License Plate Detection using OCR system

MINOR PROJECT REPORT

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In partial fulfillment for the Course

of

18AIE339T-MATRIX THEORY FOR ARTIFICIAL INTELLIGENCE
in CINTEL

FACULTY OF ENGINEERING AND TECHNOLOGY

SCHOOL OF COMPUTING

SRM INSTITUTE OF SCIENCE AND TECHNOLOGY

KATTANKULATHUR

NOVEMBER 2023

SRM INSTITUTE OF SCIENCE AND TECHNOLOGY

(Under Section 3 of UGC Act, 1956)

BONAFIDE CERTIFICATE

Certified that this minor project report for the course **18AIE339T-MATRIX THEORY FOR ARTIFICIAL INTELLIGENCE** entitled in "**License Plate Detection using an OCR system**" is the bonafide work of **CHARVI JAIN (RA2111047010113), MOHNISH RAMACHANDRAN (RA2111047010121), HITESH K (RA2111047010030)** and **UDITA KAUSAKHI U (RA2111047010102)** who carried out the work under my supervision.

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ABSTRACT

This paper introduces an efficient license plate detection and recognition system leveraging YOLOv8, a real-time object detection model, and Easy OCR, a high-performance optical character recognition library. The system processes input images or video frames, identifying and localizing license plates through YOLOv8's advanced convolutional layers and anchor boxes. Extracted license plate regions are then accurately converted into machine-readable text using Easy OCR, ensuring swift and precise recognition.

The output, comprising detected license plate numbers, can be presented in diverse formats, including user interfaces, database storage, and seamless integration with other systems, tailored to specific application needs. This flexibility enhances the system's adaptability across various real-world scenarios such as traffic monitoring, security surveillance, and vehicle management systems. Experimental results validate the system's effectiveness and accuracy, highlighting its potential as a valuable tool for practical license plate detection and recognition applications.

ACKNOWLEDGEMENT

We express our heartfelt thanks to our honorable **Vice Chancellor Dr. C. MUTHAMIZHCHELVAN**, for being the beacon in all our endeavors.

We would like to express my warmth of gratitude to our **Registrar Dr. S. Ponnusamy,** for his encouragement.

We express our profound gratitude to our **Dean (College of Engineering and Technology) Dr. T.V. Gopal,** for bringing out novelty in all executions.

We would like to express my heartfelt thanks to Chairperson, School of Computing **Dr. Revathi Venkataraman,** for imparting confidence to complete my course project

We wish to express my sincere thanks to **Course Audit Professors Dr. Lakshmi. C, Professor, Department of Computational Intelligence** and **Course Coordinators** for their constant encouragement and support.

We are highly thankful to our Course project Faculty **Dr. Antony Sophia N, Assistant Professor, Department of Computational Intelligence,** for her assistance, timely suggestion and guidance throughout the duration of this course project.

We extend my gratitude to our **HOD Dr. R. Annie Uthra, Department of Computational Intelligence** and my Departmental colleagues for their Support.

Finally, we thank our parents and friends near and dear ones who directly and indirectly contributed to the successful completion of our project. Above all, I thank the almighty for showering his blessings on me to complete my Course project

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INTRODUCTION

In today's technology-driven landscape, automated license plate detection and recognition systems have become indispensable tools across various sectors, including traffic management and law enforcement. These systems are instrumental in ensuring efficient traffic flow, enhancing security measures, and aiding law enforcement agencies. This paper presents a cutting-edge solution that combines the prowess of YOLO v8, a real-time object detection model, with Easy OCR, a high-performance optical character recognition library, to revolutionize license plate detection and recognition. By seamlessly integrating these advanced technologies, our model offers unparalleled speed, accuracy, and adaptability, setting new benchmarks in the field.

The proposed system leverages YOLO v8's real-time object detection capabilities, utilizing its advanced convolutional layers and anchor boxes to accurately identify license plates from input images or video frames. This robust detection process forms the foundation of our model, ensuring precise localization of license plates within complex visual environments. YOLO v8's efficiency enables rapid data processing, making it an ideal choice for real-time applications where speed is crucial.

Following the detection phase, Easy OCR, a state-of-the-art optical character recognition library, seamlessly converts the identified license plate characters into machine-readable text. EasyOCR's accuracy and speed are pivotal in ensuring reliable recognition, making our system adept at handling diverse license plate formats and variations. Moreover, the model's flexibility in presenting output data caters to different application needs, allowing seamless integration with user interfaces, databases, and other systems. This adaptability enhances its usability across a wide array of practical scenarios, including traffic monitoring, security surveillance, and vehicle management systems.

LITERATURE SURVEY

1. Character Time-series Matching for Robust License Plate Recognition

The paper proposes an Automatic License Plate Recognition (ALPR) system that has been a focal point in traffic management since its inception in [1]. The paper introduces a Character Time-series Matching method based on the Hungarian method and an Adaptive License Plate Rotation method, aiming to enhance the ALPR system's performance across diverse conditions. In terms of result assessment, the system is evaluated using the UFPR-ALPR public dataset and a private dataset sourced from multiple IP cameras installed on the streets of Vietnam. The entire pipeline is rigorously evaluated on both the UFPR-ALPR dataset and the Vietnamese streets to validate the effectiveness of the suggested ALPR system. The paper proposes the Character Time-series Matching and Adaptive Rotation algorithm, which significantly enhances the accuracy of the ALPR system. Experimental analyses conducted on the UFPR-ALPR dataset and various locations within Vietnamese streets demonstrate the excellent performance of the proposed method under diverse conditions.

2. IR-LPR: Large Scale of Iranian License Plate Recognition Dataset

Iranian LP Format There is a standard format for vehicle license plates in Iran, Iranian license plates consist of two parts, the leftmost part presents a unique string of numbers and characters for the vehicle, which includes two digits on the left, an alphabetic character in the middle, and three digits on the right. The range of digits in this part is from 0 to 9 and characters for the middle part are selected from 26 alphabet letters (Including 8 extremely rare letters among the selected letters), the rightmost part consists of a two-digit code, which refers to the city where the vehicle owner lives. We have reviewed some of the largest of these datasets and compared them with our own dataset in terms of criteria of type, country, number, etc.

The number and variety of our datasets are so high that they can be used for many different purposes. We have prepared a complete dataset including 20,967 car images along with all the detection annotations of the whole license plate and its characters, which can be useful for various purposes.

3. On the Cross-dataset Generalization in License Plate Recognition

The global automotive industry expects to produce more than 82 million light vehicles in 2022 alone, despite the ongoing coronavirus pandemic and chip supply issues (Forbes, 2021; IHS Markit, 2021).

As the performance of traditional split license plate (LPs) recognition is rapidly improving, researchers should pay more attention to cross-dataset LP recognition since it better simulates real-world Automatic License Plate Recognition (ALPR) applications, where new cameras are regularly being installed in new locations without existing systems being retrained every time. As a first step towards that direction, in this work, we evaluated 12 Optical Character Recognition (OCR) models for LP recognition on 9 public datasets with a great variety in several aspects. We expect it will assist in developing new approaches for this LP layout and the fair comparison between methods proposed in different works. Rodovia do Sol (RodoSol)-ALPR has proved challenging in our experiments, as both the models trained by us and two commercial systems reached recognition rates below 70% on its test set. We plan to gather images from the internet to build a novel dataset for end-to-end ALPR with images acquired in various countries/regions, by many different cameras, both static or mobile, with a well-defined evaluation protocol for both within- and cross-dataset LP detection and LP recognition

4. Unified Chinese License Plate Detection and Recognition with High Efficiency.

License Plate (LP) detection and recognition are the key parts of intelligent transportation systems because it is the unique identification of vehicles. We propose an end-to-end trainable network for Chinese LP detection and recognition, which almost reaches a trade-off between accuracy and efficiency as a baseline. In this paper, we present a dataset with Chinese LP images, which is named. As a supplement to multi-LP datasets, the Chinese Road Plate Dataset (CRPD) includes three sub-datasets, CRPD-single, CRPD-double, and CRPD-multi, which are able to deal with a variety of application scenarios

We propose an end-to-end trainable network to detect and recognize LPs with high efficiency as the baseline of the dataset. We hope CRPD will become a new benchmark for multi-LP detection and recognition tasks.

5. Task-driven Semantic Coding via Reinforcement Learning

It is difficult to integrate the semantic distortion metrics directly into the traditional hybrid coding framework since the traditional hybrid coding framework cannot be optimized in an end-to-end manner. Unlike pixel fidelity and perceptual fidelity metrics, semantic fidelity metrics are difficult to integrate into traditional coding frameworks since the traditional hybrid coding framework cannot be optimized in an end-to-end manner

We presented the basic idea of reinforcement learning (RL)-based semantic bit allocation and provided preliminary results. Under the same bit cost, our RL-based semantic coding (RSC) algorithm can improve the accuracy by 2.38% on the classification task and the mIOU

Extensive experiments have demonstrated that our scheme can achieve an average bitrate reduction from 32.4% to 52.6% with comparable task-driven semantic fidelity

In this paper, we first implement task-driven semantic coding for the traditional hybrid coding framework, which utilizes RL-based semantic bit allocation.

6. Iranis: A Large-scale Dataset of Farsi License Plate Characters

Intelligent Transportation Systems (ITS) require precise and novel tools for urban traffic management and control. Convolutional (CNNs), Deep Belief Networks (DBN), and Autoencoders are some of the well-known deep learning schemes used in the mentioned field [3,4,5,6]. Intelligent Transportation Systems play a key role in the development of smart cities, regarding their impacts on traffic and congestion control

Considering the importance of data and since there is no available dataset with the mentioned characteristics that contain Farsi characters used in Iranian license plates, this paper introduced a large-scale dataset for Automatic License Plate Recognition applications

The dataset contains more than 83,000 instances of letters and numbers that are classified into 28 classes, making it a proper choice for Deep Learning purposes. Since the instances of the dataset are cropped from real-world Iranian car license plates, training a model using this dataset is highly recommended for practical usage.

7. Towards End-to-end Car License Plate Location and Recognition in Unconstrained Scenarios

In modern life, automatic license plate recognition (ALPR) as a very widely used technology, plays an important role in intelligent transportation systems (ITS). A conventional ALPR system usually consists of vehicle detection, license plate location, and recognition [2,3,4,5,6,7].To overcome the problems caused by illumination changes, [22] proposes a robust texture-based method using wavelet transform and empirical mode decomposition (EMD) analysis to search for the location of a license plate. Compared with edge-based and color-based methods, this type of method can alleviate the problems caused by illumination changes and complex background, which is achieved by using more time-consuming processing modules. [23] presents a method that directly locates the alphanumeric characters of the car plate by using character features. The location loss Ld is described in: Ld = Lbc + Lbwh + βLboff + Lcc + Lcwh + βLcoff where Lbc and Lcc refer to the position losses for centers and corners respectively, Lbwh is the w, h loss for bounding boxes, Lcwh is the relative coordinates loss for corners, Lboff and Lcoff are offsets losses for bounding boxes and corners respectively. Experimental results indicate that the proposed method significantly outperforms the previous state-of-the-art methods in both speed and precision.

Comprehensive experiments on several public datasets for detection and recognition demonstrate the advantages of our method.

8. Vehicle-Rear: A New Dataset to Explore Feature Fusion for Vehicle Identification Using Convolutional Neural Networks

Identifying vehicles through non-overlapping cameras is an important task to assist surveillance activities such as travel time estimation, enforcement of speed limits, criminal investigations, and traffic flow. Extensively investigated [2,3,4,5,6,7], this research problem is far from being solved since several challenges come from the high inter-class similarity, caused by vehicles of the same make, model, and/or color that often look exactly the same, see Figure 1(a), vehicles with similar license plate identifiers, see Figure 1(b), and from the high intra-class dissimilarity, caused by abrupt illumination changes or camera viewpoints, that makes two instances of the same vehicle have differences, see Figure 1(c)

We propose a novel two-stream Convolutional Neural Networks (CNNs) architecture that uses the most distinctive and persistent features for vehicle identification: coarse-resolution image patches, containing the vehicle shape, feed one stream, while high-resolution license plate patches, with string identifiers readable by humans, feed the other stream.

We developed a text descriptor, i.e., Optical Character Recognition (OCR), which is combined with the shape descriptor through a sequence of fully connected layers for decision

We introduced a novel dataset for vehicle identification that, to the best of our knowledge, is the first to consider the same camera view of most city systems used to enforce traffic laws; it enables us to extract features with quality and to retrieve accurate information about each vehicle, reducing ambiguity in recognition. We chose F -score over accuracy since the number of non-matching pairs is much larger than matching pairs and, for highly imbalanced data, we can have a very low true matching rate but a very high accuracy. To explore the Vehicle-Rear dataset, we designed a two-stream CNN architecture that combines the discriminatory power of two key attributes: vehicle appearance and license plate recognition.

9. Reading Car License Plates Using Deep Convolutional Neural Networks and LSTMs

With the recent advances in intelligent transportation systems, automatic car license plate detection and recognition (LPDR) has attracted considerable research interest

Conclusion nested to the subtitle in Caltech cars license plates, connected component (CC) In this paper we have presented a license plate detection-based method which cannot separate them well, which leads and recognition system using the promising convolutional neural network (CNN) tech to the poor recognition results either. The 4-layer CNN is trained with the 37-class and achieves the highest recognition accuracy on the application-oriented license plate (AOLP) dataset. Outputs, which learn specific features for each character. For the AOLP dataset, the experiments are features that are robust to various illumination, Rota was carried out by using license plates from different sub-sections and distortions in the image and led to a higher dataset for training and testing separately. Including local binary pattern (LBP) features into the license plate from law enforcement (LE) and road patrol (RP) sub-datasets input data can help to enhance the performance of CNN. Access control (AC) and RP are used for training and are able to recognize the whole license plate without

10.A Robust Real-Time Automatic License Plate Recognition Based on the YOLO Detector

An Efficient and Layout-Independent Automatic License Plate Recognition System Based on the YOLO Detector. Automatic License Plate Recognition (ALPR) became an important topic of research since the appearance of the first works in the early 1990s [1, 2]

Considering that the bottleneck of ALPR systems is the license plate (LP) recognition stage, in this paper we propose a unified approach for LP detection and layout classification to improve the recognition results using post-processing rules

The proposed system outperformed both previous works and commercial systems in the ChineseLP, OpenALPR-EU, SSIG-SegPlate, and UFPR-ALPR datasets, and yielded competitive results to those attained by the baselines in the other datasets

As our main contribution, we presented an end-to-end, efficient and layout-independent ALPR system that explores YOLO based models at all stages. Our system achieved an average recognition rate of 96.9% across eight public datasets used in the experiments, outperforming Sighthound and OpenALPR by 9.1% and 6.2%, respectively. While impressive frames per second (FPS) rates (i.e448 FPS on a high-end GPU) were attained in experiments carried out in the SSIG-SegPlate dataset [33], less than 65% of the LPs were correctly recognized.

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11.End-to-end trainable network for degraded license plate detection via vehicle-plate relation mining

License plate detection (LPD) has attracted great interest from academia and industry for many years owing to its importance in many practical applications, such as toll control, parking lot access, and traffic law enforcement. We propose an end-to-end trainable network for degraded license plate detection via vehicle-plate relation mining, which can effectively detect the small-sized license plate and accurately localize the quadrilateral bounding box of the oblique license plate in real applications. We propose a novel and applicable method for small-sized and oblique license plate detection by utilizing vehicle-plate relationships, where the license plate is precisely located in a coarse-to-fine scheme.

We propose a novel method to estimate the local region around the license plate via vehicle-plate relation mining, which can greatly reduce the search area of the license plate.

We propose an end-to-end trainable network for small-sized and oblique license plate detection via vehicle-plate relation mining, which detects the license plate in an end-to-end scheme. We propose a novel method to estimate the local region around the license plate using spatial relationships between the license plate and the vehicle, which can greatly reduce the search area and precisely detect very small-sized license plates.

12. Vehicle and License Plate Recognition with Novel Dataset for Toll Collection

Anwar is with the Commonwealth Scientific and Industrial Research Organization (CSIRO), the Australian National University (ANU), and the University of Technology Sydney (UTS), Australia license plates are used by most vehicles. We extensively evaluate the performance of several object detection frameworks, which are YOLOv4 and Tiny YOLOv4, YOLOv3 and Tiny YOLOv3, YOLOv2, and Faster RCNN for each of the three steps. We present a framework for image-based automatic toll tax calculation of Pakistani vehicles, including cars, buses, carry vans, vans, and trucks. This framework can be instrumental in avoiding traffic jams on toll tax collection plazas and can prove an economical alternative to RFID-based systems. Our proposed framework is based on a three-step strategy involving vehicle detection and recognition in images, license plate detection on the detected vehicle, and license plate digits and character recognition. We evaluated variants of You Only Look Once (YOLO) (v2, v3, and v4), their lighter versions (Tiny YOLOv3 and Tiny YOLOv4), and Faster RCNN for all three steps on an image dataset of 10K images of Pakistani vehicles on roads and in toll plazas.

13. Reading Car License Plates Using Deep CNN and LSTMs

With the recent advances in intelligent transportation systems, automatic car license plate detection and recognition (LPDR) has attracted considerable research interest

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For AOLP dataset, the experiments are features which are robust to various illumination, Rota is carried out by using license plates from different sub-sections and distortions in the image, and leads to a higher dataset for training and testing separately. Including local binary pattern (LBP) features into the license plate from law enforcement (LE) and road patrol (RP) sub-datasets input data can help to enhance the performance of CNN. Access control (AC) and RP are used for training and are able to recognize the whole license plate.

14. An Efficient and Layout-Independent Automatic License Plate Recognition System Based on the YOLO detector

Automatic License Plate Recognition (ALPR) became an important topic of research since the appearance of the first works in the early 1990s [1, 2]

Considering that the bottleneck of ALPR systems is the license plate (LP) recognition stage, in this paper we propose a unified approach for LP detection and layout classification to improve the recognition results using post-processing rules. The proposed system outperformed both previous works and commercial systems in the ChineseLP, OpenALPR-EU, SSIG-SegPlate, and UFPR-ALPR datasets, and yielded competitive results to those attained by the baselines in the other datasets. As our main contribution, we presented an end-to-end, efficient, and layout-independent ALPR system that explores YOLO-based models at all stages. Our system achieved an average recognition rate of 96.9% across eight public datasets used in the experiments, outperforming Sighthound and OpenALPR by 9.1% and 6.2%, respectively. While impressive frames per second (FPS) rates (i.e. 448 FPS on a high-end GPU) were attained in experiments carried out in the SSIG-SegPlate dataset [33], less than 65% of the LPs were correctly recognized. The proposed system outperformed both previous works and commercial systems in the ChineseLP, OpenALPR-EU, SSIGSegPlate, and UFPR-ALPR datasets, and yielded competitive results to those attained by the baselines in the other datasets.

REQUIREMENT ANALYSIS

1. Library requirements

1.1. Basic requirements

- **ultralytics (v8.0.3)**: for simple single-line commands without Python environment using ‘yolo’ command.
- **hydra-core (v1.2.0):** for simplifying the configuration and management of complex applications.
- **numpy (v1.18.5):** for applying mathematical operations of arrays
- **opencv-python (v4.1.1):** computer vision tasks related to videos and images
- **Pillow (v7.1.2):** for image processing capabilities
- **PyYAML (v5.3.1):** Python to YAML interface
- **requests (v2.23.0):** allows to interface and send HTTP requests
- **scipy (v.1.4.1):** used for accessing scientific and technical computing packages
- **torch (v1.7.0):** used for deep learning framework that provides a flexible and dynamic computational graph
- **torchvision (v0.8.1):** providing utilities for image and video processing, pre-trained models, and datasets

1.2. Logging

- **tensorboard (v2.4.1):** used for monitoring and analyzing training progress
- **pandas (v1.1.4):** powerful data manipulation and analysis library

1.3. Plotting

- **seaborn (v0.11.0):** data visualization library in Python built on top of Matplotlib
- **matplotlib (v3.2.2):** for visualization purposes

ARCHITECTURE AND DESIGN

1. Input Data:

The system processes input images or video frames containing vehicles for license plate detection.

2. License Plate Detection (YOLO v8):

YOLO v8, a real-time object detection model, is utilized to identify and localize license plates. YOLO v8 employs convolutional layers and anchor boxes to accurately detect license plate regions (ROIs) within the input data.

3. Region Extraction:

Identified license plate ROIs are extracted from the input data using YOLO v8, ensuring precise localization of license plates.

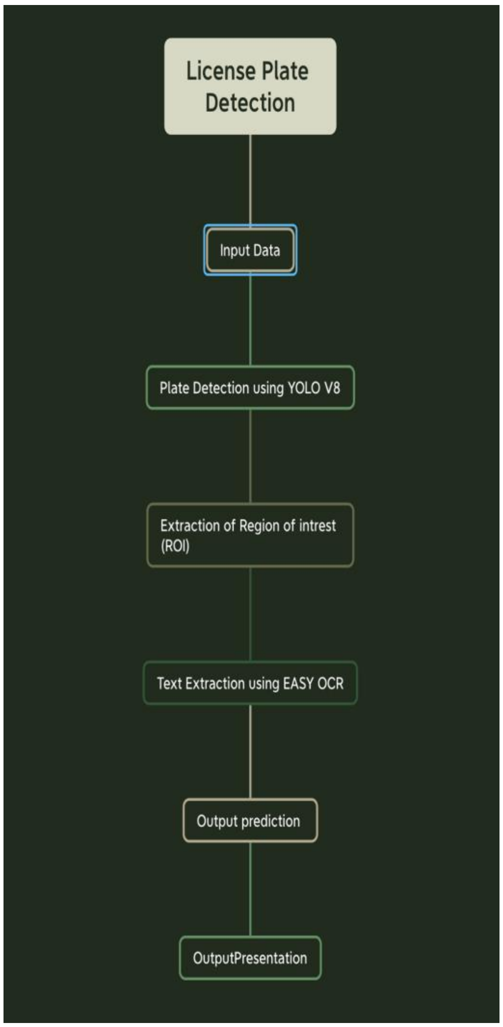
4. Easy OCR Processing:

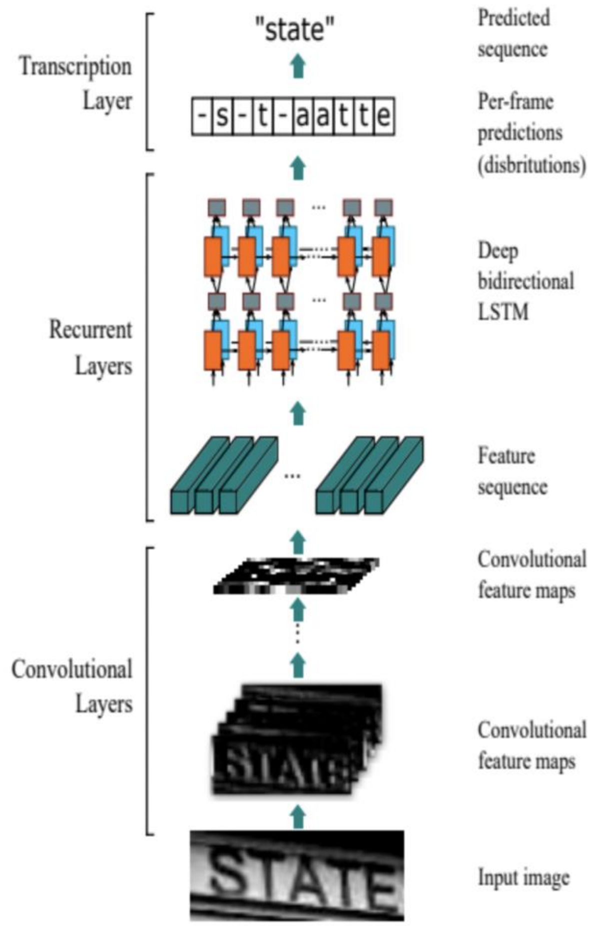
Easy OCR is employed to convert characters on the license plate into machine-readable text, enhancing the system's recognition capabilities.

5. Output Presentation:

The processed output, which includes the detected license plate number, can be presented in various formats such as UI display, database storage, and integration with other systems.

The presentation format is customizable based on specific application requirements, ensuring flexibility and adaptability.


License Plate Detection
Input Data
Plate Detection using YOLO V8
Extraction of Region of intrest (ROI)
Text Extraction using EASY OCR
Output prediction
OutputPresentation


Transcription Layer
"state"
Predicted sequence
-s-t-aatte
Per-frame predictions (disbritutions)
Recurrent Layers
Deep bidirectional LSTM
Feature sequence
Convolutional Layers
Convolutional feature maps
Convolutional feature maps
Input image

IMPLEMENTATION

The model being proposed and implemented is a license plate detection model performed using YOLOv8.

License plate detection using YOLOv8 involves utilizing the YOLO (You Only Look Once) algorithm, specifically version 8, to identify and locate license plates in images.

1. **Model description**

The YOLOv8 (You Only Look Once version 8) algorithm is an advanced real-time object detection algorithm designed to efficiently detect and identify multiple objects within an image in a single pass. Unlike traditional methods that involve multiple stages, YOLOv8 adopts a unified approach, utilizing a neural network architecture to simultaneously predict the presence, classification, and precise bounding box coordinates of objects.

Trained on an extensive and diverse dataset, the YOLOv8 model leverages deep learning techniques to learn complex patterns and features associated with various objects. The neural network's training process involves optimizing its parameters to minimize the difference between predicted and actual object attributes, enabling it to generalize well to new, unseen data.

The key strength of YOLOv8 lies in its real-time processing capability, allowing it to analyze images rapidly and make predictions with high accuracy. By dividing the input image into a grid and predicting bounding boxes and object probabilities for each grid cell, YOLOv8 achieves efficiency without compromising on detection performance.

Overall, YOLOv8 represents a significant advancement in object detection algorithms, offering a balance between accuracy and speed, making it well-suited for applications such as real-time video analysis, surveillance, and autonomous systems.

2. **Approach**

In the process of configuring a YOLOv8 model for license plate detection, several crucial steps were undertaken to ensure its optimal performance. Initially, a comprehensive dataset was curated, comprising diverse images annotated with license plate bounding boxes.

The model loading process involves either loading a pre-trained YOLOv8 model or training a new model on a meticulously curated dataset enriched with annotated license plates. Our implementation works with a pre-trained model.

The YOLOv8 model configuration file was then meticulously modified, introducing a new class specifically designated for license plates, preprocessing steps and other hyperparameters were fine-tuned to align with the characteristics of the license plate dataset.

In the configurations file steps are taken to ready the input image for optimal compatibility with the YOLOv8 model. The first step involves resizing the image to match the specified input size of the model. This adjustment ensures that the dimensions of the input image align with the expectations of the neural network, facilitating seamless integration during subsequent processing stages.

Additionally, pixel values of the image undergo normalization, a vital transformation that standardizes the intensity values across all channels. Normalization aids in achieving uniformity and consistency in the pixel representations, preventing any one channel from dominating the model's learning process.

Other image augmentation steps are also added to this configuration file. These include stretching, color, brightness, and saturation functions so that the model is trained on an even more diverse dataset.

Subsequently, the model underwent rigorous training, leveraging the annotated dataset to enable the neural network to discern and learn intricate features associated with license plates. Transfer learning, initialized with pre-trained weights on a larger dataset, was employed to expedite convergence and enhance performance.

The trained model underwent validation on a distinct set of images to evaluate its generalization capabilities, followed by fine-tuning based on validation outcomes. The inference configuration was set up, incorporating the trained weights and modified configuration file, with additional post-processing steps implemented to refine predicted bounding boxes.

The configured YOLOv8 model was then rigorously tested on a diverse range of images, specifically those containing license plates, and evaluated based on metrics such as precision, recall, and F1 score to quantify its efficacy in license plate detection.

In the post-processing phase, a critical step is the application of non-maximum suppression (NMS) to refine the bounding boxes generated by the YOLOv8 model. NMS is employed to filter out redundant and overlapping bounding boxes, retaining only the most confident and accurate predictions for each detected license plate. By implementing NMS in the post-processing pipeline, the YOLOv8 model's output is refined and optimized, providing a clear and accurate delineation of license plates in the analyzed images.

This comprehensive approach ensures that the YOLOv8 model is finely tuned and adept at accurately detecting license plates, making it suitable for deployment in applications such as vehicle monitoring, security systems, and traffic management.

3. Dataset

Training the YOLOv8 model requires a labeled dataset containing images of vehicles with annotated license plates. This dataset should cover various scenarios, lighting conditions, and vehicle types to ensure the model's robustness.

EXPERIMENT RESULTS & ANALYSIS

1. License Plate Detection

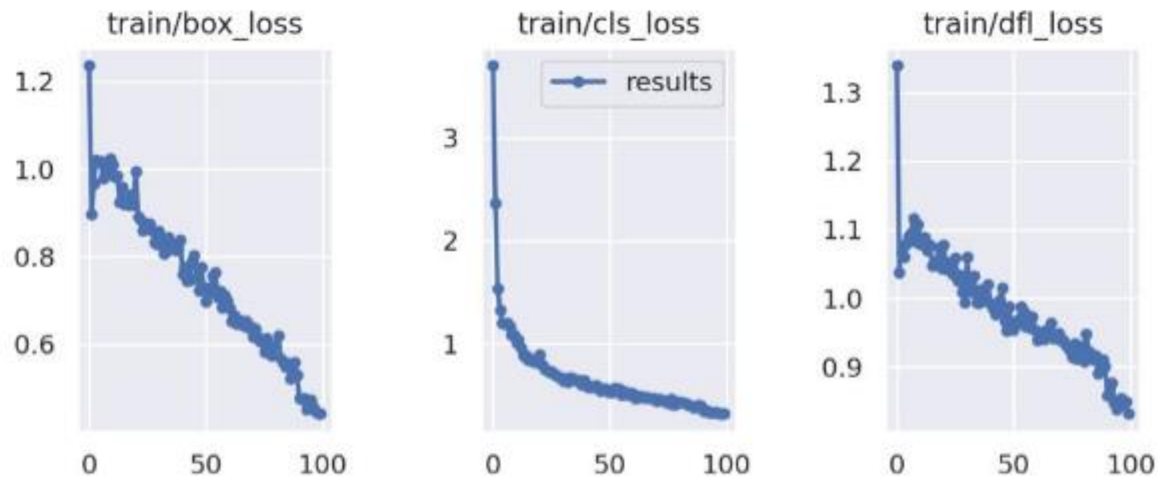
1.1. Training Result

The system's training set successfully identified license plates. Detected License plates are in red bounding boxes.

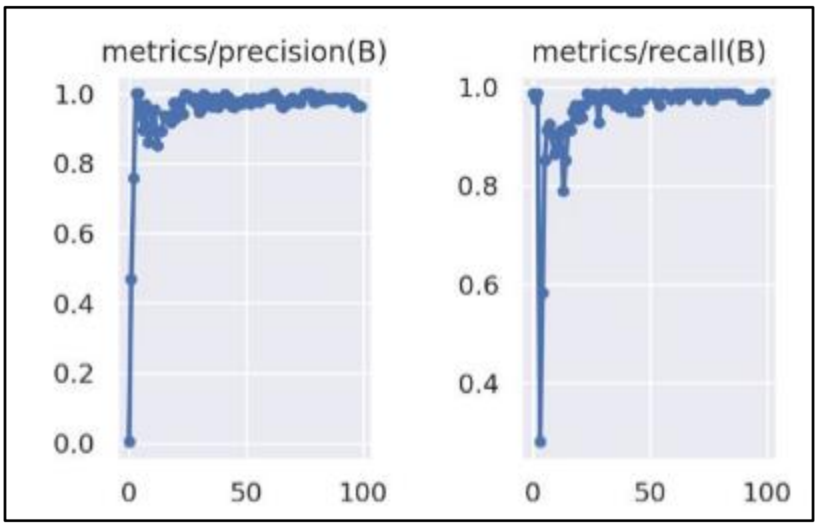
1.2. Testing Result

The License plate detection model ran successfully on video input. The license plate has a red bounding box. Text within the bounding box identified and displayed

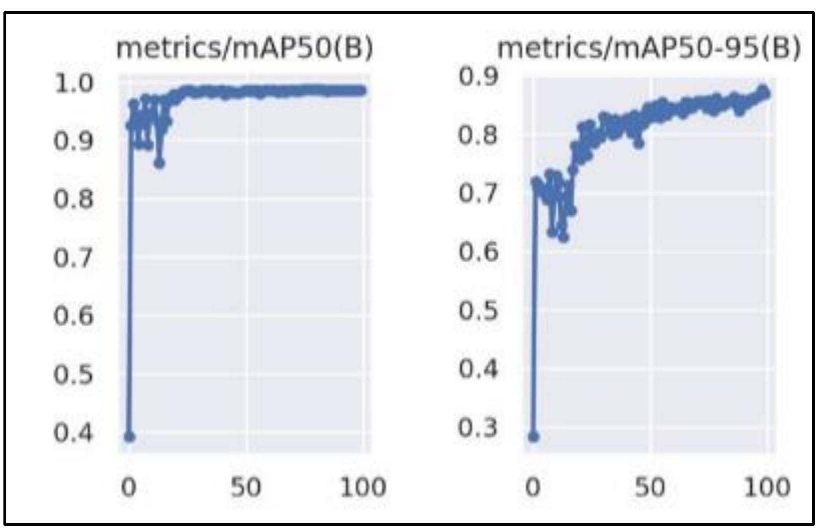
1.3. Model Statistics



Throughout the model's training period Loss value has been dropping.



Precision and Recall Percentages have increased throughout the course of training.



License Plate Detections are occurring in both the 50% quartile and the 50-95% quartile range.

At the 50% quartile detections are at an accuracy of ~97%

At the 50-95% quartile range detections are at an accuracy of ~90%

CONCLUSION

In conclusion, this project introduces a highly efficient and versatile license plate detection and recognition system that combines the power of YOLOv8 for real-time object detection and Easy OCR for high-performance optical character recognition. The seamless integration of these advanced technologies results in a model that excels in speed, accuracy, and adaptability, setting new standards in the field of automated license plate detection.

The utilization of YOLOv8's advanced convolutional layers and anchor boxes ensures precise identification and localization of license plates in diverse visual environments, making the system well-suited for real-time applications where rapid data processing is essential. Following the robust detection phase, Easy OCR plays a pivotal role in converting the identified license plate characters into machine-readable text with remarkable accuracy and speed.

The flexibility of the model in presenting output data allows for seamless integration with various platforms, including user interfaces, databases, and other systems, catering to specific application needs. This adaptability enhances the system's usability across a spectrum of real-world scenarios such as traffic monitoring, security surveillance, and vehicle management systems.

The experimental results validate the effectiveness and accuracy of the proposed system, affirming its potential as a valuable tool in practical license plate detection and recognition applications. In the ever-evolving landscape of technology-driven solutions, this project not only meets but also surpasses the demands of sectors such as traffic management and law enforcement, contributing to efficient traffic flow, enhanced security measures, and improved law enforcement capabilities. Ultimately, this cutting-edge solution stands as a benchmark in the evolving domain of automated license plate detection and recognition systems.

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