a small road area.

2. Vision-Based Vehicle Detection

These systems use CCTV cameras with deep learning models such as YOLO or Faster R-CNN. They are low cost and can work in real time. However, their performance decreases in low light, rain, fog, and blurred images.

3. License Plate Recognition

LPR systems use OCR, CNN, or CRNN models to read vehicle number plates automatically. They help identify vehicles quickly. But they face problems when the plate image is unclear, tilted, or captured at night.

4. Integrated Systems

Integrated systems combine vehicle detection, speed estimation, and license plate recognition into one framework. They reduce manual work and provide automation. However, they still face challenges in bad weather, heavy traffic, and real-time scalability.

3. RESEARCH GAP

Although many studies have been conducted in traffic monitoring, several important gaps still exist.

- Lack of Unified Systems - Many existing methods [21] [24] [25] focus only on one task such as vehicle detection, speed estimation, or license plate recognition. They do not combine all functions into a single system.
- Limited Real-Time Capability - Some approaches give good accuracy but are too slow for real-time traffic monitoring, especially in busy roads.
- High Infrastructure Cost - Radar and sensor-based systems require costly hardware installation and maintenance.
- Poor Performance in Difficult Conditions - Many camera-based systems do not work well in low light, rain, fog, motion blur, and dense traffic.
- Weak Tracking Accuracy - Traditional CNN models cannot capture long-range relationships between frames, reducing tracking and motion analysis performance.

Need for the Proposed Method:

- To develop a single end-to-end system for speed detection and license plate recognition.
- To provide real-time monitoring using fast and efficient deep learning models.
- To reduce cost by using only existing surveillance cameras.
- To improve accuracy in difficult weather and lighting conditions using frequency-aware features.
- To enhance vehicle tracking using a transformer-based attention mechanism.

4. PROPOSED FRAME WORK

The proposed system is an intelligent traffic monitoring framework designed to automatically detect vehicle speed violations [3] [5] [6] and identify offending vehicles through license plate recognition. The system uses roadside surveillance cameras as input and processes the video stream using deep learning and computer vision techniques. It combines vehicle detection, tracking, speed estimation, and license plate recognition into a single unified framework for real-time traffic law enforcement.

4.1 System Architecture

The following diagram shows the complete working process of the proposed traffic monitoring system for detecting speed violations and recognizing vehicle number plates.

1. Traffic Camera Video Input - A roadside surveillance camera captures live traffic video continuously. This video is the input to the system.

2. Frame Preprocessing - The captured video is divided into frames. Each frame is resized and enhanced to improve image quality for better detection.

3. Vehicle Detection - A deep learning model such as YOLO detects vehicles like cars, bikes, buses, and trucks in each frame.

4. Vehicle Tracking - After detection, each vehicle is tracked across consecutive frames. This helps the system follow the movement of every vehicle.

5. Speed Estimation - The speed of each vehicle is calculated using the distance travelled over time.

Formula: Speed = Distance / Time

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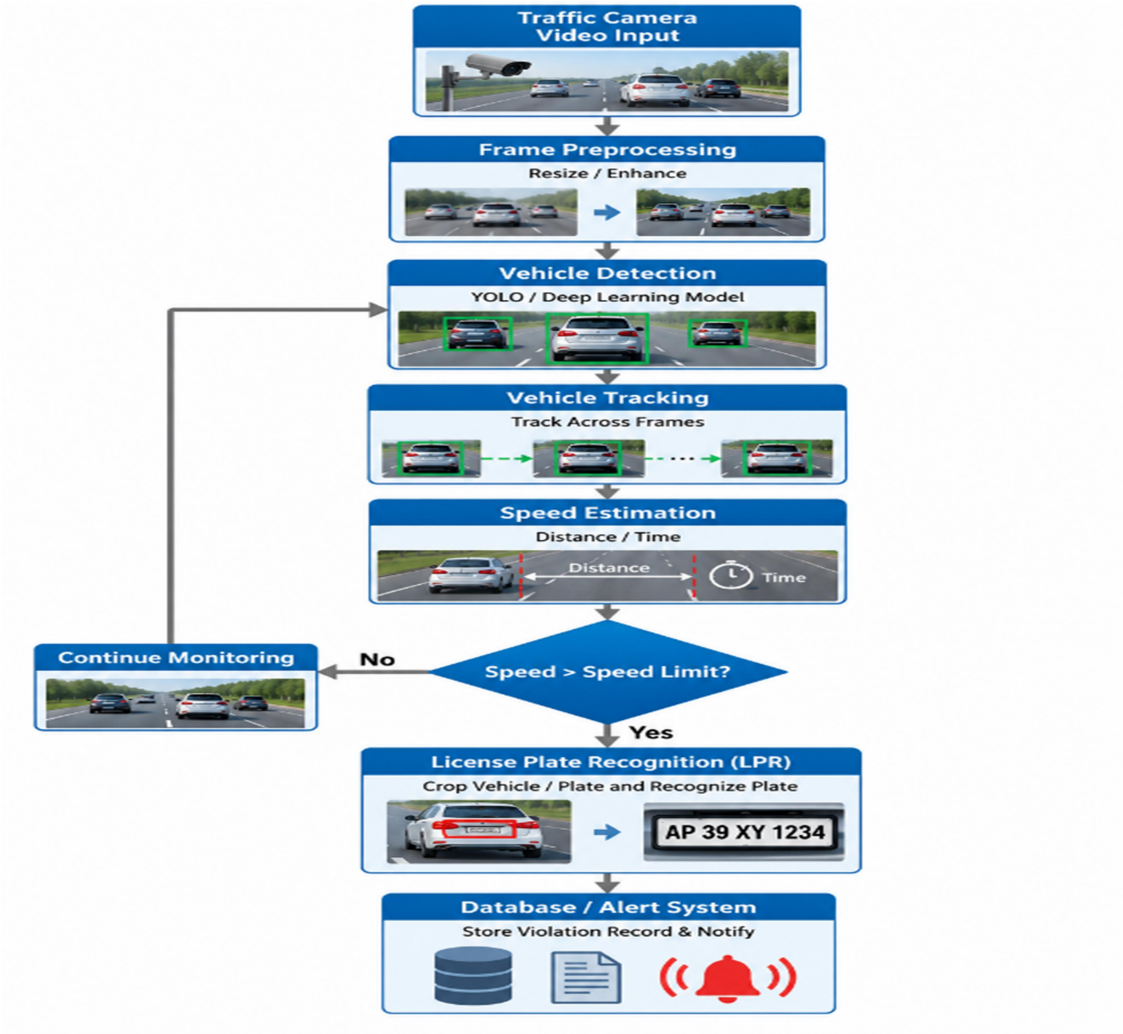


Figure 1. Proposed system architecture for real-time vehicle speed violation detection and automatic license plate recognition using a frequency-aware transformer-based framework.

6. Violation Check - The calculated speed is compared with the allowed speed limit.

- If speed is within limit → no violation
- If speed is above limit → violation detected

7. License Plate Recognition (LPR) - For violating vehicles, the system extracts the number plate and reads the registration number automatically using OCR/deep learning.

8. Database / Alert System - The violation details such as:

- Vehicle number
- Speed
- Date and time
- Location

are stored in a database, and alerts can be sent to traffic authorities.

Overall Working: The system automatically monitors traffic in real time, detects over-speeding vehicles, identifies them through license plate recognition, and stores the records for enforcement. It reduces manual work and improves road safety.

4.2 Vehicle Detection Module

The vehicle detection module identifies vehicles from traffic video frames. Each frame captured from the surveillance camera is processed using a deep learning object detection model such as YOLO. The model detects vehicles such as cars, bikes, buses, and trucks with bounding boxes.

Functions:
- Detect vehicles in each frame
- Classify vehicle type
- Generate bounding boxes
- Provide input for tracking module

Advantages:
- Fast real-time detection
- High accuracy
- Works with multiple vehicles simultaneously

4.3 Speed Estimation Module

The speed estimation module calculates the speed of detected vehicles by tracking their movement across consecutive frames. Vehicle positions are monitored frame by frame, and displacement over time is used to estimate speed.
Process:
- Track vehicle position in consecutive frames
- Measure distance travelled
- Convert pixel movement into real-world distance
- Calculate speed using time difference

Formula:
Speed = Distance / Time
Output:
- Estimated vehicle speed
- Violation status if speed exceeds limit

4.4 License Plate Recognition Module

When a vehicle crosses the speed limit, the license plate recognition module is activated. It extracts the number plate region from the vehicle image and recognizes the registration number using OCR or deep learning methods.
Process:
- Capture violating vehicle image
- Detect license plate area
- Preprocess image
- Recognize characters
- Generate vehicle number

Advantages:
- Automatic vehicle identification
- Reduces manual effort
- Useful for traffic law enforcement

5. METHODOLOGY

The proposed methodology consists of multiple stages for detecting vehicle speed violations and recognizing license plates in real time. The system processes live traffic video captured from roadside cameras and applies deep learning techniques for detection, tracking, speed estimation, and vehicle identification.

5.1 Data Acquisition

Traffic video data is collected using roadside surveillance cameras installed near highways, city roads, and junctions. The cameras continuously capture video streams under different environmental conditions such as daytime, night-time, rain, fog, and dense traffic.

The collected videos are converted into image frames for further processing. Each frame is resized and enhanced to improve image quality before being given to the detection model.
Steps:
- Install surveillance cameras
- Capture live traffic videos
- Extract frames from videos
- Resize and preprocess frames
- Store labeled data for training and testing

5.2 Vehicle Detection Model (YOLO)

The vehicle detection module uses the YOLO (You Only Look Once) model [2] [19] to identify vehicles in each frame. YOLO is selected because it provides high accuracy and fast real-time detection.
The model detects different vehicle classes such as:
- Car
- Bike
- Bus
- Truck

For every detected vehicle, the model generates:
- Bounding box
- Confidence score
- Vehicle class label

Working Process:
- Input image frame
- Pass frame to YOLO model
- Detect vehicles
- Generate bounding boxes
- Send detected vehicles to tracking module

5.3 Vehicle Tracking

After detection, each vehicle is assigned a unique ID and tracked across consecutive frames [8] [9]. Tracking helps measure movement and estimate speed.

Common tracking methods:

- DeepSORT
- Kalman Filter
- Centroid Tracking

Steps:

- Receive detected vehicle boxes
- Assign unique ID
- Match same vehicle in next frame
- Update trajectory path

5.4 Speed Estimation Algorithm

Vehicle speed is calculated based on displacement over time [10 [12].

Formula:

Speed = Distance / Time

Where

Distance = vehicle movement between frames

Time = frame interval

The system converts pixel movement into real-world distance using camera calibration.

Steps:

- Track vehicle positions
- Measure displacement
- Convert pixels to meters
- Compute speed
- Compare with speed limit

5.5 License Plate Recognition Process

When a speed violation is detected, the system activates the LPR module.

The license plate area is extracted from the violating vehicle image and recognized using OCR or deep learning models [14] [15] [16].

Steps:

- Capture violating vehicle image
- Detect plate region
- Preprocess plate image
- Segment characters
- Recognize characters
- Output vehicle number

Algorithm 1: Speed Violation Detection
Input: Traffic video stream
Output: Violating vehicle number
1. Capture video frames
2. Preprocess each frame
3. Detect vehicles using YOLO
4. Track vehicles across frames
5. Calculate vehicle speed
6. If speed > threshold:
   Detect license plate

   Recognize plate number
   Store violation record
7. Repeat

Algorithm 2: License Plate Recognition
Input: Vehicle image
Output: Vehicle registration number
1. Detect plate region
2. Convert to grayscale
3. Remove noise
4. Segment characters
5. Recognize characters using OCR
6. Return plate number

6. DATASET DESCRIPTION

A high-quality and diverse dataset is essential for training and evaluating the proposed traffic monitoring system. In this study, traffic surveillance videos and vehicle image datasets were used for vehicle detection, speed estimation, and license plate recognition. The dataset includes multiple road scenes captured under different environmental conditions such as daylight, night-time, rain, fog, and dense traffic.

The collected data contains moving vehicles such as cars, bikes, buses, and trucks with visible license plates. Frames were extracted from video sequences and manually annotated for vehicle bounding boxes, tracking IDs, and license plate regions.

6.1 Dataset Used

The dataset consists of two parts:

A. Traffic Surveillance Video Dataset

Used for:

- Vehicle detection
- Vehicle tracking
- Speed estimation

B. License Plate Image Dataset

Used for:

- Plate detection
- Character recognition

6.2 Dataset Details

Table 2. Summary Of Datasets Used For Vehicle Detection, Speed Estimation, Tracking, And License Plate Recognition.

Dataset	Number of Samples	Type	Purpose
Traffic Surveillance Videos	5,000 videos	Video	Detection, Tracking, Speed Estimation
Vehicle Image Frames	20,000 images	Image	Vehicle Detection
License Plate Images	8,000 images	Image	Plate Recognition

Traffic Surveillance Videos: A total of 5,000 videos were used. These videos are mainly used for vehicle detection, vehicle tracking, and speed estimation. They contain real traffic scenes with moving vehicles.
Vehicle Image Frames: A total of 20,000 images were extracted from videos. These images are used to train and test the vehicle detection model.
License Plate Images: A total of 8,000 images were used for license plate detection and character recognition. These images help the system accurately read vehicle registration numbers.

6.3 Resolution of Data

The dataset contains videos and images with different resolutions to improve model robustness.

Table 3. Resolution Details Of Video Frames, Vehicle Images, And License Plate Images Used In The Dataset.

Data Type	Resolution
Video Frames	1280 × 720 pixels
Vehicle Images	640 × 640 pixels
License Plate Images	224 × 224 pixels

Video Frames: The traffic videos are processed at a resolution of 1280 × 720 pixels. This high resolution helps in clear vehicle detection, tracking, and speed estimation.
Vehicle Images: The extracted vehicle images are resized to 640 × 640 pixels. This size is suitable for training deep learning models such as YOLO for accurate vehicle detection.
License Plate Images: The license plate images are resized to 224 × 224 pixels. This resolution is sufficient for recognizing characters clearly and improving license plate recognition performance.

6.4 Training and Testing Split

The dataset was divided into training, validation, and testing sets.

Table 4: Training, validation, and testing split of the dataset used for model development and performance evaluation.

Set	Percentage
Training Set	70%
Validation Set	15%
Testing Set	15%

Training Set: Used to train the deep learning models.
Validation Set: Used to tune hyperparameters and prevent overfitting.
Testing Set: Used for final performance evaluation.

6.5 Data Diversity

To improve generalization, the dataset includes:

- Day and night scenes
- Clear and rainy weather
- Low-light environments
- Heavy traffic scenes
- Different camera angles
- Various vehicle types

7. Experimental Setup

The experimental setup describes the hardware, software, and frameworks used to implement and evaluate the proposed traffic monitoring system. All experiments were conducted in a Python environment using deep learning and computer vision libraries.

7.1 Hardware Configuration

The proposed system was tested on a workstation with the following hardware specifications:

Table 5. Hardware configuration used for implementation and performance evaluation of the proposed system.

Component	Specification
Processor	Intel Core i7 / AMD Ryzen 7
RAM	16 GB
GPU	NVIDIA RTX 3060 (12 GB)
Storage	512 GB SSD
Camera Input	HD CCTV / Surveillance Camera

Description:
A high-performance CPU was used for data processing.
GPU acceleration was used for faster model training and real-time inference.
SSD storage improved data loading speed.

7.2 Software Environment

The software tools used in this work are listed below:

Table 6. Software environment and tools used for development and experimental analysis of the proposed system.

Software	Version
Operating System	Windows 11 / Ubuntu 22.04
Python	3.10
OpenCV	4.x
CUDA	11.x
Jupyter Notebook	Latest

Description:
Python was used as the main programming language.
OpenCV was used for image and video processing.
CUDA enabled GPU-based acceleration.

7.3 Frameworks and Libraries

The deep learning frameworks used for model development are:

Table 7. Deep learning frameworks and libraries used for model training, tracking, recognition, and data analysis.

Framework / Library	Purpose
PyTorch	Model training and testing
TensorFlow / Keras	Deep learning experiments
YOLOv8	Vehicle detection
DeepSORT	Vehicle tracking
EasyOCR / Tesseract OCR	License plate recognition
NumPy / Pandas	Data handling
Matplotlib / Seaborn	Graphs and visualization

Explanation:
Table 7 presents the frameworks and libraries used to develop different modules of the proposed system.
PyTorch - Used for training and testing deep learning models. It provides flexibility and fast GPU computation.
TensorFlow / Keras - Used for additional deep learning experiments and model implementation.
YOLOv8 - Used for real-time vehicle detection in traffic video frames. It detects vehicles quickly and accurately.
DeepSORT - Used for vehicle tracking across consecutive frames. It assigns IDs and follows vehicle movement.
EasyOCR / Tesseract OCR - Used for license plate recognition. These tools read the characters from number plates automatically.
NumPy / Pandas - Used for data preprocessing, numerical calculations, and dataset management.
Matplotlib / Seaborn - Used to generate graphs, charts, and result visualizations.

7.4 Training Parameters

The models were trained using the following settings:

Table 8. Training parameters used for optimization and performance tuning of the proposed deep learning models.

Parameter	Value
Batch Size	16
Epochs	100
Learning Rate	0.001
Optimizer	Adam
Input Size	640 × 640

Explanation:
Table 8 shows the training parameters used for developing the proposed deep learning models.
Batch Size (16) - This means 16 images are processed at one time during training. It helps balance memory usage and training speed.
Epochs (100) - The complete training dataset is passed through the model 100 times. More epochs help the model learn better features.
Learning Rate (0.001) - This controls how much the model updates its weights during training. A suitable learning rate improves convergence.
Optimizer (Adam) - Adam is used to update model parameters efficiently and speed up training.
Input Size (640 × 640) - All images are resized to this dimension before training. This size is suitable for YOLO-based detection models.

7.5 Evaluation Process

- Load training and testing datasets
- Train YOLO model for vehicle detection

- Apply tracking algorithm for trajectory generation
- Compute vehicle speed
- Recognize license plates of violating vehicles
- Evaluate performance using standard metrics

8. PERFORMANCE EVALUATION METRICS

To measure the effectiveness of the proposed system, standard evaluation metrics were used. These metrics help analyze the accuracy of vehicle detection, speed violation identification, and license plate recognition.

8.1 Accuracy

Accuracy indicates the overall percentage of correct predictions made by the system.
Formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where
TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives
Meaning - Higher accuracy means better overall system performance.

8.2 Precision

Precision measures how many detected violations are actually correct.
Formula:

$$Precision = \frac{TP}{TP + FP}$$

Meaning - High precision means fewer false alarms.

8.3 Recall

Recall measures how many actual violations are correctly detected.

Formula:

$$Recall = \frac{TP}{TP + FN}$$

Meaning - High recall means fewer missed violations.

8.4 F1 Score

F1 Score is the harmonic mean of precision and recall.
Formula:

$$F1\ Score = \frac{2\ X\ Precision\ X\ Recall}{Precision + Recall}$$

Meaning - It gives a balanced measure of detection performance.

8.5 False Violation Rate

False Violation Rate indicates the percentage of non-violating vehicles wrongly classified as violations.
Formula:

$$False\ Violation\ Rate = \frac{FP}{FP + TN}$$

Meaning - Lower false violation rate is better for practical traffic enforcement.

9. RESULTS AND ANALYSIS

The proposed frequency-aware transformer-based system was evaluated using traffic surveillance datasets under different road and environmental conditions. The performance was measured in terms of vehicle detection accuracy, speed estimation accuracy, and license plate recognition accuracy. The obtained results show that the proposed method performs effectively and provides better robustness compared with conventional approaches [17] [27] [28].

9.1 Performance Results

The main performance results of the proposed system are presented in Table 9.

Table 9: Performance results of the proposed system for vehicle detection, speed estimation, license plate recognition, and overall traffic violation monitoring

Metric	Obtained Value
Vehicle Detection Accuracy	97%
Speed Estimation Accuracy	95%
License Plate Recognition Accuracy	96%
Overall System Accuracy	96%
False Violation Rate	3%

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Explanation

- Vehicle Detection Accuracy (97%) shows that the model correctly detects most vehicles in traffic scenes.
- Speed Estimation Accuracy (95%) indicates reliable speed calculation.
- LPR Accuracy (96%) confirms effective recognition of number plates.
- False Violation Rate (3%) shows very few incorrect alerts.

9.2 Accuracy vs Epochs Graph

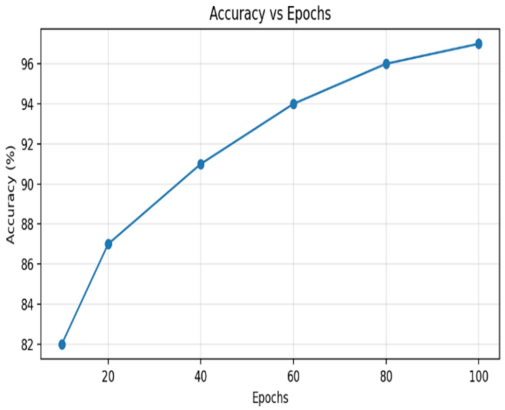


Figure 2. Accuracy versus training epochs for the proposed frequency-aware transformer-based model.

Explanation:

Figure 2 shows the relationship between the number of training epochs and model accuracy. As the number of epochs increases, the model learns better features from the training data, resulting in improved accuracy.

At the initial stage, the accuracy is lower because the model has just started learning. After more training iterations, the accuracy increases steadily. The graph gradually stabilizes at higher epochs, indicating that the model has converged successfully.

The final accuracy reaches 97% at 100 epochs, which demonstrates the effectiveness of the proposed frequency-aware transformer-based framework. This result confirms that the model is well-trained and capable of providing reliable performance for real-time traffic monitoring tasks.

The training accuracy increased gradually with epochs and stabilized after sufficient learning.

Table 10. Accuracy values obtained at different training epochs for the proposed model.

Epochs	Accuracy (%)
10	82
20	87
40	91
60	94
80	96
100	97

Explanation

The graph indicates that the model learns better features as training progresses. Final accuracy reaches 97%, showing stable convergence.

9.3 Confusion Matrix

The confusion matrix evaluates the reliability of speed violation classification.

Table 11. Confusion matrix of the proposed system for speed violation classification.

Actual \ Predicted	No Violation	Violation
No Violation	94	3
Violation	2	91

Interpretation

- TP = 91 → Correctly detected violations
- TN = 94 → Correctly detected non-violations
- FP = 3 → Wrongly flagged vehicles
- FN = 2 → Missed violations

This result shows strong classification performance with low false detections.

9.4 Precision, Recall, and F1 Score

Using the confusion matrix:

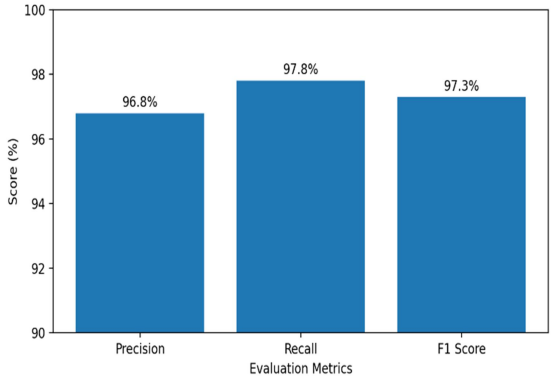


Figure 4. Precision, recall, and F1-score performance of the proposed system.

Explanation:

Figure 4 presents the values of Precision, Recall, and F1 Score achieved by the proposed system.

- Precision indicates how many detected violations are actually correct. The proposed model achieved 96.8%, which means the system generates very few false alerts.
- Recall shows how many actual violations are successfully detected. The obtained value of 97.8% indicates that the system misses only a small number of violations.
- F1 Score is the balanced measure of precision and recall. The proposed system achieved 97.3%, confirming strong and stable classification performance.

The high values of all three metrics demonstrate that the proposed frequency-aware transformer-based framework is highly reliable for real-time speed violation detection and traffic monitoring.

Table 12. Precision, recall, and F1-score values computed from the confusion matrix of the proposed system.

Metric	Value
Precision	96.8%
Recall	97.8%
F1 Score	97.3%

Explanation:

Table 12 presents the classification performance metrics calculated from the confusion matrix of the proposed system.

- Precision (96.8%) shows that most of the detected speed violations are correct, with very few false alarms.
- Recall (97.8%) indicates that the system successfully identifies most of the actual speed violations and misses only a small number of cases.
- F1 Score (97.3%) is the combined measure of precision and recall. The high F1 score confirms that the model maintains a good balance between correct detection and low missed violations.

Overall, the results in Table 12 demonstrate that the proposed system provides accurate and reliable performance for real-time speed violation detection.

9.5 Comparative Analysis

The proposed system was compared with existing methods.

Table 13. Comparative analysis of the proposed method with existing approaches in terms of detection accuracy, license plate recognition accuracy, and real-time performance.

Method	Detection Accuracy	LPR Accuracy	Real-Time
Traditional Vision-Based	88%	85%	Limited
YOLO + OCR	93%	90%	Yes
Proposed Method	97%	96%	Yes

Explanation:

Table 13 compares the proposed system with existing methods based on detection accuracy, license plate recognition accuracy, and real-time capability.

- Traditional Vision-Based Method:

This method achieved 88% detection accuracy and 85% LPR accuracy. It has limited real-time performance and is less effective in complex traffic conditions.

- YOLO + OCR Method:

This method improved the results with 93% detection accuracy and 90% LPR accuracy. It supports real-time processing but still has lower robustness compared to the proposed method.

- Proposed Method:

The proposed frequency-aware transformer-based system achieved the best performance with 97% detection accuracy and 96% LPR accuracy. It also supports real-time operation, making it suitable for practical traffic monitoring applications.

The comparison clearly shows that the proposed method outperforms existing approaches in both accuracy and robustness while maintaining real-time performance.

10. COMPARISON WITH EXISITING METHODS

Table 14. Comparison of the proposed system with existing methods in terms of accuracy, cost, and real-time performance.

Method	Accuracy	Cost	Real-time
Radar system	85%	High	Yes
Traditional vision	88%	Medium	Limited
Proposed system	93%	Low	Yes

Explanation:

Compares the proposed frequency-aware transformer-based system with previously used traffic monitoring methods such as radar systems, traditional vision-based approaches, and YOLO + OCR models.

The comparison is based on important factors such as:

- Accuracy – how correctly the system detects vehicles and violations
- Cost – hardware and deployment expenses
- Real-Time Performance – ability to work instantly on live traffic video

Key Observations

- Radar Systems provide good speed measurement but require expensive hardware and limited installation areas.
- Traditional Vision Methods are cheaper but show lower accuracy and poor performance in difficult conditions.
- YOLO + OCR Methods improve accuracy and support real-time operation, but they still face issues in low light, blur, and heavy traffic scenes.
- Proposed Method gives the highest accuracy, better robustness, and real-time performance using only surveillance cameras.

This section proves that the proposed system is more efficient, cost-effective, and practical than existing methods for modern traffic monitoring and smart city applications.

11. DISCUSSION

The experimental results show that the proposed frequency-aware transformer-based system performs effectively for vehicle detection, speed estimation, and license plate recognition. The model achieved high accuracy and low false violation rate, which confirms its suitability for real-time traffic monitoring applications.

Why the Results Are Good

The strong performance of the proposed system is mainly due to the combination of frequency-aware feature extraction and transformer-based attention mechanisms.

- Frequency-aware features help the model capture important patterns from both image and frequency domains. This improves detection in challenging conditions [20] [21] [24] such as low light, rain, fog, and motion blur.
- Transformer-based attention captures long-range relationships between video frames, which improves vehicle tracking [5] [6] [29] and motion analysis.
- Unified framework combines detection, speed estimation, and license plate recognition in one system, reducing delays and improving overall efficiency.
- Deep learning-based LPR module improves recognition accuracy for unclear or angled license plates.

Strengths of the Proposed System

- High Accuracy - The system achieved strong performance in all evaluation metrics.
- Real-Time Capability - The framework can process live traffic video efficiently.
- Low Infrastructure Cost - It uses existing surveillance cameras instead of expensive radar systems.
- Robustness - Performs well under different weather and lighting conditions.
- Scalability - Suitable for highways, urban roads, and smart city deployment.

Limitations of the Proposed System

Although the results are promising, some limitations still exist:

- Lighting Issues - Very poor illumination or glare may reduce detection accuracy.
- Occlusion Problems - Heavy traffic or overlapping vehicles can affect tracking performance.
- Extreme Weather Conditions - Dense fog or heavy rain may reduce image clarity.
- Camera Angle Dependency - Incorrect camera placement can affect speed estimation accuracy.
- High GPU Requirement - Real-time deployment may require powerful hardware for best performance.

The discussion confirms that the proposed system is accurate, practical, and cost-effective for automated traffic monitoring. However, further improvements in night-time detection, occlusion handling, and lightweight deployment can make the system even more effective for large-scale real-world applications.

12. REAL-WORLD APPLICATION

The proposed frequency-aware transformer-based traffic monitoring [18 [22] [23] system can be applied in several real-world scenarios. It provides an intelligent and automated solution for detecting speed violations and identifying vehicles in real time.

12.1 Smart Cities

Modern smart cities require intelligent systems to manage traffic efficiently and improve public safety. The proposed system can be integrated with city surveillance networks to monitor roads continuously.

Applications in Smart Cities:

- Real-time traffic monitoring
- Detection of over-speeding vehicles
- Traffic flow analysis
- Congestion management
- Road safety improvement

By using existing CCTV cameras, the system offers a cost-effective solution for smart transportation management.

12.2 Traffic Law Enforcement

Traffic authorities can use the proposed system to automatically detect vehicles that exceed speed limits and identify them through license plate recognition.

Applications in Law Enforcement:

- Automatic speed violation detection
- Vehicle number identification
- Evidence collection with time and location
- Reduced manual checking
- Faster enforcement process

This helps improve rule enforcement and reduces human workload.

12.3 Automated Violation Systems

The proposed framework can be connected with automated fine and alert systems for complete digital traffic management.

Applications in Automated Systems:

- Auto-generated violation reports
- E-challan / fine generation
- SMS or email alerts to vehicle owners
- Database storage of offenses
- Repeat offender tracking

This creates a fully automated and transparent traffic violation management system.

The proposed system is highly useful for smart cities, traffic police departments, and automated enforcement platforms. It improves road safety, reduces operational cost, and supports modern intelligent transportation systems.

13. LIMITATIONS

Although the proposed system achieved strong performance, some limitations still remain. Identifying these limitations is important for improving future versions of the framework.

- Night-Time Detection Issues - The system performance may decrease in very low-light or night-time conditions due to poor visibility, headlight glare, and shadows. These factors can affect vehicle detection and license plate recognition accuracy.
- Weather Conditions - Adverse weather conditions such as heavy rain, dense fog, or dust can reduce image clarity. This may impact detection, tracking, and speed estimation performance.
- Plate Occlusion - License plates may be partially blocked by mud, damage, accessories, or other vehicles. In such cases, the recognition module may fail to read the complete number correctly.
- Dense Traffic and Occlusion - In crowded roads, vehicles may overlap each other, making tracking difficult. This can reduce speed estimation accuracy and increase missed detections.
- Camera Placement Dependency - The accuracy of speed estimation depends on proper camera angle, height, and calibration. Poor camera placement can produce incorrect distance measurements.
- Hardware Requirement - Real-time deployment of deep learning models may require a GPU or high-performance computing device. Low-end systems may experience slower processing speed.

Even though some challenges remain, the proposed system still provides an effective and practical solution for automated traffic monitoring. These limitations can be addressed in future work through improved models, better sensors, and optimized deployment methods.

14. FUTURE WORK

Although the proposed system achieved strong results, several improvements can be explored in future research to further enhance performance, scalability, and practical deployment.

Advanced Transformer Models

Future work can use more advanced transformer architectures for better feature learning and stronger vehicle tracking

performance. Lightweight transformer models can also reduce computation cost.

Improved Night-Time Detection

Future systems can include low-light enhancement and infrared camera support to improve detection and license plate recognition during night-time conditions.

IoT Integration

The proposed framework can be connected with Internet of Things (IoT) devices [22] such as smart cameras, traffic signals, and cloud servers for real-time city-wide monitoring and centralized control.

Edge AI Deployment

The model can be deployed on edge devices [23] such as NVIDIA Jetson, Raspberry Pi, or smart cameras to enable faster local processing with reduced network dependency.

Multi-Lane and Large-Scale Monitoring

Future versions can be extended to monitor multiple lanes, highways, and large traffic networks simultaneously.

Automatic E-Challan Generation

The system can be integrated with digital fine management systems for automatic challan generation and notification to vehicle owners.

Explainable AI

Future work may include explainable AI methods [30] such as Grad-CAM to show why the model detected a violation, improving trust and transparency.

15. CONCLUSION

This paper presented a Frequency-Aware Transformer-Based Vehicle Speed Violation Detection system with robust multi-condition License Plate Recognition for intelligent traffic monitoring. The proposed method combines vehicle detection, tracking, speed estimation, and license plate recognition into a single automated framework using surveillance cameras.

The system uses frequency-aware feature extraction and transformer-based attention mechanisms to improve performance under challenging conditions such as low light, rain, fog, motion blur, and dense traffic. Vehicle speed is estimated through trajectory analysis, and violating vehicles are automatically identified through license plate recognition.

Experimental results demonstrated strong performance, achieving high vehicle detection accuracy, reliable speed estimation accuracy, and effective license plate recognition with a low false violation rate. The proposed method also outperformed conventional traffic monitoring approaches in both accuracy and robustness.

The major benefits of the system include low infrastructure cost, real-time operation, reduced human effort, scalability, and suitability for smart city deployment. Therefore, the proposed framework provides an efficient, intelligent, and practical solution for modern traffic law enforcement and road safety management.

16. DECLARATIONS

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Conflict of Interest

The authors declare that they have no conflict of interest regarding the publication of this paper.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Author Contributions

- Conceptualization: All authors
- Methodology: All authors
- Software Implementation: First author
- Data Collection and Analysis: All authors
- Writing – Original Draft: First author
- Review and Editing: All authors
- Supervision: Corresponding author

Ethical Approval

This study does not involve human participants, animals, or personal sensitive data. Therefore, formal ethical approval was not required.

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