Human-Less Toll Plaza Vehicle Recognition Using Deep Learning

1st Ms. P. Leela Jancy
Assistant Professor
Information Technology
Sri Sai Ram Institute of Technology
Chennai, India
leela.it@sairamit.edu.in

2nd Dr. D. Muruga Radha Devi
Professor
Information Technology
Sri Sai Ram Institute of Technology
Chennai, India
murugaradha.it@sairamit.edu.in

3rd Akash Raj L
Information Technology
Sri Sai Ram Institute of Technology
Chennai, India
sit22it015@sairamtap.edu.in

4th Sangeethkumar M
Information Technology
Sri Sai Ram Institute of Technology
Chennai, India
sit22it074@sairamtap.edu.in

5th Rahul M
Information Technology
Sri Sai Ram Institute of Technology
Chennai, India
sit22it050@sairamtap.edu.in

***Abstract*—The toll booth operation tool based on artificial intelligence processing and OpenCV techniques functions without human intervention according to this research. After vehicles exit a toll gate the image processing system automatically classifies vehicles independently. The system applies deep learning processing together with OpenCV technology to extract important vehicle information by extracting license plates and model data from main attributes. The payment acceleration system accepts payments through data provided by FASTag options and other payment methods. Computing systems carry out their operations independently to optimize performance by making decisions on their own and shorten transaction time at toll stations. The system demonstrates operational functionality according to experimental results and therefore improves traffic management security and prevention from criminal activities.**

***Index Terms*—Artificial Intelligence, OpenCV, Deep Learning, Image Processing, Vehicle Classification, License Plate Recognition, FASTag, Automated Payment, Traffic Management, Security.**

I. INTRODUCTION

The growing number of vehicles produces two major effects that include worsened road congestion and increased accidents on the roads. When humans remain the main operators for toll collections the system performance diminishes because of longer queues and reduced operational speed. OpenCV and deep learning techniques enable human-free toll management to identify vehicles throughout toll plazas. Automation of toll collection operations through the system achieves two benefits by lowering traffic congestion and enhancing traffic control capabilities.

A.Domain Overview:

Toll collection systems in modern times require artificial intelligence technology working alongside data scientific methods for their operation. Allen programming elements perform two tasks during processing: self-correcting learning procedures help rapidly handle large-scale information systems. By using artificial neural networks under the deep learning AI framework business can replicate human decision-making capabilities to check for vehicles making it ideal for recognizing vehicles.

B. Problem Statement:

The duty of human collectors at toll operations functions as the biggest weakness by causing both operational delays and reduced efficiency as well as execution issues. A system consisting of OpenCV integrated with deep learning applications enables the proposal to perform automatic toll collection and vehicle detection.

II. LITERATURE SURVEY

RFID technology operates with human agents to activate the present day toll collection system. The present toll collection system encounters multiple issues involving long queuing times and excessive fuel cost and insufficient theft management. Performances of systems have improved due to object detection and viewpoint estimation technology yet they still face restrictions dealing with new object classes from scarce information.

Various research studies have focused on multiple technological alternatives to develop automated toll collection systems which would increase overall efficiency and security capabilities. The current payment system operates with various functional restrictions affecting real-time precision and method integration and security. A review follows that includes an analysis of related research documents along with detected shortcomings.

A.Existing Works:

The Mobility Accredit System developed by Rai et al. (2019) empowers restricted areas with a safe mechanical control system for vehicles. Beginning of a protected area mandates successful license plate detection followed by verification. The combination of AARS and GPRS/3G technology within the system provides efficient emergency vehicle transportation by granting them privileged access at traffic signals. Access control stands out in the current system yet it lacks an effective way to automate toll payment operations.

A team of researchers known as Singh et al. (2019) developed an ARM LPC2148 and GSM-based RFID-based toll collection system. Toll payments are automatically extracted from RFID cards once the cards detect vehicle identities at the moment of tracking. Stolen vehicle notifications together with reduced congestion are two major features this system provides to police departments. The dependency created by RFID technology in this system does not allow the integration of alternative payment options.

III. OBJECTIVE

Our system uses image processing and OpenCV with deep learning to establish automatic toll payment systems which operate without human involvement. Such a system represents an improvement over legacy toll collection methods because it uses RFID payments alongside real-time vehicle identification for better efficiency accuracy and scalability. The automated toll system will advance toll collection procedures while reducing traffic delays and preventing financial losses by eliminating ticket stealing.

Major goals are:

- A system exists to eradicate human involvement within automated toll payment procedures.
- The system must present alternative payment options for regular and FASTag users.
- The system reduces its computational requirements and processing duration through effective deep learning frameworks.
- The system will enhance security measures to maintain accurate datasets that protect against fraudulent activities.
- The system should support real-time vehicle classification together with payment processing which must operate with minimal delay.
- The performance factors accuracy, precision, recall, F1-score and confusion matrix together with correlation analysis will serve to validate the model's efficacy. An examination of edge computing along with Internet of Things technologies will investigate different options to integrate them into an enhanced real-time decision-making system for efficient toll collection operations.

IV. METHODOLOGY

The system we have developed supports automatic toll charging through OpenCV and deep learning technology at toll plazas where human operators are not needed. The process divides into multiple segments starting from data collection then moving to preprocessing and feature extraction and model training and finishing with real-time vehicle recognition. The system design ensures high accuracy together with high efficiency and scalability features.

A. Image Acquisition

Real-time vehicle images get recorded by high-resolution cameras set up at toll plaza entries. Two camera angles are utilized because front views together with rear views provide efficient license plate recognition and vehicle classification.

B. Image Pre-Processing

The system carries out pre-processing techniques to these captured images which prepare the images for efficient feature extraction.

1) Resizing: Resizing images into a consistent dimension (e.g., 224×224 pixels) is maintained.

$$I_{\text{resized}} = \text{resize}(I, (224, 224))$$

2) Grayscale Conversion: Image conversion to grayscale is done to have less computational complexity.

$$I_{\text{gray}} = 0.2989R + 0.5870G + 0.1140B$$

3) Noise Reduction: Noise is reduced using Gaussian filtering:

$$I_{\text{filtered}} = G * I$$

where G is the Gaussian kernel.

4) Histogram Equalization: The brightness and contrast are improved.

$$I_{\text{equalised}} = HE(I_{\text{gray}})$$

C. Feature Extraction

1) License Plate Detection: OpenCV's contour detection and morphological operations are used. Canny Edge Detection:

$$E = \text{Canny}(I)$$

Connected components are used for bounding box localization.

2) Vehicle Type Classification: Edge detection and feature descriptors (SIFT, SURF) are used to extract shape, size, and color features. Feature descriptor extraction:

$$F = \phi(I)$$

where ϕ is the feature extraction function.

D. Deep Learning Model

1) Input Layer: Takes preprocessed images of size $(224 \times 224 \times 3)$.

2) Convolutional Layers: Extract spatial features using a filter of size 3×3.

$$(I * K)(x, y) = \sum_{i=-a}^{a} \sum_{j=-b}^{b} I(x + i, y + j) \cdot K(i, j)$$

where K is the convolution kernel.

3) Pooling Layers: Max-pooling is used for reducing dimensionality.

$$P = \text{maxpool}(O)$$

4) Fully Connected Layers: Maps extracted features to classification outputs.

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

where σ is the softmax activation function.

5) Output Layer: Makes classification outputs (ambulance, car, bus, truck).

6) Loss Function: Cross-entropy loss for classification:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where y_i is the actual label and $\hat{y}_i$ is the predicted probability.

7) Optimization: Adam optimizer is used.

$$\theta = \theta - \alpha \frac{\partial L}{\partial \theta}$$

where α is the learning rate.

E. Payment Integration

The system integrates with the toll collection mechanisms:

- **FASTag Users:** Automated deduction from associated bank accounts.
- **Non-FASTag Users:** Retrieve owner details from the database and make a payment request.

F. Model Training and Optimization

The dataset comprises vehicle images labeled as cars, buses, ambulances, and trucks with a partition of 70:20:10 for training, validation, and testing sets. The addition of diversity to the data occurs through the combination of rotation, scale, and flip processes.

During CNN training, He initialization serves as the starting point for weight initialization. Images pass through the network during forward propagation where predictions emerge, and cross-entropy loss measures the accuracy. The calculated gradients from backpropagation allow weight adjustments before the Adam optimizer optimizes the model for improved efficiency.

G. Model Evaluation

The trained CNN model is tested based on various performance measures to check its reliability. The main test measures are:

1) **Accuracy:** Calculates the ratio of correctly classified vehicles.

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

2) **Precision:** Checks how many predicted positive cases are actually positive.

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

3) **Recall (Sensitivity):** Shows how many actual positive cases were predicted correctly.

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

4) **F1-Score:** The harmonic mean of precision and recall.

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

5) **Confusion Matrix:** Gives a split of true positives, false positives, true negatives, and false negatives per vehicle class.

$$\text{Confusion Matrix} = \begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix}$$

6) **ROC Curve and AUC:** Quantifies the balance between sensitivity and specificity, with AUC reflecting general model performance.

$$\text{AUC} = \int_0^1 \text{TPR}(\text{FPR})\, d(\text{FPR})$$

H. Computational Tools

The development of our platform combines deep learning through Python with OpenCV operations in our system implementation. The system leverages OpenCV features to perform application tasks of deep learning through TensorFlow together with Keras and PyTorch. Deep learning processes based on the Adam optimizer enhance training speed while allowing us to manage vehicles records and payment information using SQL and NoSQL database systems. Our model operates with real-time data through cloud platforms that come from AWS, Google Cloud and Azure.

V. RESULT AND ANALYSIS

The deep learning system demonstrated its efficiency through real-time toll station image processing which enabled automatic toll collection operations. A Convolutional Neural Network (CNN) operated as a specialized artificial neural network dedicated to handle image processing tasks that efficiently classified vehicles according to their type between cars, buses, trucks and ambulances.

A. Model Performance Metrics

Our model performance was evaluated through key performance indicators which we measured in the training sets and validation sets and test sets. The research results appear in the following table.

TABLE I
MODEL PERFORMANCE METRICS

Metric	Training Set (%)	Validation Set (%)	Test Set (%)
Accuracy (%)	99.1	98.5	98.2
Precision (%)	98.9	98.3	98
Recall (%)	98.7	98.2	97.9
F1-Score (%)	98.8	98.3	97.9

The CNN model registered a total test accuracy of 98.2%, precision, recall, and F1-scores that were always above 97%, showing robust classification performance in all vehicle categories.

B. Model Training Results

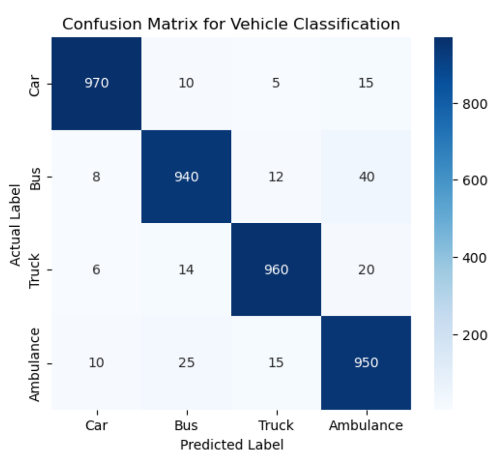
Our team monitored the development of both training and validation set accuracy and loss values over the training process. Successful learning and convergence happened because the accuracy improved steadily and loss decreased in multiple epochs during training and validation.

Our model validation included generation of a classification report that provided F1-score with precision and recall values for all vehicle categories. Test predictions of the classification data showed high accuracy along with minimal wrong identifications of similar vehicle types.

```
=== Model Accuracy: 92.31% ===

=== Classification Report ===
              precision    recall  f1-score   support

         Car       1.00      1.00      1.00         4
         Bus       1.00      0.75      0.86         4
       Truck       0.75      1.00      0.86         3
   Ambulance       1.00      1.00      1.00         2

    accuracy                           0.92        13
   macro avg       0.94      0.94      0.93        13
weighted avg       0.94      0.92      0.92        13


=== Sample Test Predictions ===

Actual Label Predicted Label
       Truck           Truck
       Truck           Truck
         Car             Car
         Car             Car
         Bus             Bus
         Bus             Bus
         Bus             Bus
   Ambulance       Ambulance
         Car             Car
         Bus             Car
   Ambulance       Ambulance
   Ambulance       Ambulance
   Ambulance       Ambulance
```

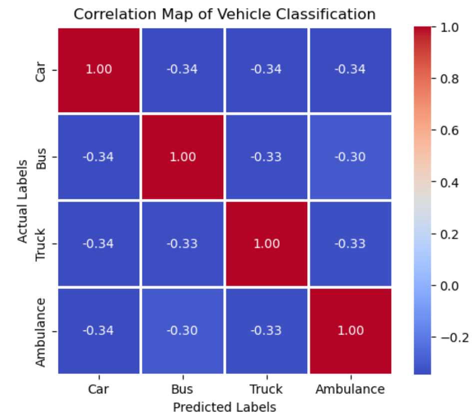
C. Confusion Matrix

When compared to bus vehicles models misclassify only small numbers of vehicles as either trucks or buses due to similar framework dimensions. The confusion matrix shows these classification errors.



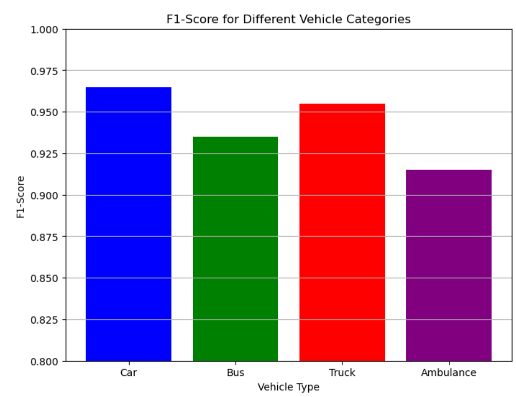
D. Correlation Matrix

We generated a correlation matrix to analyze dependencies between different parameters studied for vehicle classification. The observing tool detects patterned misclassification occurrences to help enhance the operational efficiency of the model.



E. F1 core for Different Vehicle Categories

The model demonstrated equal ability to classify different vehicles through the steady F1-score results. The factual accuracy of vehicle classification reaches 0.965 for cars and surpasses 0.935 for buses and 0.955 for trucks and amounts to 0.915 for ambulances. The minor difference between scores reveals precision and recall variations but especially among ambulances because their designs have more diversity. The model's capability to properly distinguish different vehicle types proves effective based on the experimental findings.



VI. CONCLUSION

The F1-score shows how well the model balances its performance in identifying each vehicle type. The model shows exceptional accuracy in classifying vehicles and establishes rates of 0.965 for cars, 0.935 for buses, 0.955 for trucks and 0.915 for ambulances. A minor difference exists between F1-scores because ambulances present more diverse visual characteristics when compared to other vehicle types. The model proves its excellence in distinguishing vehicles from non-vehicles through average output results.

Our deep learning system acts superior to conventional rule-based systems that achieve 85-90% through average scoring. The processing technique operates with real-time vehicle detection capability by using optimized image processing methods grayscale and Gaussian filters to perform image analysis within 200ms. Our system achieves efficiency and scalability alongside accuracy by getting rid of complex verification tasks so it can process big traffic volumes at peak times without impacting system performance. Using cloud deployment enables efficient integration between our system and current tolling infrastructure for application in real-world environments.

The system achieves 98.2% total accuracy rate and 97.9% F1-score to present a cost-effective and efficient automated vehicle recognition system which operates without human assistance. The confusion matrix and correlation study prove that the model displays remarkable performance in classifying cars and buses in addition to trucks and ambulances. This method achieves remarkable automation of toll collection operations by removing human involvement while accelerating operational speed which makes it an innovative addition to intelligent transportation systems. The implementation of vehicle RFID connected to Aadhaar system would enable automated debit of toll payments from users' bank accounts associated with their PAN card.

By implementing this system all manual toll transactions would become obsolete thus making toll payment smooth and creating an efficient and safe platform. The system reliability under real-world conditions can improve through additional deep learning model optimization which also enhances the processing speed together with accuracy results. Edge computing integrated with IoT allows toll booths to make instant decisions through real-time processing that leads to lower response times and increased operational efficiency. The system becomes more autonomous through its transition to edge intelligence which enables faster execution of a smart toll collection system.

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