Integrating YOLOv5 and CNN for Number Plate Recognition in Automated Parking Systems

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***Abstract*— Automatic Number Plate Recognition (ANPR) is an increasingly popular methodology that enables the identification of vehicles by scanning their license plate number. Despite the widespread adoption of ANPR technology in other sectors like toll booths, law enforcement, etc. The parking of vehicles still largely relies on outdated and traditional methods. In order to be effective, parking space management systems must contain the most recent technical advancements. Automatic parking systems have the potential to resolve the issues associated with collecting parking tickets, waiting in long queues, making on-the-spot payments, monitoring parking lots, enhancing security, storing number plate details, and tracking vehicles entering and leaving the lot. We have developed an object detection model using YOLOv5 (You only look once) to detect number plates and implemented deep learning Convolutional Neural Network (CNN) character recognition model to read the characters on the vehicle's number plate. In here, we discuss the parking lot management systems, the proposed solution, and its promising features, scanning each vehicle plate and recording entry/exit timestamps for fare calculation and payment. We also analyze the accuracy and performance of our models, highlighting areas of improvement and opportunities for future research.**

***Keywords*— ANPR (Automatic Number Plate Recognition), Machine learning, CNN (Convolutional Neural Network), Optical character recognition, Object detection.**

I. Introduction

Automatic Number Plate Recognition (ANPR) is an image processing technology that utilizes a vehicle's number plate to identify it [1]. ANPR is widely used in many areas such as police force, traffic management, toll agencies as well as parking management services. YOLO (You Only Look Once) is a popular object detection model which is known for its accuracy and speed. CNN (Conventional Neural Network) identifies different characters by comparing their differences in forms and properties.

In recent years, the population of the world has been increasing rapidly. In various cities, people are using their private vehicles for travelling. In the city people are facing problems parking their vehicles. Parking has become a serious problem due to the increasing number of private vehicles. Finding a parking spot takes a lot of time. Managing the entry and exit of vehicle in parking area is a hectic job. The one who is there in the parking place has to keep track of date, time, and vehicle number. The dedicated staff needs to do this data entry. However, maintaining such kind of parking space system manually needs lots of human resource.

Therefore, to overcome this, we have implemented an Automated Parking System with ANPR. In this system, whenever an automobile enters the parking area the digital camera will capture and detect the vehicle's plate and will store the details and entry information in the system. An empty parking slot will be allocated to the vehicle. And at exit time the system will automatically calculate the parking price and will notify the vehicle's owner.

Automated Parking System uses OpenCV for recognizing vehicles. CNN is utilized for character recognition, while YOLOv5 is employed to identify vehicle license plates. We used two data sets and trained the model to get better accuracy. Among others, the datasets of car images were used to train the YOLO-V5 model for number plate detection and other one was of different characters which trained the CNN model for recognition of characters.

The reasons why we implemented Automated Parking System are:

- Reduces manual work.
- Decreases management cost.
- Reduce Traffic near parking area.
- Minimum time is required.
- Consumption of less fuel
- Less stress

The remaining sections are organized as follows. Analysis and survey are discussed in Section II. In Section III, Proposed methodology is well discussed. Implementation and experimental results are presented in Section IV. In Section V, different ideas which we are planning are mentioned. Section VI concludes the paper. And In Section VII, various references are written which we had referred to for this paper.

II. Related Work

A smart parking system was built by Dharmini Kanteti [2] in which a CMOS sensor identifies the license plate of the automobile, the data is checked with the database, and the user is assigned his desired space. The ultrasonic sensors are activated, and the timing begins when the user reaches the designated circular parking place. As the user exits, he should give the information from his smart card to confirm that he exited and that it will be useful when he wants to exit from the parking space.

By the study of integrated sensors in smartphones and Bluetooth connection, Rosario Salpietro [3] accomplished automated identification of parking activities carried out by users. An adaptive technique enables the dissemination of the information over the target scenario once the parking event has been identified, employing a combination of internet connectivity to a distant server and device-to-device connections using Wi-Fi direct links.

The wired sensor systems are used by Georgios Tsaramirsis [4]. Sensors can be divided into two categories: invasive and non-intrusive. The majority of the time, intrusive sensors are mounted directly on paved surfaces or in cracks in the surface of the road. On-intrusive sensors, on the other hand, are also known as above-ground sensors since they are situated above the travel lane and keep watch on both sides of the road. The drawback of intrusive sensors is that because they need to be installed by cutting into the pavement, their use reduces the lifespan of the pavement.

Using cloud based IoT architecture, Basavaraju S. R. [5] built a smart parking system that includes a cloud service provider that offers cloud storage to store data on the state of parking spaces in a parking area. The central server maintains the complete smart parking system's data, including the number of spaces, car availability, etc. This has been accomplished by Robin Grodi [6] so that the car will occupy the designated space. RFID sensors can identify whether a car or other things are nearby. The system requires a mechanism to alert drivers when a car is identified or when a parking space is occupied. The parking spot will only be identified in close proximity; there is no GPS sensor to locate parking spaces from a distance.

Several authors have discussed the LP detection stage using object detection CNNs. Montazzolli and Jung [7] used a single CNN set up in a cascaded method to detect both automotive frontal-views and its LPs, achieving high recall and accuracy rates. CNNs were specially modified for LP detection by Hsu et al. [8], who then demonstrated that the enhanced versions outperformed the originals. Rafique et al. [9] employed Region-based CNN (RCNN) and Support Vector Machines (SVM) to detect LPs, pointing out that RCNNs are best suited for real-time systems.

Using characters cut from regular text, Li, and Chen [10] trained a network to perform character-based LP recognition, exceeding past techniques in recall and accuracy rates. By first extracting a group of possible LP regions using a weak Sparse Network of Winnows (SNoW) classifier and then filtering them using a strong CNN, Bulan et al. [12] significantly improve the baseline approach.

Menotti et al [11] recommendation to use random CNNs instead of picture pixels or back-propagation learning to extract features for character identification performed considerably better. Li and Chen's suggestion [10] is to do character recognition as a sequence labelling problem. A Recurrent Neural Network (RNN) with Connectionist Temporal Classification (CTC) is used to classify the sequential data since it can recognize the whole LP without character-level segmentation.

Svoboda et al. [13] used a text deblurring CNN to produce high-quality LP deblurring reconstructions, which may be especially useful in character recognition, but they did not actually carry out the character recognition. ALPR systems based on DL techniques frequently handle character segmentation and recognition. Montazzolli and Jung [7] recommend using CNN to separate and distinguish the characters in a cropped LP. They segmented more than 99% of the characters properly and beat the baseline by a significant margin.

Using a series of deep CNNs, Masood et al. [14] proposed an end-to-end ALPR system. As this is a commercial system, not much is disclosed on the CNNs that were employed. In a single forward pass, Li et al [15].'s proposed unified CNN can simultaneously find and identify LPs. Also, by sharing a lot of its convolutional features, the model size is significantly reduced.

Khaled Zaatouri suggested a YOLO-based traffic light control system in the publication [16]. A state-of-the-art system, YOLO is a complete convolution network that uses a single neural network to process the whole image. Because it only allows for one viewing, YOLO is exceedingly quick.

Using conventional methods, the feature extraction procedure creates one or more feature vectors. employed Support Vector Machine to extract features, and then used Local Phase Quantization (LPQ) and Local Binary Patterns (LBP) as classifiers (SVM). Later, the authors [17] Almeida, P., Oliveira, L.S., Silva, E., Britto, A., and Koerich developed new techniques based on the modification of cameras and parking areas. These techniques apply the Quaternionic Local Ranking Binary Pattern (QLRBP) for feature extraction, the Support Vector Machine (SVM), and the k-nearest neighbors (k-NN) for classification. The SVM classifier in [8] uses the LBP and the Histogram of Oriented Gradients (HOG) as feature extractors. The preceding approaches have the benefit of being simple to use, but their accuracy is not particularly good.

III. PROPOSED SYSTEM

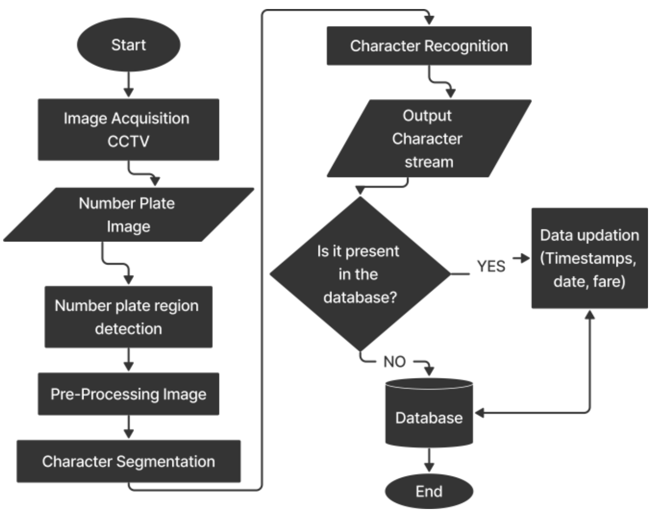

Fig. 1. System Overview

The proposed ANPR system using YOLOv5 and a CNN to recognize the characters has the potential to recognize number plates accurately and efficiently deal with real-world problems, which in turn is useful for a variety of applications, such as law enforcement, parking management, and toll collection. As discussed above in Fig. 1, shows the complete overview of how the parking system will work. The purpose of this portion is to give detailed information of our proposed model. Our system for capturing the number plates of vehicles entering a parking lot follows these main steps:

- Image Acquisition: Use the CCTV camera at the entry/exit barrier to take a picture of the license plate.
- Detection Area of Vehicle Plate: Use the YOLOv5 object detection model to detect the specific area of the vehicle plate from the image of the vehicle.
- Pre-Processing of detected number plate region: Apply image pre-processing techniques like cropping, grayscale conversion, contour detection and Hough transformation to the number plate image to optimize detection capabilities.
- Character segmentation and recognition: Isolate individual character segments on the number plate and utilize our Convolutional Neural Network (CNN) model for character recognition.
- Database validation and storage: Check if the number plate is registered in the database, record the entry timestamp, and assign a parking slot number before opening the barricade. For unregistered vehicles, prompt the user to register. Repeat the number plate detection process when the vehicle approaches the exit barricade to update the database with the exit timestamp and calculate the parking fare.

Overall, this system offers an efficient and automated way to manage the entry and exit of vehicles in a parking lot while improving the user experience and reducing congestion.

IV. Implementation

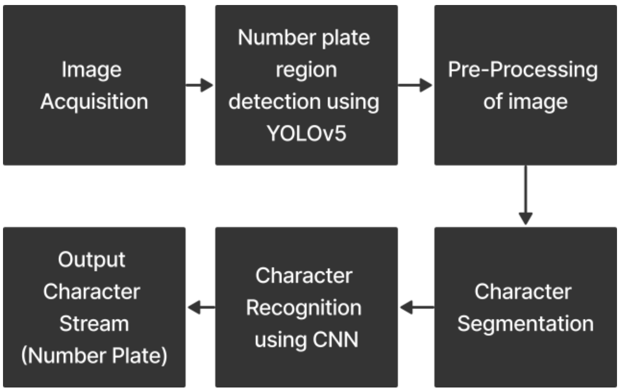

Fig. 2. Workflow of the system

We use two machine learning models in our system that collaborate to recognize characters on a vehicle's number plate from an image. The first model focuses on object detection and seeks to identify the number plate's bounding box or region of interest within the image. Meanwhile, the second model employs a convolutional neural network (CNN) to recognize characters on the vehicles number plate and convert the image input into a text output, using the region of interest identified by the object detection model.

The implementation is done as per the steps below:

A. Data Collection:

The first step in implementing our system was to collect a dataset of images of vehicles with number plates. We gathered data from online sources like Kaggle, and by capturing images of vehicles using our mobile phones. After obtaining sufficient data, we labeled and annotated the images, marking the specific region corresponding to the number plate in each image.

Once we had a labeled dataset, we sent the data for further processing to train our object detection model. Labeling the dataset with the vehicle plate area allowed our object detection model to learn how to identify the vehicle plate's location in an image. This stage of data collection and labeling is critical in machine learning model implementation. A well-labeled dataset with diverse examples is essential for training an accurate and effective model to detect the number plate region in new images. Although the process of collecting and labeling data may be time-consuming, it is essential for the final model to perform effectively.

To train the YOLOv5 model, a dataset of 433 images was collected and divided into 85% for training and 15% for testing purposes.

For the CNN character recognition model, a dataset of 6659 images was used, consisting of thirty-six classes including numbers 0-9 and alphabets a-z. The dataset was split into 70% for training and 30% for testing.

B. Training the YOLOv5 model:

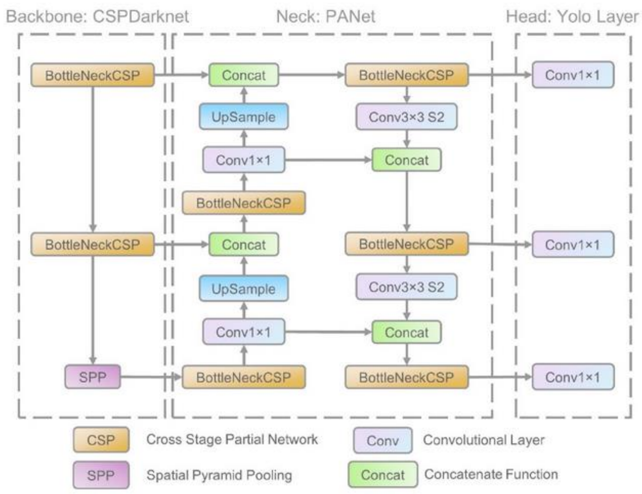

Fig. 3. Network architecture for YOLOv5

YOLOv5 is a widely used object detection algorithm in computer vision programmes, such as ANPR, because of its accuracy and speed in detecting objects in images and videos. It improves on previous versions of YOLO by using a single-shot detector approach that processes the entire image just once to detect all objects. The approach being implemented is unique in itself from the various methods that use region proposals and reduces computational complexity, resulting in faster and more precise object detection.

There are three primary parts to the YOLOv5 network architecture: the backbone network, neck network, and head network. The backbone network extracts feature from input images using the Efficient Net architecture, which is known for its efficient neural network models that achieve state-of-the-art results on image recognition tasks. The neck network fuses feature from different backbone network layers to improve object detection accuracy and reduces the resolution of feature maps to enable easier detection of smaller objects. The head network predicts bounding boxes and class probabilities using anchor boxes of different sizes and aspect ratios for bounding box prediction and the SoftMax function for assigning class probabilities. Overall, the YOLOv5 architecture is efficient and accurate, making it perfect for different computer vision programmes, including ANPR. Its use of anchor boxes and a single-shot detector approach increases speed and accuracy, while the Efficient Net-based backbone network provides excellent feature extraction capabilities. It took 0.849 hours to complete 100 epochs. We used a computer with GPU Nvidia RTX 2060 with 6GB graphics memory and 16 GB RAM, with Intel i7 10th Generation.

```
YOLOv5s summary: 157 layers, 7012822 parameters,
                Class     Images  Instances
                  all         65         65

0 gradients, 15.8 GFLOPs
     P            R         mAP50
 0.887        0.964        0.954          0.6
```

Fig. 4. YOLOv5 training summary

We trained the YOLOv5 model for one hundred epochs on our custom dataset and got a precision of 88.7%, recall of 96.4% and mean average precision of 95.45%.

C. Image preprocessing:

Image preprocessing is an essential step in automatic number plate recognition (ANPR) systems, as it helps to enhance the quality of the image being input and extract the relevant features for character recognition. Several of the most widely used image-processing methods for ANPR include cropping, Hough transform, contour detection, grayscale conversion, and character segmentation.

We used OpenCV which provides wide functions that allow us to access and manipulate image and video data from different sources, like cameras, video files, and image files, OpenCV provides a powerful and flexible set of tools for data processing, and is widely utilize in a variety of fields, including robotics, self-driving cars, and medical imaging.

Fig. 4. Number plate detection

In Fig. 4 The vehicle number on the number plate is detected with an accuracy of 90%. Once we get the bounding box, we send the image for further processing.

- Cropping: The first step in ANPR is to extract the region of interest (ROI), i.e., the number plate, from the input image. This can be achieved by cropping the detected image to focus on parts of the area where the vehicle plate is located. By doing this, we can reduce the amount of irrelevant information and make it easier to determine & identify the characters on the vehicle's plate.

Fig. 5. Image after cropping.

- Hough Transform: The Hough transform is a method of feature extraction that may be used to identify straight lines and edges in an image. In ANPR, the Hough transform helps us in recognizing the edges of the number plate, which can then be used for further process. Here we convert the cropped image into gray scale binary image and then apply Hough edge detection algorithm and then calculate at what angle the automobile plate needs to be rotated for the detected edges to become horizontal.

Fig. 6. Hough transformation

- Contour Detection: Contour detection is another feature extraction approach that can be used to detect the boundaries of objects in an image. We have detected the contours on the number plate which helps us differentiate between individual characters, this helps us in the detection of characters on the vehicle plate.

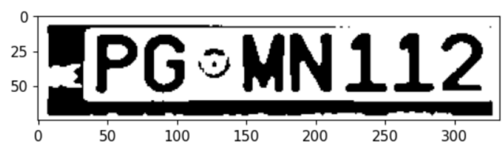

Fig. 7. Contour detection

- Grayscale Conversion: Converting the input image to grayscale can simplify the image processing pipeline and make it easier to extract the features needed for character recognition. By converting the image to grayscale, we can reduce the dimensionality of the input data and eliminate the need to process color information.
- Character Segmentation: Once the number plate region has been extracted from the input image, the next step is to split the characters on the plate. We used contour detection to split the individual characters. By segmenting the characters, we can extract the individual images of characters and feed them to an algorithm that can detect characters for further processing.

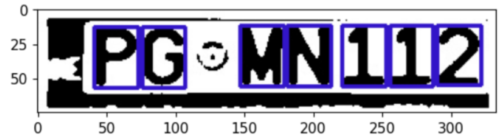

Fig. 8. Character Segmentation

Overall, these image preprocessing techniques can be implemented in combination to increase the efficiency of the ANPR system, extracting the necessary elements from the source image. By reducing the dimensionality of the input data and focusing on the relevant features, we can make it easier to detect and identify the characters displayed on the number plate, even in challenging lighting and environmental conditions.

D. CNN model for character recognition:

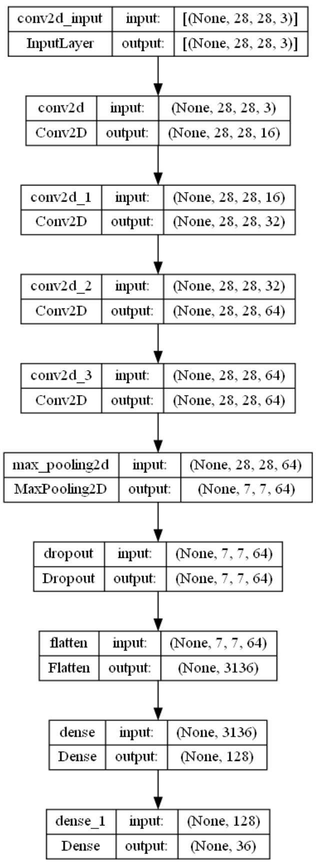

Fig. 9. CNN model layers

Once the individual characters have been segmented from the vehicle plate, the next step is to identify these characters using a machine-learning model. One popular approach for the recognition of characters is to use the Convolutional Neural Network (CNN). CNNs are a type of deep neural network that can learn to recognize patterns in images and other high-dimensional data. Speech recognition, computer vision, and natural language processing are just a few of the many areas where they have been used effectively.

We first need to train the model on a dataset of labeled character images to construct a CNN model for character recognition in ANPR. This dataset should include a variety of characters with different fonts, styles, and sizes, to ensure that the model can recognize characters accurately under different conditions. During training, the CNN will learn to recognize the features that are common to different characters, such as edges, corners, and other distinctive patterns. Once the model has been trained, we can use it to identify the characters in the input image. To do this, we feed the individual character images to the model and use its output to generate a text string representing the recognized characters on the number plate. By training the model on a diverse dataset of labeled character images, we can ensure that it can recognize characters accurately under a variety of conditions, making it a robust and reliable component of ANPR system.

We trained our model on the dataset of characters which include thirty-six classes which are ranging from 0-9 and a-z. We performed 80 epochs and the accuracy we got by training the CNN model on our characters dataset is 89.66%.

E. Database updation and validation:

The ANPR technique uses machine learning models to draw out the vehicle plate characters of a vehicle approaching a parking lot entrance or exit. The system then checks the plate against the local parking lot database to dictate if the vehicle is registered. If so, the entry timing and the exit timing stamps are recorded, and fare is calculated during exit. If not, the system prompts the user to register using an automated process that captures personal and vehicle details. This system offers an automated and efficient way to manage parking lot entry and exit, reducing congestion and improving user experience.

V. Results

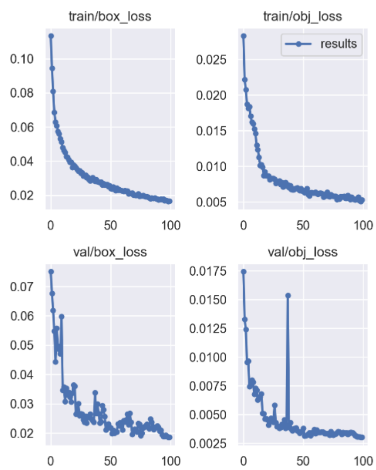

Fig. 10a. Graphical results of YOLOv5 object detection model

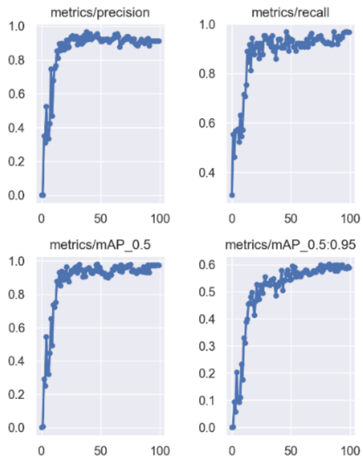

Fig. 10b. Graphical results of YOLOv5 object detection model

Fig. 10a. shows the training and validation loss graphs of the implemented model, the x-axis depicts the total of epochs on which our model is being trained and the y-axis depicts the loss values and as the slope indicates our graph has decreasing loss resulting that lower the loss, better will be the performance.

Fig. 10b. shows the graphical representation of precision, recall and Mean Average Precision(mAP) with an IoU (Intersection over union) threshold of 0.5 for the YOLOv5 model custom-trained on a dataset of vehicle images. Here the x-axis depicts the total of epochs and y-axis depicts the values in a range of 0-1 transforming into a percentage system. The precision and recall values indicate how accurately the model can detect the number plates of vehicles in the images.

Based upon the results shown in Fig. 10, the YOLOv5 model achieved a precision of 88.7%, which means that 88.7% of the detections made by the model were correct. The recall value was 96.4%, which means that the implemented model was able to detect 96.4% of the actual number plates in the images.

The mean average precision (mAP) for the model was 95.45%, which represents the average accuracy across all feasible recall settings. This suggests that the model was able to achieve high precision and recall across a range of detection thresholds.

Overall, these results indicate that the YOLOv5 model can accurately detect the number plates of vehicles in the images, with high precision and recall values. These results are an important indicator of performance and ability of the ANPR system to effectively manage parking lot entry and exit.

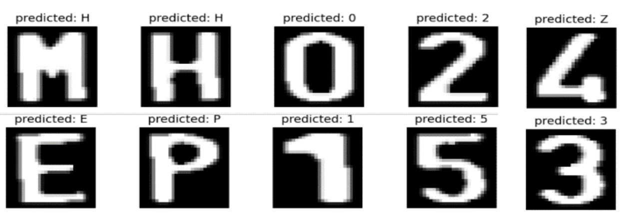

Fig. 11. Character recognition using CNN model.

Fig. 11. shows the different segments of vehicle plate, along with the corresponding photographs and the predictions made by the CNN model for each segment. The results indicate that the CNN model was able to identify the characters in the vehicle plate with 80% correctness.

This level of accuracy is crucial for ensuring that the ANPR model can correctly identify and process the vehicle plates of vehicles entering and exiting the parking lot. With accurate character recognition, the system can efficiently update the parking lot database, record the entry, and exit time stamps, and calculate the fare for registered vehicles.

Overall, the successful detection and recognition of vehicle plate characters using the CNN model is a crucial element of an effective ANPR system, and can help to better the accuracy, efficiency, and security of parking lot management.

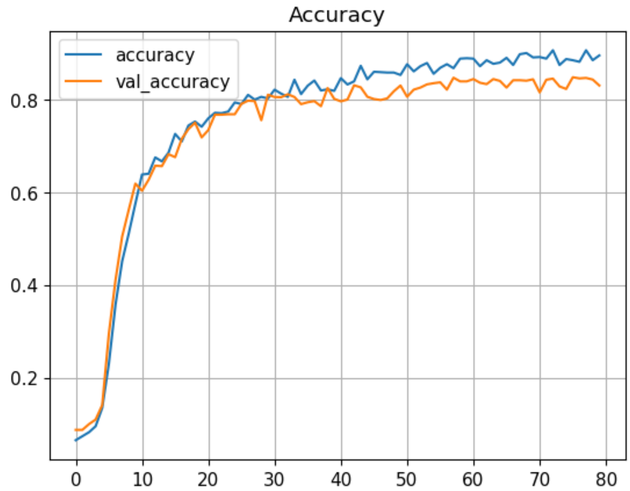

Fig. 12. Accuracy graph of CNN character recognition model

Fig. 12. shows a visual representation of the accuracy of training and validation for the CNN model used for character recognition in the ANPR system. The graph displays the training and validation accuracy during the training procedure.

As we can see from the graph, the training and validation accuracy steadily improve as the system is trained. This tells us that the implemented model is learning to recognize characters more accurately over time.

The high level of accuracy achieved by the CNN model is essential for ensuring that the ANPR model can accurately detect and determine the characters on vehicle number plates.

This accuracy, combined with the precision and recall values achieved by the YOLOv5 model for object detection, provides a strong foundation for the ANPR model to effectively manage parking lot entry and exit, update the parking lot database, and compute the fare for registered vehicles.

Overall, the accuracy results shown in Fig. 12 are an important indicator to show the value of the CNN algorithm to recognize the characters and the effectiveness of the ANPR system.

Fig. 13. Loss graph of CNN character recognition model

Fig. 13 shows the graphical representation of the loss evolution during the training and validation of the CNN model for character recognition in the ANPR system. The graph displays the training and validation loss during the training process. As we can see from the graph, both the training and validation loss steadily decrease with time, demonstrating the model is successfully learning to recognize characters in the input images.

The loss values are an important indicator of the model's performance during training, as they indicate how well the model is fitting the training data. The decreasing loss values in Fig. 13 demonstrate that the model is effectively improving its performance and fitting the training data better over time.

The success of the CNN system in reducing the loss values is an important factor in achieving high-accuracy results, as the model's ability to minimize the dissimilarity among the predicted and actual outputs is critical for successful character recognition. This, in turn, enables the ANPR system to accurately determine and identify the number plates of vehicles and provide effective parking management.

Overall, the loss evolution shown in Fig. 13 is an important indicator of the execution of the CNN model for the recognition of characters and highlights its effectiveness in improving its performance and fitting the training data better over time.

VI. Future Scope

The Parking Management sector is growing rapidly. There are many automations happening in the industry like our current implementation of the ANPR system which has successfully developed the required models for number plate detection and character recognition. As of now we used YoloV5 for number plate detection and CNN for recognition of characters. Moving forward, the next step is to pivot the application side, which will involve creating a user and parking lot admin portal. Users can use this web application to easily locate the nearest parking lot and ensure that there are parking spots available. The application will also offer payment options for parking acknowledgment on the user side. In our existing system we use stripe payment gateway for easy payment interaction.

On the admin side, the parking lot manager will have the privilege of a lot of information and features, such as monitoring the total amount collected, viewing statistics about the parking lot usage, and an emergency entry/exit feature.

There is much room for future improvements, such as integrating the system with smart city infrastructure, improving the accuracy of the models, and enabling real-time monitoring of parking lot occupancy.

The ANPR technology has been rapidly advancing in the recent period and exists many potential areas for future development and application. Some of the possible future scopes for ANPR include:

- Integration with artificial intelligence: By integrating ANPR systems with artificial intelligence, it becomes feasible to enhance the accuracy and reliability of number plate recognition. This can be done through deep learning, machine learning and image recognition. By implementing a system with a high accuracy model will make it more usable.
- Cloud-based ANPR systems: Cloud-based ANPR systems can enable real-time processing and can cut down on the system's computational expense as well. It can help to scale the system across different geographical locations.
- Law enforcement: ANPR technology can be enforced by law enforcement agencies to identify vehicles with outstanding fines, stolen vehicles, or vehicles involved in criminal activities.
- Autonomous vehicles: Due to its ability to recognize and track other on-road cars, ANPR can be extremely useful in the advancement of autonomous vehicles.
- Environmental sustainability: ANPR systems can also be used to control and monitor traffic congestion, which can help to reduce vehicle emissions and improve the environment.
- App based: ANPR system can build as a mobile application will helpful user to use it anytime anywhere easily. Easily finding nearby available parking slot
- Fast Payment: ANPR is currently using stripe payment gateway. In future to make payment fast and secure we can use PayPal, Braintree, and Adyen as a payment Gateway.
- Integrate Blockchain: For make it more secure and fast we can use blockchain. We can make our system a Decentralized App and upscale the efficiency of the product.
- Integration with other technologies: ANPR can be merged with other technologies such as GPS tracking, facial recognition, and machine learning to develop a more powerful system for monitoring and surveillance.

Overall, ANPR has a bright future and the ability to drastically alter many facets of our everyday life.

VII. CONCLUSION

The purpose of this research is to solve problem and challenges associated with car park vehicle identification details formed the basis for this research. The main aim of this research was to develop an automatic number plate recognition system for car park management, using Optical Character Reignition (OCR) on a mobile device. We have also addressed the issue of parking places. Current system goes manually, and we want to be updated it technically that's what we have mentioned all analysis and our work in this paper. Our model performance demonstrates the accuracy of system implementation, achieving 95% improvement over the existing system. We have also shown the potential to have a broad impact on real-world applications.

The completion of the implemented approach resulted in the following benefits:

- Elimination of the hard copy occurrence book and the need to have to physically write onto the book, because all the vehicle details records will be digitized.
- Hastening of the car park vehicle identification process including the entry and exit process, thus shortening the time duration.
- Accurate recording of vehicle information.
- Provides a means of easy information sharing.

In addition, the proposed system has the potential to be extended to various other areas, such as broken number plate recognition, real-time input, and unsupervised parking lots space detection. The system has enormous potential to be applied in various sectors, including educational institutes, commercial complexes, residential areas, airports, stadiums, and event management.

In conclusion, our research paper presented a new parking system that utilized the YOLOv5 object detection algorithm and CNN model to recognize the characters. Our methodology was created to address the drawbacks of earlier parking technologies that depended on human car identification and monitoring.

Our results showed that the YOLOv5 model had a precision of 88.7%, which was significantly higher than the precision of traditional object detection models. Additionally, the CNN model to recognize the characters achieved an accuracy of 89.66%, which was also higher than the precision of traditional character recognition models.

Overall, our model showed significant improvements in the accuracy and precision of parking system operations. By automating the process of identifying and tracking vehicles, our model reduced the risk of human error and provided a more efficient parking management system. This research highlights the potential of using advanced machine learning techniques such as YOLOv5 and CNNs in developing more effective and efficient parking systems.

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