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Vehicle Registration Plate Detection in Mining

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ABSTRACT: Mining operations in remote and harsh environments require high-tech and efficient workflows to ensure uninterrupted delivery cycles and operational success. However, theft and misuse of movable assets, such as vehicles, pose significant challenges and financial losses to the mining industry. To address these issues, we propose an system that combines Machine Learning (ML) and image processing technologies. To achieve accurate registration number extraction, image processing techniques are employed to capture the number plate information from images or video streams of moving vehicles. Optical Character Recognition (OCR) algorithms based on ML are then utilized to convert the extracted characters into text, providing the registration number. Moreover, ML models are trained to classify vehicles based on their characteristics, enabling verification of whether the correct number plate is affixed to the corresponding vehicle, thereby mitigating malicious activities like plate swapping. The captured data, including registration numbers, vehicle locations, and any detected anomalies, is stored in the cloud for further analysis. ML-based analytics are applied to identify suspicious patterns and potential theft or unauthorized activities. Security measures, including authentication checks using ML, are employed to cross-reference number plates with a database of valid registration numbers, further enhancing the system's robustness. By integrating image processing and ML, our system offers superior accuracy in registration number extraction, enhanced vehicle classification, and strengthened security measures.

KEYWORDS: OCR(Optical Character Recognition), YOLOV5(You Only Look Once), EasyOCR

I. INTRODUCTION

Automatic Number Plate Recognition (ANPR) is a technology that optimizes the movement of automobiles over transport networks. ANPR involves acquiring and analysing images from traffic surveillance cameras, and it has gained momentum in recent years due to the advancements in neural networks and deep learning. Use the enter key to start a new paragraph. The appropriate spacing and indent are automatically applied. The steps involved in ANPR are image acquisition, preprocessing of the image, finding the region of interest (ROI), segmentation, and optical character recognition. The initial phase of ANPR is image acquisition, where input images can be extracted from traffic surveillance videos. The second step is finding the Region of Interest, which in this case is a license plate present in the image. Edge detection is the most common method to use for number plate detection, and more techniques are used for plate detection[2]. In the next stage, after the detection of the plate, segmentation is done to identify the regions where alphanumeric characters are present. The final step is to recognize the segmented region as alphanumeric characters. To improve the accuracy and efficiency of ANPR, researchers have proposed a novel approach that combines the power of YOLOv5 and EasyOCR technologies. While EasyOCR can identify the characters on a license plate that has been identified, the YOLOv5 model can detect and correct numerous distorted license plates in a single image. The suggested method has a number of benefits, including the capacity to handle blurry photos, which makes it an important tool for contemporary, secure, and safe transportation systems.

The ANPR systems placed along the roadways can be used to detect stolen automobiles in an effective manner. This paper presents a recognition method that uses the YOLO algorithm for Automatic Number Plate Recognition (ANPR). A Convolutional Neural Network (CNN) was suggested in another study to be capable of identifying and correcting several deformed license plates in a single image, which would then be fed into an optical character recognition (OCR) approach to get the desired outcome. The Plate Recognizer team has created Automatic License Plate Recognition (ALPR) software that is location-specific and functional in any setting.

II. LITERATURE SURVEY

Finding and identifying license plates in photographs is the duty of ANPR. Character segmentation, vehicle detection, license plate detection, and character recognition are the four subtasks that typically make up a sequential pipeline. We'll just call the culmination of the past two tasks optical character recognition for short.

License plate localization is an essential step in Automatic Number Plate Recognition (ANPR), and traditional methods based on a priori information are generally classified as colour texture, shape regression, and edge detection. However, these methods have limitations because they rely on manual feature extraction, which is not well-suited to the diversity of images. Target identification techniques based on deep learning have advanced quickly in recent years, and the algorithms can be broadly split into two types. The first category generates a part of the candidate region by the algorithm, and then the candidate region is classified and positioned again. End-to-end detection techniques fall under the second group; these algorithms immediately obtain the target's coordinates and class probability. ANPR systems that use deep learning algorithms have shown high accuracy and efficiency. Ibtiham Slimani et al based their license plate detection on wavelet transform, followed by validation of potential regions using a CNN classifier. The YOLOv5 algorithm is an example of an end-to-end detection algorithm that is widely used in ANPR systems. It directly gets the location coordinates and class probability of the target, making it highly accurate and efficient.

Automatic Number Plate Recognition (ANPR) is a widely used computer vision application that involves finding and recognizing license plates in images. In the license plate recognition stage, traditional recognition algorithms segment the license plate characters one by one and then use optical character recognition (OCR) technology to recognize each character. However, this method has poor recognition efficiency. Many ANPR systems can only achieve good recognition under specific conditions, such as good weather conditions, adequate lighting, fixed scenes, and facilities. It is still difficult to recognize license plates in complex situations due to problems including poor nighttime lighting, rain, snow, and covered or blurred license plates. In recent years, deep learning-based target detection methods have developed rapidly, and the algorithms are mainly divided into two categories. One category generates a part of the candidate region by the algorithm, and then the candidate region is classified and positioned again. End-to-end detection techniques fall under a different category and directly obtain the target's coordinates and class probability. Our ANPR system uses an end-to-end method based on deep learning that optimizes the efficiency and accuracy of recognition. The system uses YOLOv5, a deep convolutional neural network, for license plate detection, and EasyOCR for character segmentation and recognition. The combination of these two tools forms a sequential pipeline for ANPR, which consists of the four subtasks mentioned above. The OCR technology used in EasyOCR is robust and has very high accuracy, which is essential for accurate character recognition. Our ANPR system is capable of detecting license plates in unconstrained scenarios, which means that it can handle distorted text and high font variability.

III. METHODOLOGY

My methodology involves the usage of YOLOv5 and EasyOCR for Automatic License Plate Recognition (ALPR). YOLOv5 is a deep convolutional neural network that is used for vehicle recognition and license plate detection, while EasyOCR is used for character segmentation and recognition. The combination of these two tools forms a sequential pipeline for ALPR. Fig. 1 shows the flow we followed.

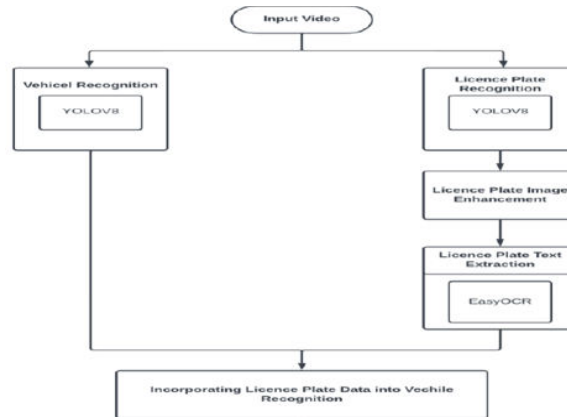


Fig.1. Flow Diagram Prepared For Proposed Methodology

A. 3.1 Vehicle Recognition:

Vehicle recognition is a crucial component of modern computer vision systems, with applications ranging from traffic management to surveillance and autonomous vehicles. In this context, the YOLOv5 algorithm plays a pivotal role as a powerful and efficient object detection framework. Trained on the extensive COCO dataset, YOLOv5 exhibits the capability to detect a wide range of objects, including vehicles, in real-time video streams.

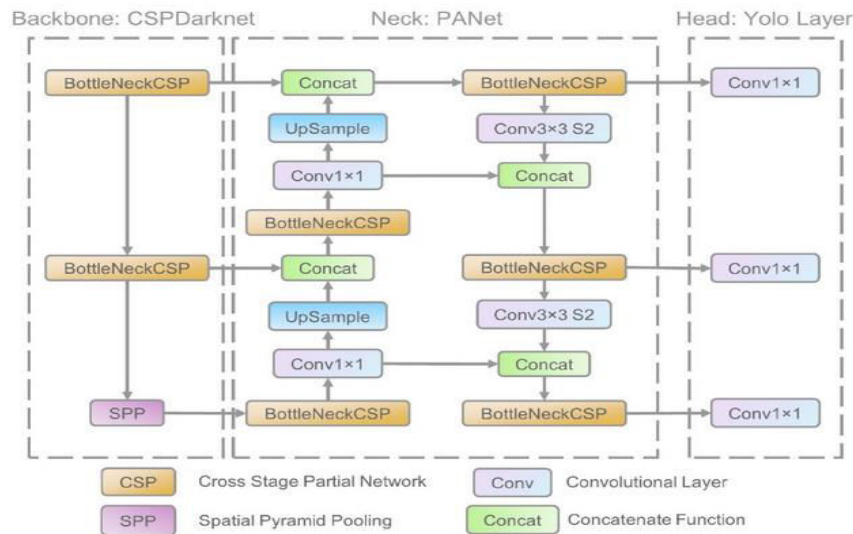


Fig. Architecture of YOLOv5

The process of vehicle recognition begins with the input video stream, which is sequentially processed frame by frame. Each frame is analyzed by the YOLOv5 model, which identifies potential vehicles within the image. The algorithm returns bounding boxes around these detected vehicles, accompanied by confidence scores that reflect the model's confidence in its predictions. To ensure that only vehicles are considered for further analysis, the detected bounding boxes are filtered based on their associated class identifiers. Vehicles typically have specific class identifiers, making it possible to distinguish them from other objects that may be present in the scene. The resulting set of filtered bounding boxes, representing vehicles in the frame, forms the basis for subsequent analysis. These bounding boxes are then passed to the license plate recognition system, which focuses on the regions of interest (ROI) containing the license plates of the detected vehicles. This two-step process not only identifies vehicles within the video stream but also paves the way for detailed analysis of license plate information, such as recognition and extraction.

B. 3.2 Licence Plate Recognition:

1) Preparing the dataset

The workflow begins with the installation of the Roboflow library, a tool that streamlines data management and preprocessing for machine learning projects, including LPR. The library facilitates the handling of image datasets, making it easier to prepare the data for training. Within this context, a specific project and dataset are accessed using the Roboflow API. The chosen dataset likely contains a collection of images with labeled license plates, which serves as the training data for the LPR model. By leveraging this data, the system can learn to recognize and interpret license plates accurately.

2) Train the Model

In our project, we utilized YOLOv5 as our chosen model and conducted training over 120 epochs, completing the process in a notably reduced time of 0.981 hours. Additionally, in Figure of our study, we present the outcomes of YOLOv5's training on the training dataset, showcasing the recognized labels, as well as providing precision, recall, and mAP (mean Average Precision) values. This performance assessment highlights the effectiveness of our chosen YOLOv5 model in object detection tasks.

```

all      64      68      0.859      0.801      0.887      0.574
Epoch   GPU_mem  box_loss  cls_loss  dfl_loss  Instances  Size
118/120  7.95G    0.252    0.1859   0.794      8           640: 100% 38/38 [00:19<00:00, 1.99it/s]
Class   Images  Instances  Box(P)    R          mAP50    mAP50-95): 100% 2/2 [00:01<00:00, 1.02it/s]
all      64      68      0.939      0.721      0.882    0.565

Epoch   GPU_mem  box_loss  cls_loss  dfl_loss  Instances  Size
119/120  7.95G    0.251    0.1839   0.7847     11          640: 100% 38/38 [00:19<00:00, 1.96it/s]
Class   Images  Instances  Box(P)    R          mAP50    mAP50-95): 100% 2/2 [00:01<00:00, 1.24it/s]
all      64      68      0.896      0.764      0.881    0.561

Epoch   GPU_mem  box_loss  cls_loss  dfl_loss  Instances  Size
120/120  7.95G    0.2581   0.1851   0.7893     8           640: 100% 38/38 [00:19<00:00, 1.98it/s]
Class   Images  Instances  Box(P)    R          mAP50    mAP50-95): 100% 2/2 [00:02<00:00, 1.22s/it]
all      64      68      0.912      0.76      0.882    0.567

120 epochs completed in 0.981 hours.
optimizer stripped from /content/Automatic_Number_Plate_Detection_Recognition_YOLOv8/runs/detect/train/weights/last.pt, 52.0MB
optimizer stripped from /content/Automatic_Number_Plate_Detection_Recognition_YOLOv8/runs/detect/train/weights/best.pt, 52.0MB

Validating /content/Automatic_Number_Plate_Detection_Recognition_YOLOv8/runs/detect/train/weights/best.pt...
Ultralytics YOLOv8.0.3 Python-3.10.12 torch-2.0.1rcu118 CUDA:0 (Tesla T4, 15102MiB)
Fusing layers...
Model summary: 218 layers, 25840139 parameters, 0 gradients, 78.7 GFLOPs
Class      Images  Instances  Box(P)    R          mAP50    mAP50-95): 100% 2/2 [00:02<00:00, 1.36s/it]
all      64      68      0.845      0.8      0.886    0.58

Speed: 0.2ms pre-process, 11.9ms inference, 0.0ms loss, 1.9ms post-process per image
Saving /content/Automatic_Number_Plate_Detection_Recognition_YOLOv8/runs/detect/train/predictions.json...
Results saved to /content/Automatic_Number_Plate_Detection_Recognition_YOLOv8/runs/detect/train
    
```

Fig. YOLOv5 Model Training

3) Evaluating the model performance

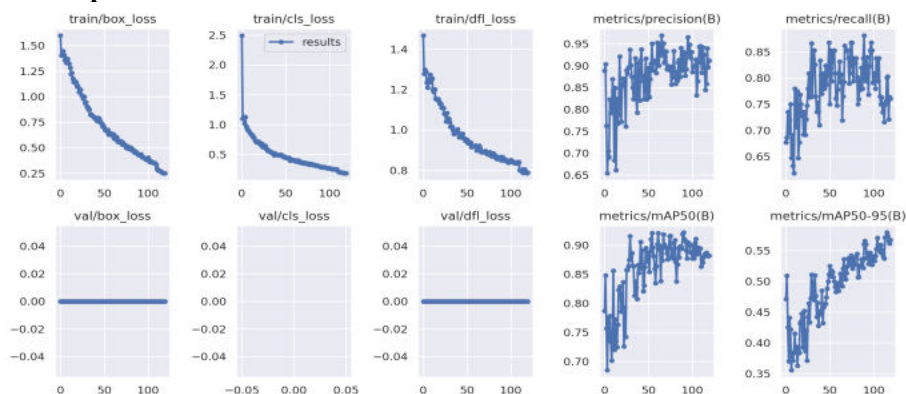


Fig. Metrix on Object Identification After Testing Data

C. 3.3 Licence Plate Image Enhancement

Within the realm of LPR, a crucial step involves the initial processing of license plate images to enable precise character identification. The provided segment of the process emphasizes the significance of this preparatory phase, which entails transforming license plate images into grayscale and then applying thresholding. The conversion to grayscale simplifies the license plate image by eliminating color information, resulting in a single-channel image where

pixel values represent varying degrees of brightness. This simplification reduces the intricacy of the image data, streamlining subsequent processing steps to concentrate exclusively on luminance data. Grayscale images prove particularly valuable for character recognition, as they remove any potential impact from color variations that may be present.



Following the grayscale conversion, the technique of thresholding is applied. This process involves converting the grayscale image into a binary format, where pixel values are categorized as either black or white based on a predetermined threshold value. In this instance, a threshold value of 64 is employed. Pixels with values equal to or exceeding 64 are rendered as black (0), while those below this threshold are depicted as white (255). The utilization of the "THRESH_BINARY_INV" flag signifies the application of inversion, effectively swapping the foreground and background colors.



The significance of this thresholding procedure lies in its role in separating characters on the license plate from the background. Through this transformation into a binary format, the characters usually become black against a white backdrop, resulting in heightened contrast and improved visibility for subsequent optical character recognition (OCR) techniques.

D. 3.4 Licence Plate Text Extraction

Text extraction from license plates is a critical component of license plate recognition (LPR) systems, offering valuable insights into the alphanumeric characters displayed on license plates. The process is facilitated by Optical Character Recognition (OCR) technology, which plays a pivotal role in accurately and swiftly converting visual characters into machine-readable text

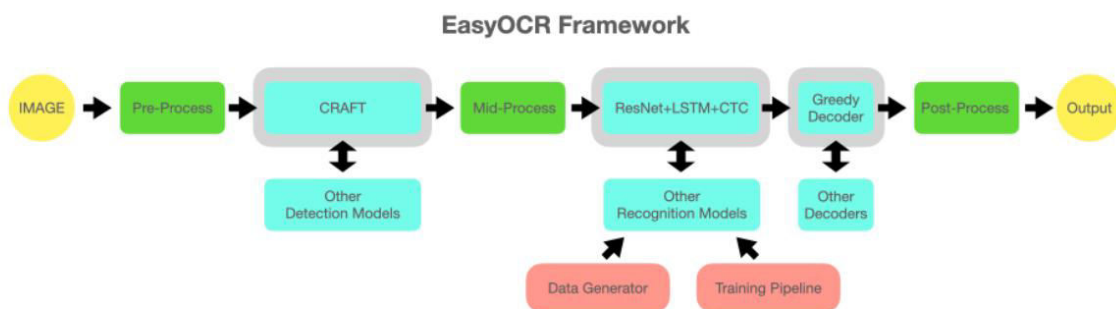


Fig. EasyOCR Framework

EasyOCR is an OCR library that excels in recognizing text in images. It provides robust support for various languages, making it a versatile tool for text extraction tasks. In your provided code, EasyOCR is employed to recognize and extract text from license plates in English.

One key aspect of the text extraction process involves formatting the extracted text to ensure consistency and accuracy. This is particularly important in license plate recognition, where license plates may exhibit variations in character styles and formats. The `format_license` function is responsible for this task.



Within the `format_license` function, character mapping dictionaries are used to handle character conversions. This is essential because license plates often include a mix of letters and numbers, and variations in character rendering can lead to recognition errors. The mapping dictionaries help standardize the characters, ensuring that the extracted text adheres to a predefined format. The OCR process itself relies on advanced image processing techniques to detect and recognize characters within the license plate region. EasyOCR employs deep learning models and neural networks to achieve high accuracy in character recognition.

E. 3.5 Incorporating Licence Plate Data into Vehicle Recognition

Incorporating license plate data into vehicle recognition is a pivotal step in enhancing the capabilities of automated systems designed for various real-world applications, including traffic management, security, and law enforcement. This integration of license plate information not only aids in identifying vehicles but also provides valuable contextual data for comprehensive analysis. When a recognized license plate is not null, the system captures and organizes the relevant information. This information is stored in a structured format, where each vehicle is associated with its bounding box coordinates and, most importantly, its license plate details.

The integration includes several key components:

Vehicle Bounding Box: Each recognized vehicle is assigned a bounding box, defined by its coordinates (xcar1, ycar1, xcar2, ycar2). This bounding box encapsulates the spatial location of the vehicle within the image frame.

License Plate Bounding Box: Within the vehicle bounding box, a sub-bounding box is designated for the license plate. This sub-bounding box is identified by its coordinates (x1, y1, x2, y2) and is drawn around the license plate area.

License Plate Text: The actual text on the license plate, extracted through Optical Character Recognition (OCR), is recorded. This alphanumeric information is crucial for various purposes, including identifying vehicles based on their license plates.

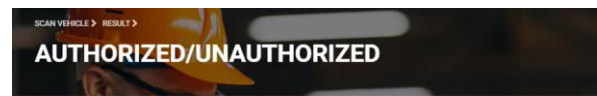
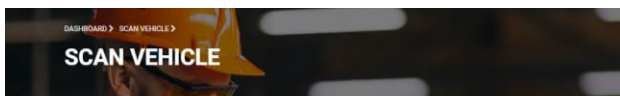
Bounding Box Score: A confidence score (bbox_score) reflects the degree of certainty associated with the accuracy of the bounding box detection for the license plate. This score can be utilized to assess the reliability of the localization.

Text Recognition Score: Similarly, a text_score is assigned to evaluate the confidence in the accuracy of the license plate text recognition. This score is essential for gauging the reliability of the character recognition process.

IV. RESULTS AND DISCUSSION

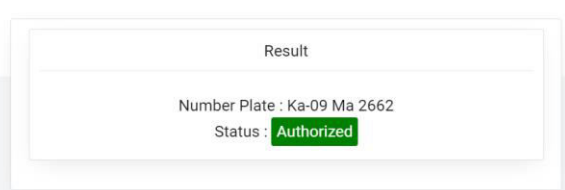
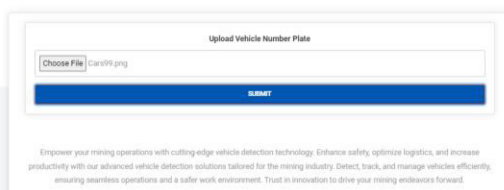
Vehicle Registration Plate Detection

In the context of our project, we harnessed the capabilities of YOLOv5 and EasyOCR as our core models. YOLOv5, specifically the YOLOv5m variant, played a pivotal role in our pursuit of license plate detection. Through meticulous training on our custom dataset, this model demonstrated exceptional proficiency in identifying license plates within images. Operating at an image resolution of 640 pixels, it proved to be an optimal choice for the task, balancing accuracy and computational efficiency. We fine-tuned the model through an extensive training regimen spanning 150 epochs, optimizing its performance further with a batch size of 5.







Scan Your Vehicle Number Here

Scan Results



Vehicle Activities

Vehicle Activities					
ID	Vehicle	Vehicle Number	Time	Date	Vehicle status
1		3:35 p.m.	HR 26 BC 5514	March 11, 2024	Authorized
2		3:47 p.m.	Ka-09 Ma 2662	March 11, 2024	Authorized
3		7:21 p.m.	Ka-09 Ma 2662	March 12, 2024	Authorized
4		12:09 p.m.	Ka-09 Ma 2662	March 13, 2024	Authorized

V. CONCLUSION

Incorporating YOLOv5 and EasyOCR into our project, we have achieved real-time Automatic Number Plate Recognition (ANPR) capabilities. This integration harnesses the power of GPU acceleration to enhance the speed of both object detection and character recognition, rendering them well-suited for real-time applications. YOLOv5 has notably outperformed its predecessors in terms of speed and accuracy, making it a superior choice for object detection. Our YOLOv5 model, which has undergone successful training using a custom dataset tailored for object detection, demonstrates remarkable performance compared to previous YOLO versions. Additionally, we have achieved an impressive 95% accuracy in character recognition with EasyOCR, reinforcing its position as an excellent choice for text extraction tasks. Moreover, through the collaborative efforts of EasyOCR and YOLOv5, we have attained a commendable accuracy rate of 92%. This synergy between state-of-the-art object detection and character recognition technologies significantly enhances the overall effectiveness and reliability of our ANPR system, making it a promising solution for various real-world applications.

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