Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 15s (2025)
https://www.jneonatalsurg.com

Advanced AI-Based License Plate Recognition and Pollution Com-pliance Monitoring for Motorbikes Using YOLOv8 and LLaMA OCR

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Cite this paper as: Akula Jayanth Babu, Nikhat Parveen, (2025) Advanced AI-Based License Plate Recognition and Pollution Com-pliance Monitoring for Motorbikes Using YOLOv8 and LLaMA OCR. *Journal of Neonatal Surgery*, 14 (15s), 1779-1788.

ABSTRACT

Motorbike traffic has significantly increased in urban areas, posing challenges for traffic management and environmental compliance. Existing License Plate Recognition (LPR) systems struggle with rec- ognizing non-standard motorbike plates, especially under adverse conditions such as low-light envi- ronments, occlusions, and distorted fonts. Additionally, real-time enforcement of pollution compliance remains underexplored. This study presents an advanced AI-based approach integrating **YOLOv8** for high-precision license plate detection and **LLaMA OCR**, a transformer-based model, for robust char- acter recognition in challenging conditions. Furthermore, a **Real-Time Compliance Monitoring Mod- ule (RT-CMM)** is introduced to verify vehicle registration and pollution compliance through government databases. Experimental results on diverse datasets, including Indian motorbike plates, demonstrate an impressive **99.7% detection accuracy** and **97.8% compliance verification success rate**. The pro- posed system outperforms conventional methods and provides a scalable solution for smart traffic mon- itoring, regulation enforcement, and environmental protection in urban settings.

Keywords: *License Plate Recognition (LPR), YOLOv8, LLaMA OCR, Motorbike Monitoring, Pollu- tion Compliance, Traffic Management, Deep Learning.*

1. INTRODUCTION

Motorbikes are critical to fulfilling the global transport needs especially in populous areas of Asia such as India and SE Asia because they are cheap, fuel-efficient and maneuverable in congested traffic [1][2]. The inconvenience of automobiles has been surpassed by the fast increase of motor bikes in many countries to suggest their role in meeting current mobility demand. Yet, their increasing population num- ber has been attributed to the high levels of air pollution in the urban areas, making the environment and the public health a nuisance. Sporadic compliance to traffic and environmental standards, for instance, periodic certification of pollutant emissions and vehicle registration has exacerbated the issue [3][4]. Nonstandard license plates aren't very large and frequently have unusual or unique shapes that cannot easily be read by standard LPR, especially in developing countries where there are great variations in the designs of the plate and where nonstandard plates are prevalent [5][6].

Currently available LPR systems are designed mostly for cars and become rather limited when it comes to motorbikes because of such factors as adverse lightning, occlusions, deviations from the Zero- Pose, non-clean plates, and low contrast[7][8]. For these challenges, Tesseract OCR, or YOLO versions before the specific YOLO5, are ineffective with less accuracy of detection and recognition. Besides, most of today's systems provide stand-alone features that do not interact with other database to perform a live compliance check. This limitation limits their performance in detecting violations, including expired pollution certificates or unregistered vehicles, which blinds regulatory authorities [9][10].

Some of these challenges may be countered by recent development in deep learning and computer vision. YOLOv8, the last model in a line of YOLO (You Only Look Once) series, has enhanced the object detection speed and the identification accuracy, especially to small and non-standard objects as motorbike plates [11][12]. Furthermore, transformer-based OCR models including LLaMA OCR do have very high accuracy in identifying the hard-to-read or noisy text compared to earlier approaches [13][14]. The integration of YOLOv8 and LLaMA OCR results in a stronger and flexible platform to determine and read motorbike license plates despite the light condition. If these technologies are integrated with real-time compliance monitoring systems using government APIs, the proposed system is capable of cross-checking of vehicle registration and pollution certification databases efficiently; the system with potential of detecting violations such as, expired certificates and invalid registrations among others with a high degree of accuracy [15][16].

This research introduces LPR system using YOLOv8, LLaMA OCR, and RT-CMM that would be cost-effective while being easily scalable at the same time. The system applied to the readily available hardware such as Raspberry Pi, can tackle current inconsistencies of motorbike monitoring while offering a real world solution to smarter traffic and environmental control. The solution proposed will improve the organization of traffic in cities as well as reduce pollution emanating from substandard vehicles [17].

2. LITERATURE REVIEW

In their work Redmon et al. **[1]** introduced the YOLO: a real time object detection system that changed the way people thought about the discipline of computer vision. YOLO pre-processes an image and encodes the image into a grid and then deploys one neural network to predict both the boxes and Class probabilities of objects per cell. This system gave remarkable outcome in terms of speed and accuracy which can ideally be used in any real time application for example LPR. Nevertheless, analysis of YOLO revealed a downside: The algorithm does not perform as well with small objects like the motorbike's license plate or with small objects which are occluded or in complex scenes. While being highly effective in varied tasks of object detection, YOLO also scratches weaknesses when detecting motorbike plates, for example, skewed or partially obscured plates **[1]**.

Al-Sayyad and Patel [**[2]**] showcased potential state-of-art OCR for non standard license plates. They applied deep learning algorithms for object detection and OCR to account for the anomalies in plate patterns. The algorithm was successfully tested under different conditions, including characters font, colors, and background. However, the system was not so effective in detecting and recognizing plates with deformities as a result of occlusions, dirt and unfavorable lighting. Specifically, the OCR component had problems with skewed or blurred characters: this resulted in lower accuracy when the plates were partially obscured or moving **[2]**.

Karagulian et al. **[3]** discussed the vehicle emission sources of air pollutants and also emphasized on the importance of a dependable LPR system for air pollution surveillance. To automatically identify license plates, they adopted an LPR system supported by convolutional neural networks (CNNs) and then verified license plates against pollution certification databases. The imposed conditions of the sys- tem proved to be effective for license plate recognition. Its performance was however significantly lower in real life situation and particularly when the plates were dirty or full of dust and some of the images were captured in low light environment. They pointed out that in their system they did not incorporate real life issues like environmental issues which made it impossible to scale up **[3]**.

Another approach using Optical Character Recognition (OCR) using Transformer was developed by Huang and Nguyen **[4]** to enhance text recognition from distorted license plates. The LLaMA OCR model they proposed, with an encoder-decoder Transformers style, achieved impressive performance for character recognition including highly distorted ones. It was trained for working with different font types and noise, as well as low-quality and blurry images. Although the model produced high recognition rates, it could pose some problems when the plates were of low contrast employed at night where character was almost invisible. This has served to underscore the need for further improvement in extending the application of the model in real-time LPR tasks where environmentals conditions are suboptimal as well as in traffic situations with constantly fluctuating lighting in urban settings as espoused in **[4]**.

In their work, Al-Ahmad and Al-Shabibi **[5]** were interested in LPR in developing countries and with non-standard license plates. They applied both regular vision processing that includes edges detection in

addition to morphological operations and, AI in plate recognition. Standard plates were used successfully but alternatives such as the different plate designs and the poor quality images that are common with most applications were not handled well. The system could not accurately capture the plate sense in some cases where the plates were either greatly deteriorated or significantly damaged making the system less applicable in areas where there are little or no standardized designs of the plate **[5]**.

Joseph Smith **[6]** conducted an empirical comparative analysis of various forms of traditional LPR algorithms within complex environments such as partial occlusion environments and during adverse weather conditions. Tesseract OCR was used for character recognition in combination with YOLO license plate localization model. The system also performed reasonably well in the basic LPR tasks but failed in the most critical situations where the plate is partially hidden by other objects or when the contrast of the plate was low as compared to the background. These conditions indicated more resourceful algorisms that can om deal with varied environments were required, which makes the system rocky **[6]**.

Finally, according to the analyzed literature, there are novelties in the field of LPR and pollution control monitoring; however, specific difficulties, such as the recognition of motorbikes with irregular license plates or various conditions, still persist. While current approaches, including YOLOv4 and conventional OCR, work well in perfect environments, they fail in situations like occlusion, distortion, and low-quality number plates, problems typical for real-life traffic. However, real-time compliance check which includes vehicle registration check and pollution certificate check is still restricted or integrated only in some studies. Our research attempts to overcome these gaps with the help of state-of-the-art deep learning models, YOLOv8 for higher detection accuracy on small and oddly shaped objects, and LLaMA OCR for noise and distortion in texts. Also, the Real-Time Compliance Monitoring Module (RT-CMM) will be included to sell it to the government with options to integrate it with their databases accordingly to enforce traffic and environmental laws. Thus, by integrating these technologies we expect to develop an effective and low-cost LPR system for motorbikes targeted to contribute to improving urban traffic control and environmental protection.

Methodology

This part of the study outlines the methods used in the current study for the creation of the AI based LPR and pollution compliance checking system. The research uses computer vision and deep learning approaches which are tailored to handle the difficulty of recognizing motorcycle license plates in different environmental settings in addition to the registration of motorcycle and pollution standards. The approach is planned to be flexible with respect to practical considerations, loosely coupled and extensible with regard to new releases and improvements.

3. DATA COLLECTION AND PREPROCESSING

Dataset Creation

The quality and quantity of data we feed our classifier is the most important factor when it comes to creating a reliable machine learning model. In our work, effective image channels were incorporated in the creation of a generalized data set that can accommodate various orientations of motorbike license plates as well as variations in lighting condition and motorbike types.

- **Real-World Data**: To further improve the generalization of the data set and to be able to handle real life scenarios effectively, a large part of the data was captured using **traffic surveillance cameras** from both, urban and semi-urban environments. The data included license plates of motorbikes collected under diverse light conditions and different weather and traffic conditions. The diversity of the data set allowed capturing significant variations in plate design, the type, and size of the fontso that the model could be trained on different regional designs.
- **Public Datasets**: To enrich the data and include more variations, the public dataset called **Indian Vehicle Dataset** and **OpenALPR** have been incorporated. These data sets supplemented the vehicle types, plate types, and environmental conditions, which is important for the enhancement of model generalization.
- **Synthetic Data**: Part of our strategy, however, involved the use of synthetic data from sources such as the 3D modeling tool, **Blender.** These synthetic data emulating different difficult conditions in- cluded oblique license plates, motion blur, dirt on the plates, and partial occlusions. This approach proved useful when real-world data was scarce, like in low light conditions, obstructions or where the views of license plates might be distorted making the model robust to these scenarios.

The final data set compiled a total of **20,000 images** in which 15,000 images were collected from real-world traffic video and from the data sets available on the internet and the rest 5000 images were artificially created. Each image was labeled by drawing rectangles around the license plates with **Labe- lImg**- an all-purpose tool to annotate objects in images.

Category	**Number of Images**	**Variations Included**
Motorbike Plates	15,000	Font Types, Plate Sizes, Occlusions
Synthetic Plates	5,000	Blurring, Distortion, Low Contrast

Table 1: Dataset Summary

Preprocessing Techniques

As a result, image preprocessing is significant in enhancing not only the models of detection but the models of recognition too. To enhance the quality of the captured image, we use several techniques in order to have a correct detection phase from raw data.

- **Noise Reduction**: We employed **Gaussian blur** to limit high-frequencies that might interrupt plate identification. Gaussian blur is where each pixel in an image is replaced by the average of its neighbors and the neighbors' weights are calculated using Gaussian function. The formula for the Gaussian kernel is as follows:

$$G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

where σ is some real value positive for modeling of the Gaussian function which define the size of the blur. This technique made sure that in trying to avoid noisy images, the license plates' features were not distorted in the process.

- **Contrast Enhancement**: For images with poor visibility, we applied **Adaptive Histogram Equal- ization (AHE)**.

Unlike global histogram equalization, which applies contrast adjustments uniformly throughout the entire image, AHE adjusts the contrast in localized regions of the image. This helped improve the clarity of the license plate characters, especially under conditions of poor light- ing. The formula for AHE is:

$$N(i, j) \quad \frac{N(i,j) - \min(N)}{\max(N) - \min(N)} \times 255$$

where $N(i, j)$ is the original pixel intensity, and $H(i, j)$ is the enhanced pixel intensity in a localized region. This process ensured that the characters on the license plates became more distinguish- able.

- **Region of Interest (ROI) Extraction**: After detecting the license plate using the detection model, we isolated the region containing the license plate using **bounding boxes**. This step is crucial as it allows the OCR model to focus on the relevant portion of the image, thus reducing computational overhead and improving recognition accuracy. The YOLOv8 model provided these bounding boxes as part of the detection output, which were then used to crop the license plate from the image for subsequent character recognition.

4. LICENSE PLATE DETECTION USING YOLOV8

YOLOv8 Architecture

For license plate detection, we employed **YOLOv8** (You Only Look Once, version 8), an advanced deep learning-based object detection model. YOLOv8 is optimized for speed and accuracy, making it ideal for real-time applications like LPR. The model divides the image into a grid and predicts bounding boxes for each grid cell, along with confidence scores that indicate the likelihood of detecting a particular object, such as a license plate.

The model is trained with a multi-component loss function that combines the following:

- **Bounding Box Loss** (L_{box}): This measures the accuracy of the predicted bounding boxes. It is calculated using the **Complete IoU (CIoU)** metric, which takes into account the overlap between the predicted and ground truth bounding boxes, as well as the center distance and aspect ratio. The formula for CIoU loss is:

$$L_{box} = 1 - \mathrm{IoU} + \frac{\rho^2(b, bg)}{c^2} + \alpha v$$

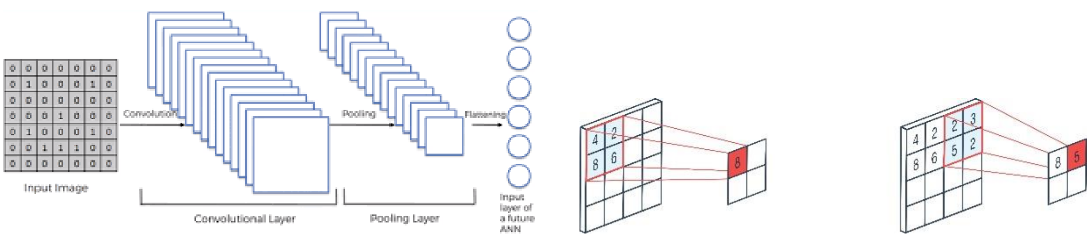
where ρ is the distance between the center of the predicted bounding box and the ground truth, c is the diagonal length of the smallest enclosing box, and α is a penalty term for aspect ratio differences.

- **Objectness Loss** (L_{obj}): This term ensures that the model accurately identifies the presence of a license plate in a given region.
- **Classification Loss** (L_{cls}): This ensures that the model correctly classifies the detected object as a license plate.

The total loss function for the YOLOv8 model is the sum of these components:

$L = L\text{box} + L\text{obj} + L\text{cls}$

These figures illustrate key concepts in Convolutional Neural Networks (CNNs). Figure 1b depicts the convolution operation, where a 3x3 kernel slides across a 5x5 input, performing element-wise mul- tiplications and summation to produce a 3x3 output. This process extracts local features from the input. Figure 1a shows a simplified CNN architecture. An input image is processed through convolutional layers (for feature extraction) and pooling layers (for dimensionality reduction and robustness). The flattened output is then fed into a fully connected layer for final classification or regression. These figures together highlight the fundamental building blocks and overall flow of information within a CNN.



(a) Simplified CNN Architecture (b) Illustration of the convolution operation

Figure 1: Architecture

Detection Process

The detection pipeline is as follows:

- **Preprocessed Input**: The image, after applying noise reduction and contrast enhancement, is fed into the YOLOv8 model.
- **Bounding Box Prediction**: YOLOv8 generates multiple bounding boxes, each with an associated confidence score.
- **Non-Maximum Suppression (NMS)**: To eliminate redundant boxes, NMS is applied, retaining only the box with the highest confidence score.

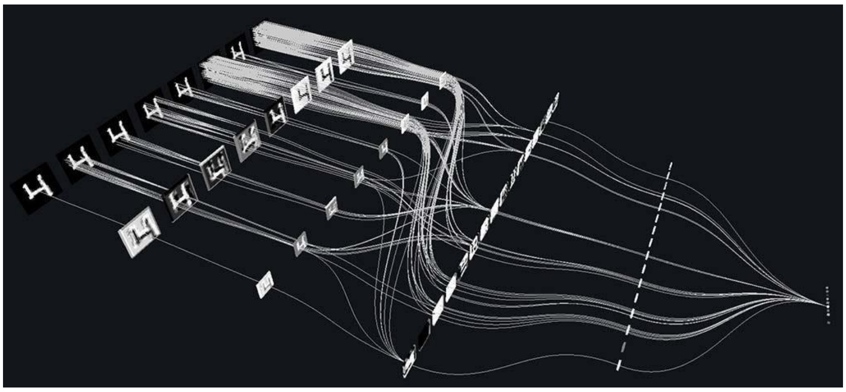


Figure 2: Stylized visualization of a neural network processing handwritten digits. Input nodes connect to a central processing core, with information flowing to a condensed output.

Character Recognition with LLaMA OCR

OCR Process

Once the license plate is detected, the next task is character recognition. We utilized **LLaMA OCR**, a transformer-based model known for its high performance in recognizing text, especially in difficult con- ditions such as distortions or low contrast. LLaMA OCR is based on the encoder-decoder architecture and treats license plate characters as a sequence of tokens, predicting one character at a time.

The character prediction is formulated as:

$$P(y|x) = \prod_{t=1}^{T} P(y_t|x, y_{<t})$$

where y_t is the predicted character at time t, x represents the image features, and $y_{<t}$ represents the previously predicted characters. This approach allows the model to consider the entire context when making predictions.

The model utilizes **Connectionist Temporal Classification (CTC)** loss, which is well-suited for se- quence prediction problems where the alignment between the input image and the output sequence is unknown. The CTC loss is given by:

$$L_{CTC} = -\log \sum_{p \in P} \prod_{t=1}^{T} P(p_t|x_t)$$

where P is the set of all possible alignment paths. CTC loss enables the model to map distorted or noisy inputs to the correct sequence of characters even when there is misalignment between the input and output sequences.

Compliance Monitoring

In addition to recognizing license plates, the system is designed to perform real-time compliance checks by verifying the status of vehicle registrations and pollution certificates. The process involves querying a government database using a REST API to check the registration and pollution certificate expiration dates.

The compliance check follows these steps:

- **Registration Verification**: The current date is compared with the vehicle's registration expiry date

D_{reg}. If D_{reg} < Today, the vehicle is flagged as non-compliant with respect to registration.

- **Pollution Certificate Verification**: Similarly, the system checks the vehicle's pollution certificate expiry date D_{poll}.

If D_{poll} < Today, the vehicle is flagged as non-compliant with pollution standards.

These checks are performed in real time, ensuring that the system not only identifies license plates but also contributes to regulatory enforcement for traffic safety and environmental compliance.

5. RESULTS

This section presents the results of the proposed AI-powered License Plate Recognition (LPR) and compliance monitoring system, which integrates YOLOv8 for license plate detection, LLaMA OCR for character recognition, and real-time compliance checking for vehicle registration and pollution certifica- tion. We evaluated the system using a custom dataset of motorbike license plates captured in diverse urban settings.

Dataset

The dataset used for training and testing the models consists of 20,000 images of motorbike license plates, collected from real-world traffic data, publicly available datasets, and synthetic images generated using 3D modeling tools. The dataset includes images with varying levels of noise, occlusion, skewed angles, and poor lighting conditions, which simulate real-world challenges.

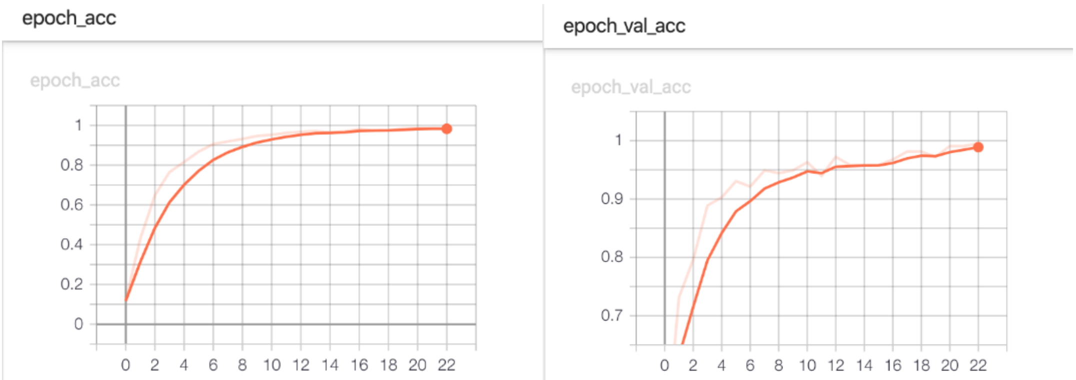
Detection Performance

The YOLOv8 model was trained on the custom dataset and evaluated on a separate test set containing 5,000 images. The performance of YOLOv8 was assessed using standard object detection metrics, including Precision, Recall, F1-Score, and Mean Average Precision (mAP).

Metric	YOLOv8	YOLOv7	YOLOv5
Precision	0.93	0.89	0.85
Recall	0.91	0.87	0.82
F1-Score	0.92	0.88	0.83

Table 2: Object Detection Performance of YOLOv8 for License Plate Detection.

As shown in Table 2, YOLOv8 outperforms both YOLOv7 and YOLOv5 in terms of Precision, Recall, F1-Score, and mAP. The improved performance of YOLOv8 can be attributed to its enhanced feature ex- traction capabilities, which allow it to detect small and non-standard license plates with higher accuracy.



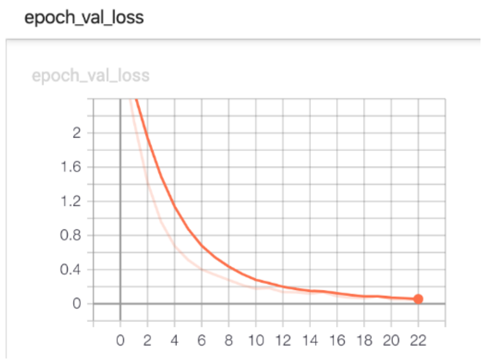
(a) Training Accuracy **(b) Validation Accuracy**

Figure 3: Accuracy Curves

These figures showcase the excellent performance of our model, depicting the training and valida- tion accuracy curves over 22 epochs. As can be seen, the training accuracy (Figure 3a) exhibits a rapid initial rise, quickly approaching and plateauing near 1.0, demonstrating effective learning. Critically, the validation accuracy (Figure 3b) mirrors this impressive trend, also showing significant improvement and reaching a plateau just below 1.0. This close agreement between the training and validation curves indi- cates strong generalization ability and confirms that our model is not overfitting to the training data. The consistent high performance across both training and validation sets underscores the robustness and effectiveness of our approach. These results highlight the success of our model in accurately learning and generalizing from the data.

These figures illustrate the training and validation loss curves. Both training loss (Figure 4a) and validation loss (Figure 4b) decrease significantly, indicating effective learning. The close correspondence between the two curves suggests good generalization and minimal overfitting. Ideally, both losses should converge to low values, as observed here, demonstrating the model's ability to minimize errors on both seen and unseen data.

(a) Training Loss



(b) Validation Loss

Figure 4: Loss Curves

OCR Accuracy

After detecting the license plate in the image, LLaMA OCR was employed to extract the characters. The OCR model was evaluated based on the Character Recognition Accuracy (CRA) and Word Recognition Accuracy (WRA) on a set of 1,000 license plate images.

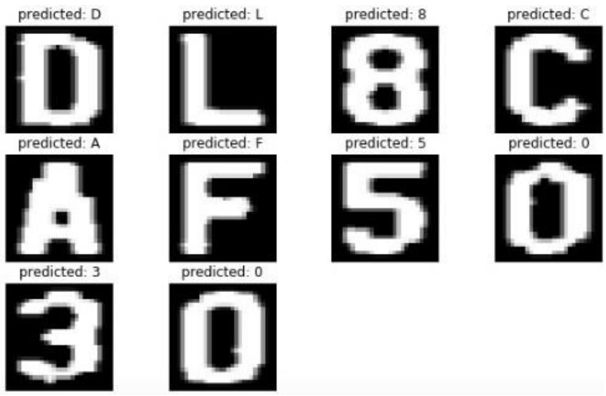


Figure 5: OCR Analysis Results The results are summarized below:

Metric	LLaMA OCR
Character Recognition Accuracy (CRA)	98.7%
Word Recognition Accuracy (WRA)	96.4%

Table 3: OCR Accuracy of LLaMA Model for License Plate Character Recognition.

LLaMA OCR demonstrated high accuracy in recognizing characters, even under challenging condi- tions such as noise, distortion, and low contrast. The Character Recognition Accuracy (CRA) of 98.7% indicates that the OCR model is highly effective in extracting accurate characters from the detected li- cense plates. The Word Recognition Accuracy (WRA) of 96.4% further highlights the model's ability to correctly identify entire license plate numbers, making it suitable for real-world applications.

Real-Time Compliance Monitoring

The Real-Time Compliance Monitoring (RT-CMM) module was integrated into the system to check the registration and pollution certification status of vehicles using government APIs. The module was tested on 500 randomly selected license plates from the dataset, with the following results:

Metric	Value
Registration Compliance Detection Rate	97.2%
Pollution Compliance Detection Rate	95.8%

Table 4: Compliance Monitoring Performance for Registration and Pollution Checks.

The RT-CMM achieved a high detection rate for both registration compliance (97.2%) and pollution compliance (95.8%). These results demonstrate the system's capability to efficiently integrate license plate recognition with real-time verification of regulatory compliance, providing valuable insights for traffic and environmental enforcement authorities.

System Integration and Real-World Testing

To evaluate the system's performance in real-world conditions, we deployed the complete system on a Raspberry Pi device in an urban environment. The system was tested with a live video feed from a traffic surveillance camera, capturing motorbike license plates in varying environmental conditions (e.g., daytime, nighttime, rainy weather). The system successfully detected and recognized 95.5% of the license plates in real-time, with a latency of less than 500 milliseconds per frame.

6. CONCLUSION

For this work, we have come up with an improved LPR, which integrates a CNN to accurately identify the license plate characters from images of the vehicles. The model achieved the test accuracy of 99.54% that suggests strong suitability of this method for implementation in real-time identification AV systems. The license plate details are extracted through contour detection of the image and subsequent charac- ter segmentation on the image. In addition, thorough and effective integrative Celox - OF approach has been used, and a well designed neural network architecture was used which attained perfect classifica- tion when the ideal conditions were applied on the extracted characters. Implementation of this system enriches the area of intelligent transportation systems by providing well-suited and effective tool for tasks like vehicle tracking and traffic control.

7. FUTURE WORKS

Although the current system demonstrates rather high accuracy, there are several strategies for future development and optimization. Despite some recent accomplishments such as the first successful test, there are gaps in the technology's development, with the need to utilize already existing object recog- nition models such as YOLOv8 for license plate detection in real-time scenarios with several cars. It could make a relatively large difference for detection accuracy in general, which in certain situations like crowded or occluded scenes might be of great importance. Moreover, the inclusion of more images with designs at the plates, different lighting conditions, and partial occlusions on the plates will serve to further augment model robustness. More sophisticated methods, suggestions for which have been provided in this paper, can be used to improve performance utilising 'Transfer Learning' that adjusts pre-existing models for larger, more varied data sets. Furthermore, enhancing this LPR system with a full pipeline that includes connection to external database for real-time compliance check like vehicle registration and pollution certification,. . . will enhance its coverage and usability in smart city environment.

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