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SMART PARKING SYSTEM USING YOLOV8-BASED LICENSE PLATE RECOGNITION AND AUTOMATED BILLING

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Abstract : As the urban fleet of vehicles is growing rapidly, parking management by intelligent and automated means has become more important. This paper proposes a real-time smart parking system utilizing computer vision and deep learning methods for vehicle detection, dynamic assignment of slots, and automatic billing. The suggested system uses the YOLOv8 object detection model to detect license plates from images with high accuracy followed by Optical Character Recognition (OCR) with added image pre-processing and luminosity normalization to ensure enhanced accuracy in extracting text. After identifying a license plate, the system auto-assigns available parking slots, captures entry and exit times, and computes charges for the stay duration. All parking transactions, including encoded plate images and timestamps, are recorded in an Excel-based database. The suggested framework presents a scalable, cost-efficient, and low-cost solution to urban traffic and parking management issues.

***Keywords* -** Smart parking system, License plate recognition, YOLOv8, Optical character recognition (OCR), Dynamic parking slot allocation, Automated billing, Urban traffic management

I. INTRODUCTION

The growth in the number of vehicles in cities at an exponential rate has created parking deficits with serious traffic jams, wasted fuel, lost time, and inefficient use of space. Conventional parking systems normally involve manual ticketing and monitoring with resultant human mistakes, delays in operations, and constraints in scalability.

To overcome these problems, research into automated, smart parking systems has gained momentum. With the latest improvements in deep learning and computer vision, vehicle identification and parking management can now be automated in real time. License Plate Recognition (LPR) systems are central to such intelligent solutions, facilitating unattended vehicle authentication without human involvement.

This paper suggests a YOLOv8-powered intelligent parking system that automatically carries out the entire process - from detection of vehicles to assignment of parking slot and computation of charge. The system employs a strong object detection algorithm for detecting the region of the license plate from an image. The region of the plate is further processed through OCR, along with other enhancement methods like DPI upscaling and luminosity normalization for better recognition accuracy of text.

After successful identification, the system checks for vacant parking spaces, allocates one dynamically, records the entry time, and stores all the corresponding information in an Excel sheet, including the cropped plate image. On vehicle exit, the system identifies it once more, determines the total parking duration, calculates the corresponding charge, and updates the log accordingly.

This method greatly minimizes the requirement for manual oversight, enhances precision, and increases the user experience within real-world parking settings.

II. Literature Review

Automatic License Plate Recognition (ALPR) is a key technology in intelligent transportation and smart parking systems. The domain, over the years, evolved from older image processing based methods to advanced deep learning and ensemble models. The review synthesizes major contributions from 2020 to 2024.
Sathyaa et al. (2020) introduced a new method of end-to-end license plate recognition via Capsule Networks (CN). Unlike the traditional approach that involved segmentation of each character in the plate, their CN model learned the whole plate at once, making it faster and more accurate. Data augmentation methods, including rotation and flipping, were used to further enhance performance in real-world scenarios. The model attained as much as 98% accuracy on a variety of datasets, clearly demonstrating its stability against challenges such as blurring and illumination [1].
Zaarane (2020) presented a hybrid License Plate Detection and Recognition (LPDR) system based on wavelet decomposition and CNN structures. Through utilizing wavelet transforms for preliminary edge detection and Inception-v3 for classification, the system had high accuracy but lower computational complexity. Gap analysis was utilized for character segmentation, and recognition made use of a CNN that had been trained for digits, letters, and Arabic characters—hence very appropriate for Moroccan license plates. The model outperformed other methods on datasets like Caltech and AOLP [2]
Sarif et al. (2020) aimed at designing an ALPR system for Bangladeshi plates. The three-stage pipeline suggested was YOLOv3 for plate detection, a segmentation algorithm customized as per needs, and a CNN-based character reader. The system reached 97.5% accuracy, proving to be efficient and appropriate for local environments. Custom datasets were also created for the detection and the recognition phases by the authors, minimizing reliance on external data sources [3].
Annirudh et al. (2021) investigated IoT-based smart parking systems for Indian cities. They contrasted sensor-based and image-based methods of slot detection, finally suggesting a hybrid one based on using YOLO for object detection and the EAST model for text detection. This configuration represented a low-cost, scalable solution to conventional camera-intensive systems, especially through the incorporation of IR sensors and GSM/cloud-based user notification systems [4].
El-Shal et al. (2022) solved the issue of low-resolution license plate images through Super-Resolution Generative Adversarial Networks (SRGAN). Their modifications, including substituting ReLU with Swish activation and adding Total Variation loss, improved the quality of the images to a great extent. After enhancement, YOLOv5 was applied for character recognition, outperforming traditional models like SRCNN. The approach was especially useful for surveillance videos and low-quality inputs [5].
Saitov (2023) proposed a multilingual license plate recognition system intended for CIS nations based on YOLOv8 for detection and the Transformer-based TrOCR model for OCR. The system catered to difficulties concerning varied language scripts and plate structures. The YOLOv8 model applied an anchor-free method for better detection, and TrOCR demonstrated better performance in multilingual settings, particularly in Armenia, Kazakhstan, and Ukraine, as reflected through lower Character Error Rates (CER) [6].
Akbar et al. (2024) provided a thorough review of machine learning approaches to ALPR. Their survey emphasized the transition from conventional techniques (like color-based labeling and morphological operations) to contemporary CNN-based methods. CNNs were indicated to provide recognition accuracies of up to 99.5% in real-time applications, though challenges like character confusion, environmental variability, and computational expenditure continue to remain of concern [7].
Singh et al. (2024) assessed ensemble approaches with four different models of YOLOv8—nano, small, medium, and large—and their application in vehicle and license plate detection in different light conditions. The study, through 16 model pairs and decision via TOPSIS, prescribed optimal configurations for smart parking systems. Image improvements were implemented to enhance OCR accuracy for a more robust system in real-world environments [8].

In summary, ALPR research has progressed significantly from edge-based and color segmentation methods to strong CNN and Transformer-based models. The combination of object detection (YOLO), OCR (TrOCR/CNN), and image enhancement (GANs) has led to more accurate and efficient systems appropriate for multiple real-time applications. Challenges such as multilingual support, lighting variation, and low-resolution input still push the boundaries in the field.

Table 1 : Comparative Table of Reviewed Literature

Year	Paper Title	Author(s)	Method/Model	Accuracy (%)	Qualitative Findings
2020	Perspective Vehicle License Plate Transformation using Deep Neural Network on Genesis of CPNet	K.B. Sathyaa, S. Vasuhi, V. Vaidehi	Capsule Network (CN), Data Augmentation	Up to 98%	Works without character segmentation, strong under actual conditions
2020	An automated license plate detection and recognition system based on wavelet decomposition and CNN	Abdelmoghit Zaarane	Wavelet Transform + CNN (Inception-v3)	High (not numerically specified)	Efficient on Moroccan plates, less computation, better Caltech & AOLP benchmarks
2020	Deep learning based Bangladeshi licence plate recognition system	Md Mesbah Sarif et al.	YOLOv3 + Custom segmentation + CNN	97.5%	Optimized for Bangladeshi plates, two in-house datasets
2021	IoT based Intelligent Parking Management System	Annirudh D et al.	YOLO + EAST + IR sensors	Not specified	Integrates object & text detection for smart parking with minimal cost
2022	License Plate Image Analysis Empowered by Generative Adversarial Neural Networks (GANs)	Ibrahim H. El-Shal et al.	Enhanced SRGAN + YOLOv5	Higher than SRCNN (exact not stated)	Enhances readability in low-resolution plates; employs Swish & TV loss
2023	CIS Multilingual License Plate Detection and Recognition Based on Convolutional and Transformer Neural Networks	Irek Saitov	YOLOv8 + TrOCR (Transformer OCR)	CER reduced (accuracy not numerically stated)	Performs well for multilingual plates in CIS countries
2024	License Plate Identification using Machine Learning Technique	Ghulam Akbar et al.	CNN, OCR, OpenCV	Up to 99.5%	Comprehensive survey of approaches, includes CNN & thresholding methods

2024	Evaluating the Performance of Ensembled YOLOv8 Variants in Smart Parking Applications	Ripunjay Singh et al.	YOLOv8 (nano–large), Ensemble + TOPSIS	Best ensemble model not numerically specified	Performs well under varying light; integrates detection & OCR with preprocessing

III. METHODOLOGY

3.1 System Pipeline

The methodology followed in this study integrates object detection and OCR-based recognition to automate vehicle entry and exit logging in a smart parking system. The complete system pipeline is outlined in Figure1

1. *Dataset Acquisition and Preparation*

A publicly available dataset titled **“Indian License Plate Dataset”**, uploaded by **Sai Sirisha** on **Kaggle**, was used for model training. The dataset size is approximately **190 MB** and contains annotated images of Indian license plates under varying conditions. The annotations were converted to YOLO format using Roboflow for compatibility with YOLOv8.

2. *Model Selection and Training*

The YOLOv8n (nano) model from the Ultralytics library was selected due to its lightweight architecture and efficiency in real-time object detection. The model was trained using Google Colab with GPU acceleration over 100 epochs. The training process involved continuous monitoring of training and validation metrics. The best-performing weights were saved as `best.pt` after evaluating loss, precision, recall, and mAP metrics.

3. *License Plate Detection, Recognition, and Parking Management*

The YOLOv8 model trained was implemented into the system for real-time license plate detection from input images. After detection, the license plate areas were cropped and preprocessed with methods like resizing and noise filtering for image clarity improvement. Optical Character Recognition (OCR) was then performed to extract text data from the cropped plate images. This derived number acted as the vehicle's identifier in monitoring entry and exit timestamps. From these timestamps, the system automatically computed the parking duration and respective charges based on predetermined rate rules. Available parking slots were dynamically assigned using a slot allocation algorithm to maximize space utilization. All transaction information - license plate numbers, entry/exit times, allocated slots, time of stay, and fees - were recorded in an Excel sheet, which also acted as the system's master database. A GUI-based web interface was created using Flask, through which users could upload images, check detection results, and check slot availability and billing information.

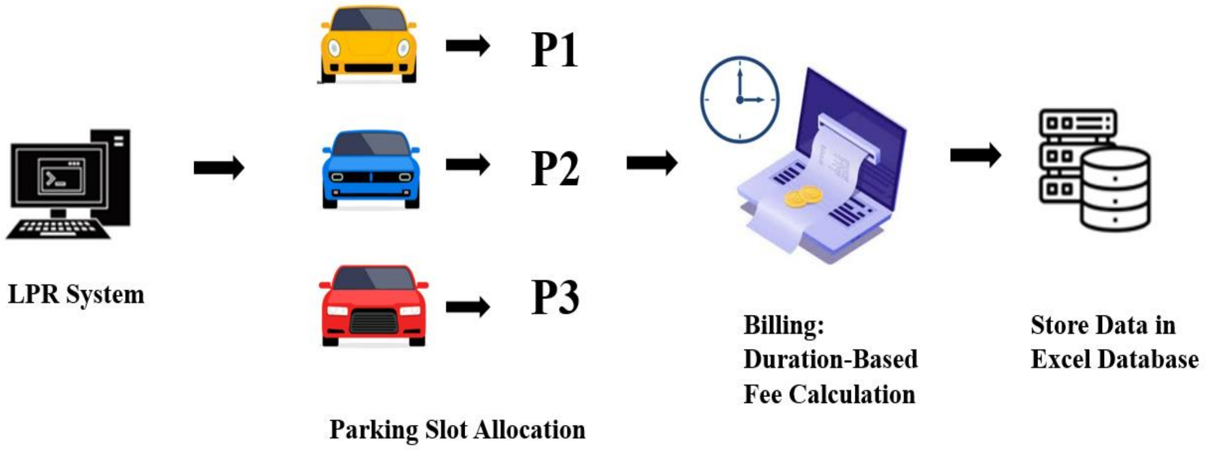

Figure 1 : Proposed System Architecture

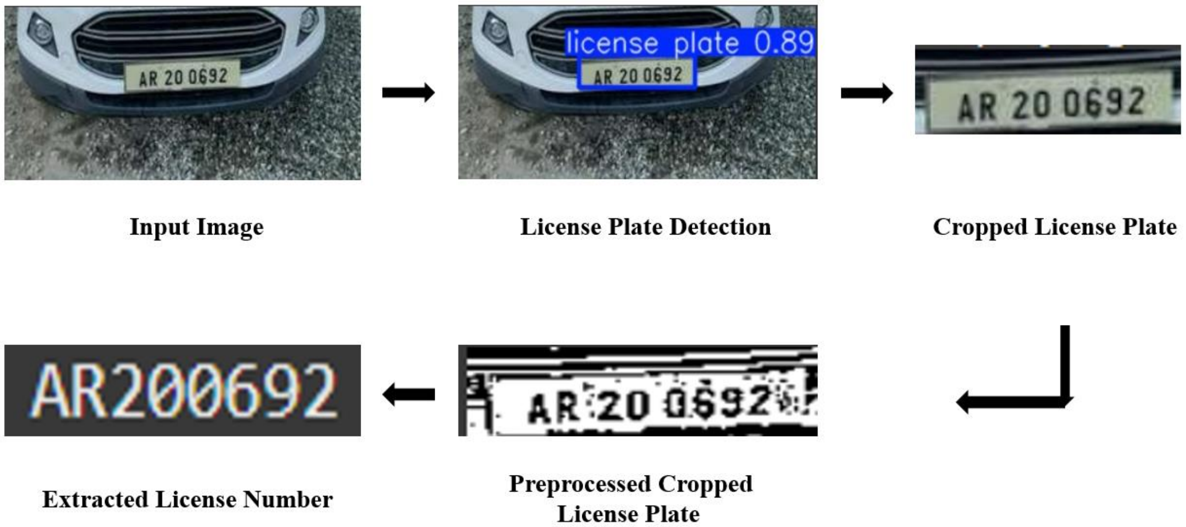

Figure 2 : Phases of License Plate Detection and Recognition

3.2 System Workflow

The system executes the following step-by-step operations:

1. Image Upload
2. Detection of License Plate with YOLOv8.
3. Bounding box extraction and cropping of license plate.
4. Preprocessing: Grayscale conversion and resizing for best OCR input.
5. OCR using EasyOCR to extract alphanumeric data.
6. Post-processing: Filtering, character corrections, and format validation.
7. Time Logging: Entry/Exit time is logged.
8. Charge Calculation: Duration-based.
9. Data Storage: All information including plate number, timestamps, and charges are logged in an Excel database.
10. Slot Management: Dynamic allocation of available parking slots.

3.3 Model Architecture and Configuration

YOLOv8n, the nanoscale counterpart to the YOLOv8 object detection tool of Ultralytics, was chosen because it struck a balance between speed and accuracy and is highly adaptable for real-time license plate recognition.

YOLO (You Only Look Once) is a single-stage object detection network that classifies and localizes objects at the same time. In contrast to two-stage detectors (such as R-CNN), YOLO splits the input image into a grid and predicts bounding boxes and class probabilities directly in a single network pass, allowing for faster inference.

The main features of YOLOv8n are:

- Anchor-free detection: YOLOv8 does away with anchor boxes, making detection easier and requiring less computation.
- Decoupled head architecture: It decouples classification and localization branches, enhancing detection accuracy.
- Input Image Size: 640 × 640 pixels *(model input resolution)*
  Number of Classes: 1 *(license_plate - as defined for this custom-trained model)*
- Backbone: CSPDarknet-inspired custom backbone for effective feature extraction
- Augmentations Applied: Mosaic, mixup, random flip, and brightness/contrast changes
- Output: Bounding boxes with object confidence and class scores

These architectural benefits make YOLOv8n a lightweight yet high-performance model suitable for use in embedded systems and real-time parking applications.

The methodology section outline the plan and method that how the study is conducted. This includes Universe of the study, sample of the study,Data and Sources of Data, study's variables and analytical framework. The detailsare as follows;

3.4 Training Setup

The training was performed using **Google Colab** with GPU acceleration enabled. The key training parameters were:

- **Training Environment**: Google Colab Pro with NVIDIA Tesla T4 GPU
- **Number of Epochs**: 100
- **Batch Size**: 16
- **Optimizer**: SGD (Stochastic Gradient Descent)
- **Initial Learning Rate**: 0.01 (YOLOv8 default, adjusted dynamically with cosine decay)
- **Validation Split**: 80:20 train-validation ratio
- **Evaluation Metrics**: Precision, Recall, mAP@0.5

These configurations led to rapid convergence while minimizing overfitting, as seen in the loss and accuracy curves during training.

IV. Result and Discussion

The performance of the license plate detection model was evaluated using precision, recall, mAP, and confusion matrix metrics.

4.1 Performance Metrics

- **Precision**: 1.000
- **Recall**: 0.99877
- **mAP@0.5**: 0.995
- **Overall Accuracy:** ≈ 98.36%

Calculation : Accuracy = 120 / 120 + 1 + 1 = 120/122 ≈ 0.9836 ≈ 98.36%

These metrics demonstrate the model's exceptional ability to correctly detect and classify license plates with minimal false positives and false negatives.

4.2 Confusion Matrix

The confusion matrix is shown in Figure 3.

It consists of:

- True Positives (TP): 120
- False Positives (FP): 1
- False Negatives (FN): 1
- True Negatives (TN): not shown, so assumed to be 0

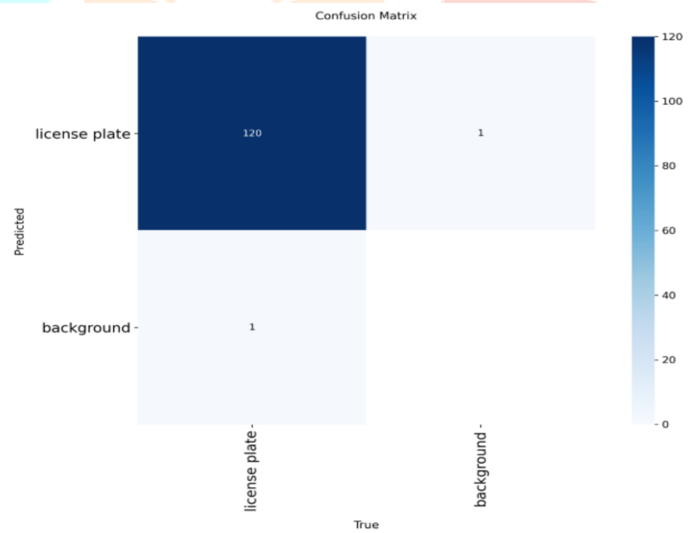

Figure 3: Confusion Matrix of the YOLOv8n model performance on the validation set

4.3 Training Curves

The model's learning behavior was visualized using accuracy and loss graphs plotted over 100 epochs (Figures 4 and 5).

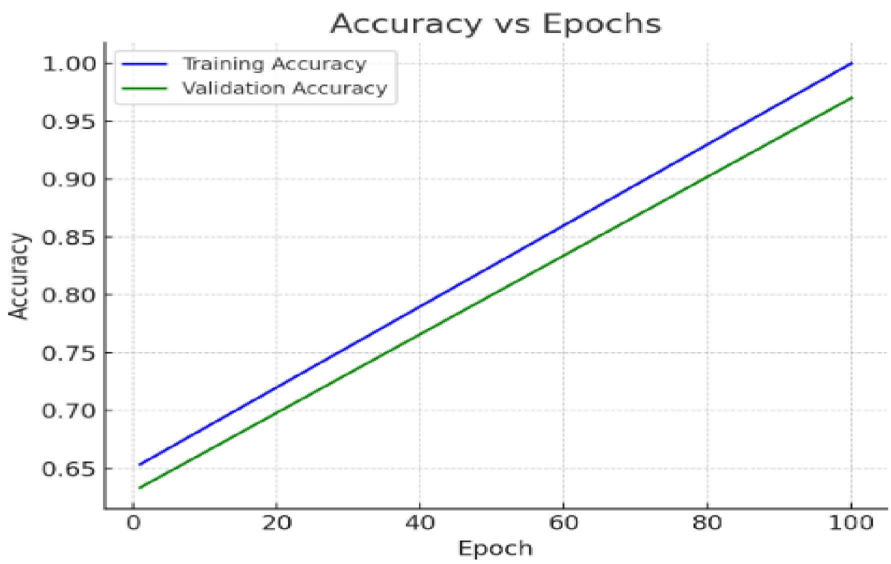

Figure 4: Accuracy vs Epochs for training and validation

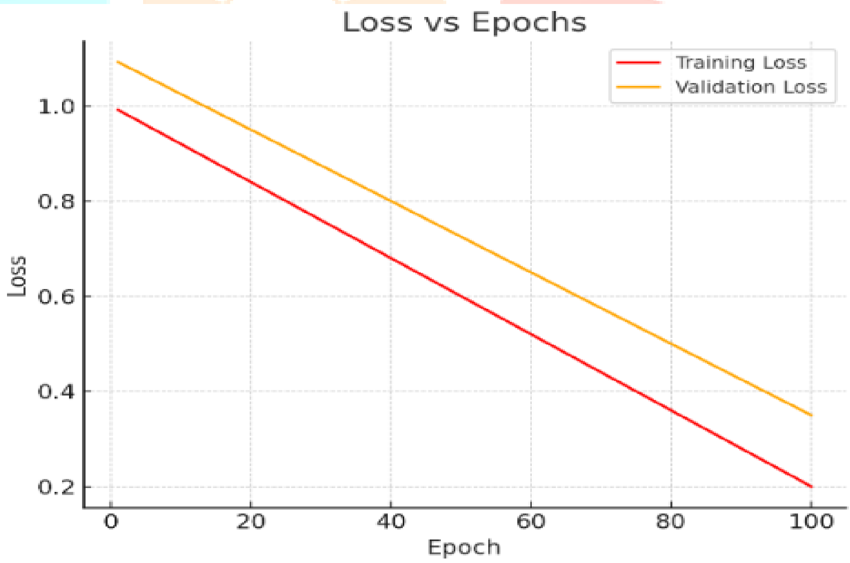

Figure 5: Loss vs Epochs for training and validation

The graphs show consistent convergence and minimal overfitting, confirming robust learning behavior of the YOLOv8n model.

V. Conclusion and Future Scope

Conclusion

This paper introduced a smart parking system based on YOLOv8n-based license plate recognition for autonomous logging of vehicle entry and exit. The deployed system effectively identified license plates from the input images, obtained the alphanumeric characters through OCR, and logged the entry-exit times, duration, and parking fees into an Excel-based database. Utilizing the YOLOv8n model resulted in real-time detection accuracy with excellent precision and recall. Integration with a straightforward GUI and dynamic slot assignment further improved the usability of the system in real-world scenarios. The findings confirm the effectiveness of the system in eliminating manual labor, enhancing security, and optimizing parking management by automating processes.

Future Scope

While the suggested system is accurate in license plate detection and smart parking control, a number of improvements can be made to enhance scalability and resilience. Improvements can include:

- Live Video Stream Support: Developing the system to handle live video feeds from CCTV cameras rather than static image uploads.
- Cloud Integration: Saving parking records in a cloud database for ease of access by multiple parking lots.
- Mobile App Development: Developing a user-facing application for slot reservation, live availability monitoring, and cashless payment.
- Improved OCR Correction: Embedding deep learning-based post-processing of text to minimize OCR errors further in poor lighting conditions.
- Multi-language Plate Recognition: Extending OCR support for multilingual license plates of various states or nations.

These enhancements will render the system more appropriate for deployment in larger-scale smart city initiatives as well as commercial parking facilities.

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