SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V11I8P124

Volume 11 Issue 8, 264-274, August 2024

Review Article

Diving Deep: A Survey of Deep Learning Techniques for Anomaly Detection in Automatic Vehicle Number Plate Recognition Systems

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Received: 11 June 2024 Revised: 14 July 2024 Accepted: 11 August 2024 Published: 31 August 2024

Abstract - *Automatic Vehicle Number Plate Recognition (AVNPR) has witnessed a transformative journey from rule-based methods to deep learning techniques, reshaping its efficacy in diverse applications. This comprehensive review outlines the application of CNNs and RNNs in key aspects of AVNPR, including license plate localization, character segmentation, and recognition. The importance of high-quality datasets in training these models is emphasized. While deep learning has greatly enhanced accuracy, challenges such as computational intensity and privacy concerns require careful consideration. This paper gives the roadmap for researchers, practitioners, and policymakers, delineating the current landscape and ethical considerations. AVNPR technology, which identifies vehicles through their number plates, faces challenges related to non-standardized formats, complex scenes, and environmental conditions, necessitating additional hardware for optimal deployment despite the use of advanced algorithms. Beyond traditional plate recognition, this system integrates anomaly detection to enhance its capabilities in diverse real-world scenarios. Incorporating anomaly detection techniques allows the system to identify and report irregularities, outliers, and unexpected events, ensuring heightened accuracy and reliability. This research aims to pay attention to the deep learning algorithms by reviewing prior work, analyzing extraction, segmentation, and recognition techniques, and offering insights into upcoming trends in this domain.*

Keywords - *Anomaly detection, AVNPR, CNN, Deep learning, RNN.*

1. Introduction

These years, the proliferation of advanced technologies, coupled with the growing need for higher security and efficiency in transportation systems, has driven the development of innovative solutions in the field of Automatic Vehicle Number Plate Recognition (AVNPR). AVNPR is a subset of computer vision and image processing that localizes license plate images without human involvement [1]. The system holds huge potential for revolutionizing various applications in intelligent transportation systems ranging from road law enforcement and traffic management to parking automation and toll collection [2].

At the heart of this transformation lies the notable progress made in deep learning techniques, which have demonstrated exceptional capabilities in handling complex visual tasks. Traditional AVNPR systems often relied on hand-crafted features and rule-based algorithms, which posed limitations in terms of adaptability to varying lighting conditions, plate formats, and image quality. Anomaly detection emerges as a promising approach to give the limitations of conventional ANPR systems. By identifying irregularities, outliers, and unexpected patterns in the data, anomaly detection techniques help improve ANPR systems' accuracy and flexibility. In addressing the limits of license plate recognition in real time and enhancing its performance, this paper introduces a CNN-based approach tailored for IoT edge technology. Experimental results demonstrate a notable improvement, elevating the detection rate to 88% from the initial 77% in real-time scenarios with unlimited situations [3].

This paper explores the combination of anomaly detection techniques in the ANPR framework, with a focus on addressing challenges such as obscured plates and non-standard plate placements. The advent of deep learning methodologies, particularly CNN and RNN, has brought about a paradigm shift in AVNPR by enabling automated feature extraction, robust generalization, and superior recognition accuracy. This review paper aims to provide a complete survey of the significant advancements in AVNPR achieved by utilizing Deep Learning (DL) techniques.

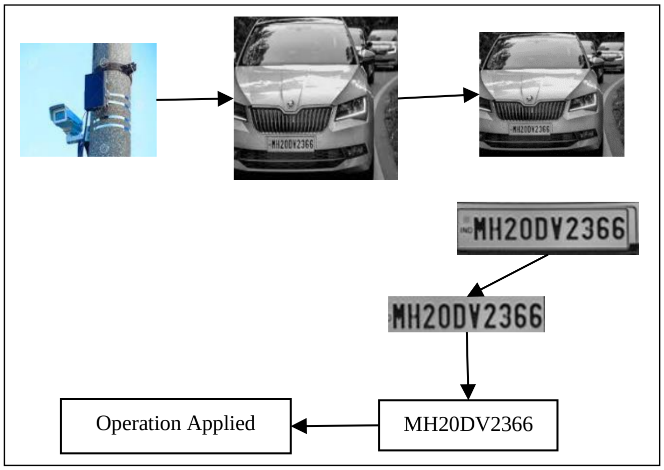

Fig. 1 An overview of AVNPR

This paper embarks on a journey through the evolution of AVNPR systems, from their rudimentary forms to the sophisticated deep learning-based approaches that dominate the current landscape. This delves into the underlying principles of CNNs and RNNs, explaining their suitability for various AVNPR-related tasks, including license plate localization, character segmentation, and character recognition.

Furthermore, this research explores the pivotal role of large-scale annotated datasets in training deep AVNPR models and discusses the nuances of data augmentation techniques that enhance the model's robustness. In addition to highlighting the achievements and critically assessing the challenges at the toll collection, correct vehicle number plate identification, which persists in the domain of AVNPR using deep learning. These include the need for considerable computational resources during training, the scarcity of diverse and representative datasets, and privacy concerns associated with the potential misuse of AVNPR technology. Addressing these challenges is imperative for the responsible and ethical deployment of AVNPR systems on a broader scale.

As we navigate through the various techniques, architectures, and strategies employed in deep learning-based AVNPR, which also emphasize real-world daily problems like parking the vehicle NP in the wrong place, these applications and success stories underscore the applied consequence of this technology. By consolidating and analyzing the existing body of knowledge, this review paper seeks to provide researchers, practitioners, and policymakers with a complete understanding of the current state, potential avenues, and limitations of automatic number plate recognition using DL techniques.

In the subsequent sections, delve into the specific categories of AVNPR tasks, showcasing how deep learning models have broken the boundaries of recognition accuracy, real-time processing, and adaptability to dynamic environments. Intelligent road transmission, especially in India or highly populated countries, provides the path for ambulances by monitoring road congestion through the AVNPR system, which is also a major issue. This exploration is presented in a table that contains a list of datasets that can be used by researchers working in the same direction.

Table 1. List of datasets

Dataset	Description	Instances	Year
SSIG – SegPlate [7]	Include Brazilian images for the license plate character segmentation problem.	2000 Brazilian license plates	2016
CD – HARD [8]	Include 102 car images from various geographic regions	102 images	2018
UFPR – ALPR [9]	Include images from 150 moving vehicles where the camera is also moving.	4500 fully annotated images over 30,000 license plate characters	2018
CCPD [10]	Include images of the roadside parking management company in the Chinese region.	Over 250K images	2018
NI-VI [11]	Include North Iraq vehicle images with Arabic fronts	1500 images	2019
CLPD [12]	Include images of cars, trucks, and buses of Chinese vehicles.	1200 images	2020
RodoSol – ALPR [13]	Include images captured by a static camera that contains information on vehicle type, plate layout, text, and position of four corners.	20000 images	2022
Indian Vehicle Datasets [14]	Include 383 raw images of Indian vehicles	383 images	2022

2. Related Review work

The field of AVNPR has witnessed extensive research and development across widespread domains and applications. This section delivers an overview of related work, highlighting key studies and contributions in the realm of AVNPR.

2.1. Intelligent Transportation, Traffic Management and Surveillance

AVNPR has been extensively applied in traffic management and surveillance systems. Research by Zhu. et al. (2018) [4] discussed the importance of estimated travel time for traffic management and intelligent transportation systems. The researchers also analyzed data from various sources to evaluate the accuracy of travel time.

M. Molina–Moreno et al. (2018) [7] addressed the issue of license-plate detection in the context of traffic surveillance. Researchers have proposed a novel scale-adaptive deformable part-based model, which, based on a well-established boosting algorithm, automatically adapts to scale during the training phase by selecting the most salient features at each scale. This method notably enhances detection efficiency by eliminating the need to evaluate at multiple scales.

Z. Akhtar et al. (2020) [10] introduced the AVNPR system, which is crucial for traffic management and requires efficient performance in noisy and low-light conditions. For the same, the researchers introduced a method with four key steps: 'preprocessing', 'number plate localization', 'character segmentation', and 'character recognition', achieving an accuracy of 90.9% in experimental testing. A.N. Alam et al. (2021) [13] emphasized the AVNPR system integrated with traffic monitoring. The researchers have used deep learning techniques for the same. The researchers have focused on low-resolution images and plates written in Bengali.

2.2. Toll Collection and Electronic Payments

In the domain of toll collection and electronic payments, AVNPR technology has revolutionized the efficiency of toll booths. Research by T. Mushiri et al. (2018) [5] addressed toll collection with enhanced security. For the same, computer vision and machine learning have been employed by researchers. The researchers have analyzed Zimbabwe's Road networks and stated that they need to automate the toll collection system. M.C. Sai et al. (2019) [9] discussed real-time security in military areas using image processing. The system captures vehicle images and processes them through segmentation, OCR, and template matching to recognize characters of number plates.

The recognized data is then compared to a database. T. Ahmed et al. (2021) [14] introduced RFID and the method of image processing automated toll collection and a road zipper device for efficient lane management. A two-step-based toll collection system minimizes traffic congestion, enhances automation, and facilitates the creation of a more intelligent transportation system. B. Hingorani et al. (2023) [22] introduced a YOLOv7 with an Optical Character Recognition (OCR) solution for real-time recognition of Indian number plates, offering a mobile application to streamline the toll booth process and minimize commuter waiting times.

P.S. Kiran et al. (2023) [24] focused on enhancing the Fast-Tag system to eliminate toll booths, saving time for travelers. The automated toll collection system relies on vehicle number recognition, utilizing OpenCV and the Tesseract OCR Engine to read license plates, identify vehicles, and send toll amounts to car owners via SMS, offering a streamlined and efficient toll payment process.

2.3. Parking Management Systems

AVNPR plays an essential role in parking management systems. Studies by N. Omar et al. (2020) [11] introduced an AVNPR-based parking management system in northern Iraq, and for the same, researchers have used a deep learning technique. A.A. Ahmed et al. (2021) [15] introduced the AVNPR System for vehicles that are illegally parked or violate some traffic regulations. For the same, researchers have developed an Android mobile app that captures the image of the towed car and allows car owners to find their vehicles and pay fines if needed.

I. Swami et al. (2021) [16] introduced an intelligent car parking management system to reduce the traffic on the roadside. Researchers tried to find out the number plate of vehicles entered and matched it with the database, and they provided slots to the car owner for parking. If the vehicle is new, then an LED glows to notify the parking manager that the vehicle is allowed to park in the visitors' area.

N.A. Abdul Rahman et al. (2022) [18] focused on both platforms (website and user application) based on a parking management system that allows users to book spots in vacant parking areas. The researchers also used integrated security measures with parking management to monitor suspicious activities in the driver's account.

R.K. Chauhan et al. (2022) [19] discussed the AVNPR-based Indian toll collection system. The author has tried to make a database for toll collection, which includes vehicle owners, their mobile number, their identity, and their linked bank account numbers, which results in traffic in the toll plaza.

2.4 Law Enforcement and Security

Law enforcement agencies have widely adopted AVNPR for vehicle tracking and security applications. The research introduced an ANVPR system that depends on image processing algorithms that impose security without using RFID techniques. The system uses different algorithms for localization, normalization, orientation, segmentation, and recognition. L.S. Pretty Joy (2019) [8] introduced the AVNPR system to identify license plates, recognize characters, and determine vehicle types. The main goal of researchers is to identify fake numbers of plates as the increasing traffic on roads necessitates an automated traffic management system. A video-based system for collecting data on multiple vehicle types is essential for monitoring traffic under various conditions. The organization can cross-reference this data with a database to identify fake plates and wanted vehicles, sending alerts to the police headquarters as needed.

A.F. Aiyelabegan et al. (2022) [17] focused on traffic violations and road-related crimes because of Nigeria's rising population and the subsequent increase in vehicles on the road. These issues contribute to road insecurity and the difficulty of vehicle tracking for law enforcement. Researchers introduced an ANPR system utilizing Machine Learning Techniques, offering a potential solution to enhance security and traffic management. P. Srikanth et al. (2022) [20] employed a system that goes past traditional methods by effectively handling distorted license plates, achieving high accuracy in license plate recognition through innovative image processing and deep learning techniques. This model enhances security by automating vehicle authentication to prevent unauthorized access to sensitive areas.

2.5. Advancements in Deep Learning

Advancements in deep learning have driven significant progress in AVNPR accuracy and robustness. S Shah et al. (2018) [6] introduce a novel automated vehicle number plate detection system with high accuracy (98.75%), which includes preprocessing, localization, extraction, segmentation, and character recognition phases, utilizing a neural network for character recognition.

Z. Selmi et al. (2020) [12] introduced an automatic framework that leverages mask region convolutional neural networks for robust LP detection, segmentation, and recognition, distinguishing itself by integrating all three stages. The framework's performance is rigorously evaluated across multiple datasets, encompassing various languages and challenging conditions, demonstrating its robustness and efficiency. Remarkably, the system achieves an impressive accuracy rate of 99.3% on AOLP and 98.9% on the Caltech dataset, highlighting its effectiveness in ALPR tasks.

R. Adak et al. (2022) [21] employed an AVNPR system using the YOLOv3 – CNN pipeline that efficiently detects number plates while handling various environmental factors such as perception angle, luminosity, etc. A.S. Tote et al. (2023) [23] presented a computer vision-based automatic number plate detection system utilizing TensorFlow for training and testing. The approach achieves an 85% accuracy in license plate detection, offering potential applications in over-speed monitoring, smart parking management, law enforcement, and electronic toll collection, contributing to enhanced safety and security on the roads.

M.A. Jawale et al. (2023) [25] discussed recent advances in license plate recognition, particularly within the context of deep learning and IoT sensors, introducing a four-step Automatic License Plate Detection and Recognition (ALPDR) system that encompasses unique methods for extraction, pre-processing, segmentation, and character recognition using various deep learning models. T. Aquaileh et al. (2023) [26] introduced an automatic system utilizing transfer learning-based deep learning techniques for the identification of Jordanian vehicles. The results indicate a high level of accuracy, with precision, recall, and F-measure values demonstrating the system's effectiveness in tasks such as license plate detection, character recognition, and vehicle logo detection, showcasing its potential for practical applications in recognizing Jordanian vehicles.

In summary, the related work in AVNPR spans a wide range of applications, from traffic management to security and beyond. Researchers have tackled challenges, proposed innovative solutions, and put the ethical and legal discourse surrounding AVNPR technology. In combination, these studies show the complexity of AVNPR and its effects on numerous areas of modern daily life.

3. Proposed Methods

The ANVPR system is divided into three phases: For each of the phases, different algorithms are used, and performance is different for each of the algorithms. Hence, the researcher listed the performance of the algorithms used in each phase so that one can differentiate and use the best algorithm.

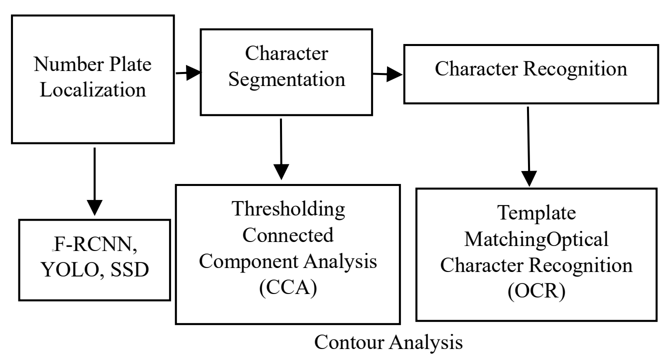

Fig. 2 Three-phase model of the ANVPR system

3.1. Number Plate Localization

3.1.1. Faster - RCNN

Faster R-CNN, which stands for "Faster Region-Convolutional Neural Network," is a popular object detection algorithm in the area of computer vision [27]. Faster R-CNN (Region-based Convolutional Neural Network) is an advanced and highly effective object detection model in computer vision. It introduced the limitations of its predecessor, the original R-CNN, and its variants, like Fast R-CNN. Faster R-CNN significantly improved the performance of object detection tasks in terms of precision and accuracy.

How Faster RCNN works

Backbone Convolutional Neural Network (CNN):Faster R-CNN starts with a CNN architecture (e.g., ResNet, VGG, or Inception) as its backbone. This CNN is pre-trained on a large dataset for image classification tasks (e.g., ImageNet). The CNN backbone is used to extract hierarchical features from the input image. These features make it tough to understand the content of the image and detect objects within it.

Region Proposal Network (RPN): The key innovation of Faster R-CNN is the introduction of the RPN. The RPN is a neural network that works on the feature maps produced by the CNN backbone. The RPN's primary role is to propose Regions of Interest (ROIs) that are likely to contain objects. It does this by sliding a small window (typically 3x3) over the feature map and making predictions for each anchor box (a set of predefined boxes of different sizes and aspect ratios).

The RPN predicts two results for each anchor box: the probability of an object being present in the box (objectness score) and the coordinates of a refined bounding box. The RPN then ranks the anchor boxes based on their objectless scores and selects the top N boxes as RoIs.

RoI Pooling: Once the RPN generates the RoIs, Faster R-CNN uses a RoI pooling layer to transform these variable-sized regions into fixed-sized feature maps. This allows the use of completely connected layers and classifiers for object classification and bounding box regression.

Object Classification and Bounding Box Regression: Faster R-CNN applies two sibling fully connected layers to each RoI: one for object classification (to determine the class of the object within the RoI) and another for bounding box regression (to refine the coordinates of the bounding box around the object). Object classification is typically done using softmax activation, and bounding box regression predicts adjustments to the coordinates of the RoI.

Non-Maximum Suppression (NMS): After object classification and bounding box regression, the model might generate multiple overlapping bounding boxes for the same object. NMS is applied to eliminate duplicate and low-confidence bounding boxes, retaining only the most confident predictions for each object. Much work has been done in the ANVPR system using Faster-RCNN.

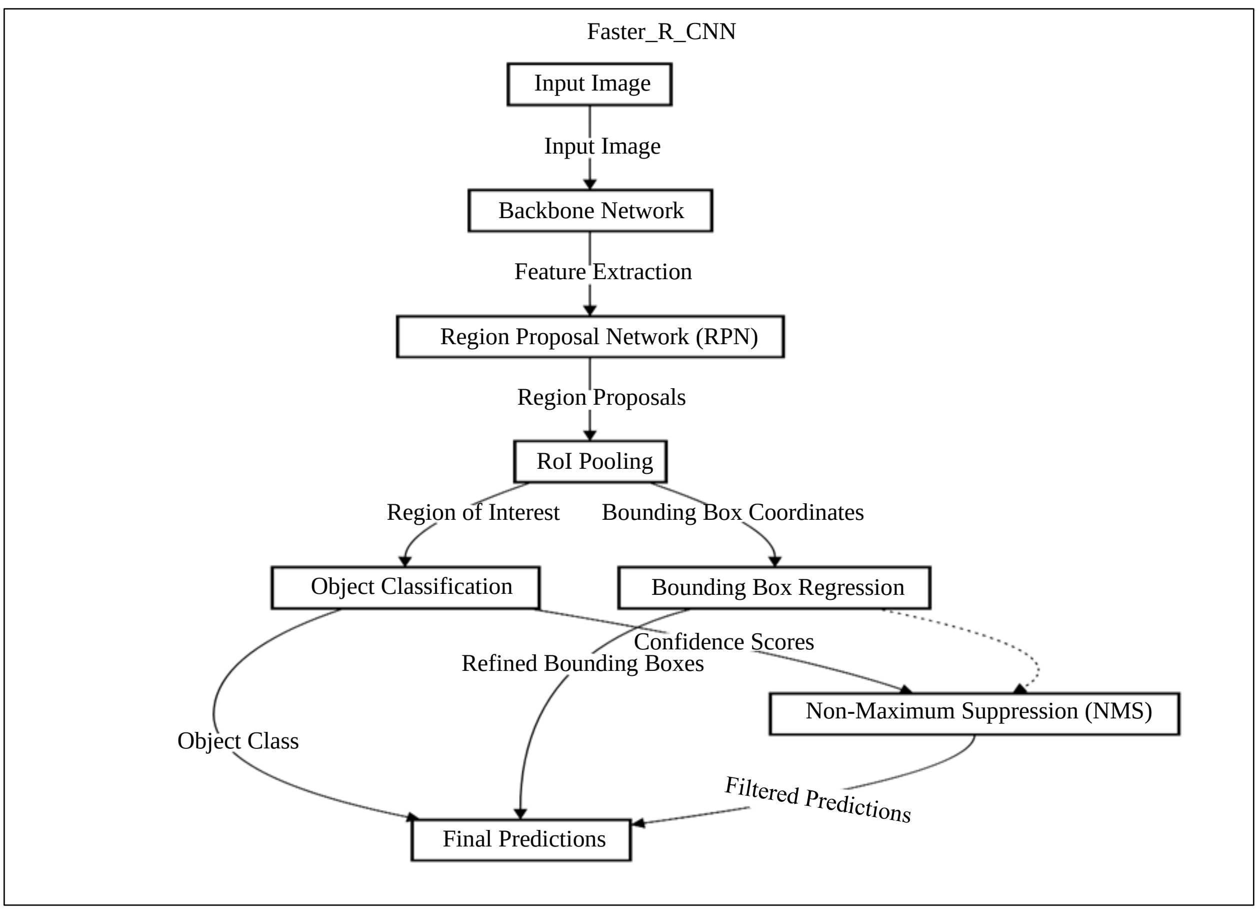

Fig. 3 An overview of faster RCNN

The paper discusses how Automatic License Plate Recognition (ALPR) recognizes anonymous vehicles entering a university campus, enhances security, and verifies authorized vehicles. The researchers used deep learning techniques, specifically Faster RCNN, for LP localization and Tesseract OCR for LP recognition. The model was trained to extract license plate numbers efficiently, achieving a minimum loss of 0.011 with the RMSprop optimizer and an initial learning rate of 0.002 [27].

The paper discusses a new Approach for License Plate Detection and Recognition (ALPD-R) using fused faster RCNN architectures, which improves detection accuracies. The researchers have used Deep Learning (DL) techniques, specifically the faster-RCNN modules, to detect license plates in images. Three faster RCNN modules are used, each trained independently using pre-trained CNN models (AlexNet, VGG16, and VGG19).

The outcomes of these modules are fused in a fusing layer. The authors also used an average operator on the X and Y coordinates of the outputs of the faster RCNN modules and a maximum operator on the width and height outputs in the fusing layer. The proposed method uses a publicly available dataset, achieving an accuracy of 97% in detecting the exact location of LP for 97 out of 100 testing images [28].

3.1.2. YOLO

YOLO (You Only Look Once) is a popular real-time object detection algorithm known for its speed and accuracy. It differs from other object detection methods in that it treats object detection as a single regression problem, predicting both the object's class and its bounding box coordinates directly from the image in one pass. A textual explanation of how YOLO works is mentioned below:

Input Image: YOLO takes an input image of any size and divides it into a grid.

Grid Cells: The image is separated into a grid of cells. Each cell is accountable for predicting objects if the center of the object falls within that cell.

Bounding Box Prediction: For each cell, YOLO predicts multiple bounding boxes (typically 2-5 boxes) with their corresponding confidence scores and class probabilities.

Each bounding box is represented by five values: (x, y, w, h, confidence). (x, y): The coordinates of the middle of the bounding box relative to the cell. (w, h): The width and height of the bounding box relative to the whole image.

Confidence: A measure of how confident the model is that the bounding box contains an object.

Class Prediction: For each bounding box, YOLO predicts class probabilities. It assigns class probabilities to each object category on which it has been trained. Class probabilities are applied independently to each bounding box.

Non-Maximum Suppression (NMS): After prediction, YOLO applies non-maximum suppression to remove duplicate and low-confidence bounding boxes and keep only the most confident ones.

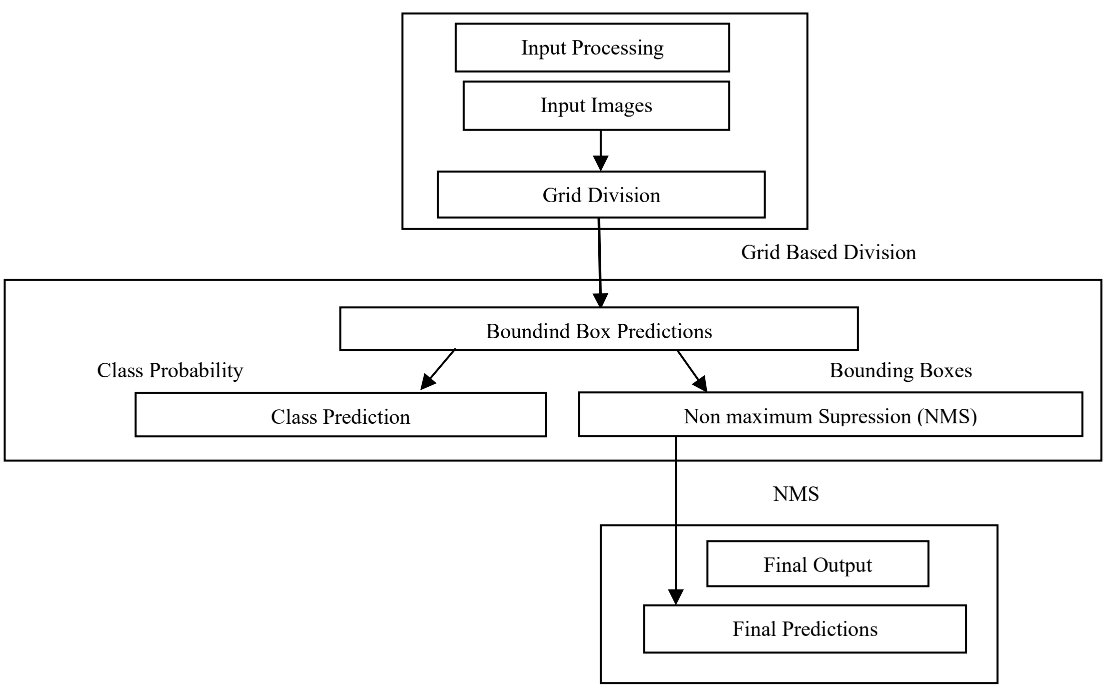

Fig. 4 An overview of YOLO

Research Using the YOLO Method

The paper presented a formal real-time License Plate (LP) detection system for non-helmeted motorcyclists using YOLO. The approach employs a single convolutional neural network, incorporating a centroid tracking method with a horizontal reference line to eliminate false positives from helmeted motorcyclists. The system achieved a commendable 98.52% overall LP detection rate, thereby enhancing motorcyclists' safety [29].

The paper explored ALPR using the YOLO-darknet deep learning framework, focusing on detecting Taiwan's car license plates. The system attains a high LP detection rate of approximately 98.22% and a license plate recognition accuracy of 78%. Furthermore, it exhibits robust performance across various environmental conditions, including rainy backgrounds, darkness, dimness, and disparities in image hues and saturation [30].

This paper combined YOLOv3 for recognition and CRNN for classification. With a thorough evaluation process, this method attains an 86% recognition rate, significantly enhancing recognition rates to 96% when exploiting temporal redundancy. This approach outperforms sighthound and Open ALPR by 9% and 4.9%, respectively [31].

The paper focused on the YOLO-V2-based end-to-end ALPR pipeline and YOLO -the YOLO-V4-based detector encompassing vehicle and LP detection for recognition, devoid of prior knowledge or additional inference steps. The evaluation, spanning five diverse regional datasets, yields an average recognition accuracy of 90.3% while maintaining acceptable Frames Per Second (FPS) performance on a low-end GPU [32].

3.1.3. SSD (Single Shot MultiBox Detector)

The Single Shot MultiBox Detector (SSD) is an advanced deep-learning model for real-time object detection in computer vision. SSD stands out for its efficiency and swiftness, making it ideal for applications requiring rapid and precise identification of objects in images or video streams.

It employs multi-scale feature maps and anchor boxes to localize and classify objects accurately, and its non-maximum suppression method ensures that only the most confident predictions are retained. SSD is deployed across a series of domains, including autonomous driving, surveillance, and robotics, where real-time object detection is of paramount importance [33]. SSD operates on a grid of fixed size and employs a set of anchor boxes to achieve this. The key equations and concepts involved are as follows:

Grid Setup: SSD operates on an image divided into a grid of size W x H. Each grid cell is responsible for predicting objects in the middle of an object that falls into the cell.

Anchor Boxes: For each grid cell, SSD utilizes a set of anchor boxes characterized by parameters:

Anchor width: wa,
Anchor height: ha.

Localization Prediction: The following equations represent the predicted bounding box coordinates for each anchor box:

Predicted x-offset: Δx_a

Predicted y-offset: Δy_a

Predicted width scaling: Δw_a

Predicted height scaling: Δh_a

These offsets are computed concerning the anchor box parameters:

$$\Delta x\_a = (x\_pred - x\_anchor) / wa \tag{1}$$

$$\Delta y\_a = (y\_pred - y\_anchor) / ha \tag{2}$$

$$\Delta w\_a = \log(w\_pred / wa) \tag{3}$$

$$\Delta h\_a = \log(h\_pred / ha) \tag{4}$$

Here, (x_pred, y_pred) and (w_pred, h_pred) are the predicted bounding box center and size values.

Class Prediction: For each anchor box, SSD predicts class probabilities for a set of object classes. The probability of an object belonging to a specific class 'C' is denoted as P(C) for that anchor box.

Final Predictions: The final predictions for each anchor box are obtained by combining the localization predictions (bounding box coordinates) with the class predictions for all object classes.

Non-Maximum Suppression (NMS):Following the prediction phase, non-maximum suppression is useful to eliminate duplicate and low-confidence bounding boxes. It retains only the most confident predictions.

In summary, SSD employs anchor boxes with parameters (wa, ha) and predicts bounding box offsets Δx_a, Δy_a, Δw_a, and Δh_a for each anchor box, in addition to class probabilities P(C).

These predictions are based on anchor box values and predicted bounding box center and size values. Non-maximum suppression is then used to refine the predictions and ensure the selection of the most reliable and confident results.

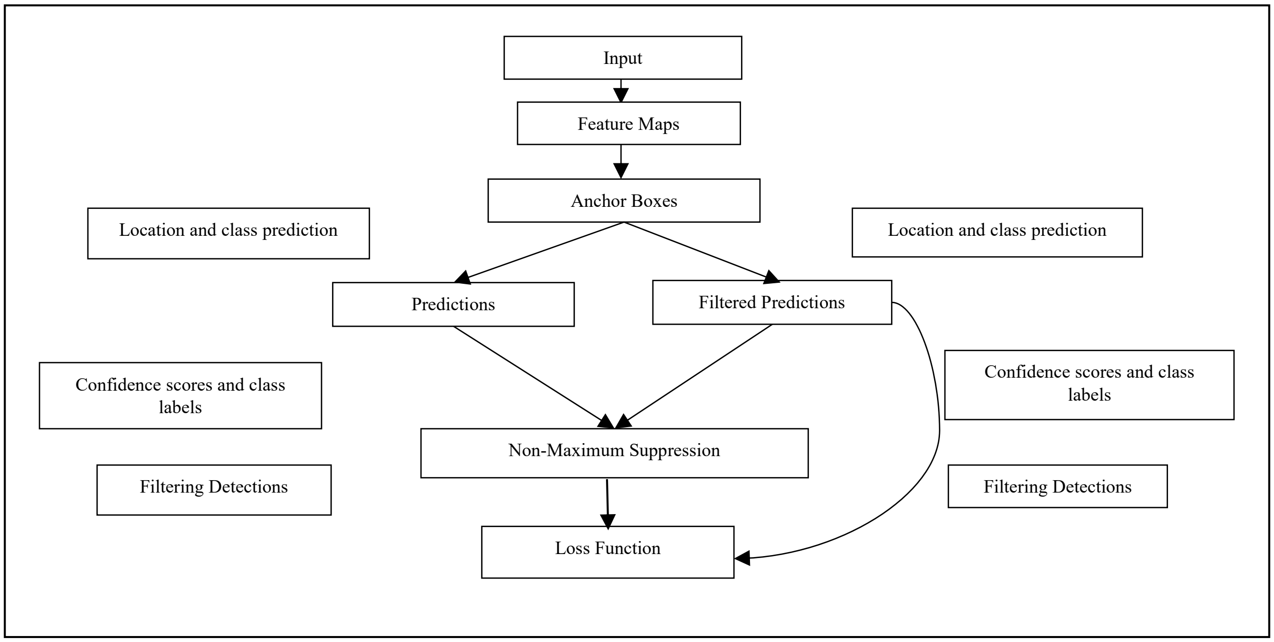

Fig. 5 An overview of the SSD approach

Researches Using the SSD Approach

This paper is thoughtfully deconstructed into three distinct sub-blocks, namely Vehicle Image/Video Acquisition, License Plate Localization(LPL), and OCR. In pursuit of a practical and straightforward setup, a webcam with reasonable resolution is ingeniously employed to capture images and videos of vehicles at designated entry points. To fulfil the crucial task of LPL, the system harnesses the power of the Single Shot Detector (SSD) architecture based on Mobilenet V1, meticulously fine-tuning the hyperparameters through rigorous experimentation to avert overfitting. The system achieves a remarkable accuracy rate of over 95% on video processing. This advancement enhances ALPR's effectiveness in applications such as parking management and traffic control [34].

This system utilizes License Plate Recognition (LPR) via the MobileNet Single Shot Detector (SSD) algorithm, offering users a convenient means to retrieve vehicle details and streamline car park management. The study compares MobileNet SSD with other object detection algorithms, highlighting the growing adoption of LPR systems within shopping centers and emphasizing the project's aim to extend this technology to mobile devices for enhanced operational efficiency [34].

3.2. Character Segmentation

Following the successful localization of the LP, the subsequent phase within the Automated Vehicle Number Plate Recognition (AVNPR) system involves the mining of characters from the identified license plates [35]. This pivotal step is essential in facilitating the accurate and efficient retrieval of alphanumeric information embedded on the license plate. The character extraction process is considered to isolate individual characters, ensuring precision in capturing the relevant alphanumeric data. Employing advanced computer vision algorithms and pattern recognition techniques, the AVNPR system analyses the segmented license plate region to identify and extract each character with a high grade of accuracy.

The character segmentation phase presents unique challenges owing to the diverse typography of license plates, variations in character spacing, and potential distortions induced by external features such as lighting conditions, etc. Accurate segmentation becomes imperative for overcoming these challenges and ensuring the subsequent identification and recognition of individual characters. Researchers have listed some procedures used in character segmentation for the AVNPR system.

3.2.1. The motivation behind Character Segmentation

Character segmentation is crucial in the AVNPR process as it contributes to the accuracy, robustness, and speed of the AVNPR system.

Accuracy: Accurate segmentation ensures that each character is identified correctly, minimizing errors in the recognition process.

Robustness: Proper segmentation allows the system to handle variations in license plate sizes, fonts, and styles.

Speed: Efficient segmentation contributes to the overall speed and performance of the ANPR system.

3.2.2. Techniques Used for character Segmentation

Thresholding: Thresholding is a common image processing technique used in character segmentation, particularly in the context of Automatic Vehicle Number Plate Recognition (AVNPR) systems. The goal of thresholding is to separate objects or regions of interest from the background based on pixel intensity. In the case of ANPR, thresholding is applied to distinguish characters on a license plate from the plate background. Otsu's method is a widely used image thresholding technique that automatically calculates an optimal threshold for image segmentation. The threshold obtained from Otsu's method is used to classify pixel intensities into two groups: those below the threshold belong to one class (e.g., background), and those above the threshold belong to the other class (e.g., foreground).

Connected Component Analysis: Connected Component Analysis (CCA) is an important image-processing technique for identifying and analyzing connected regions in a binary image. In character segmentation to ANPR systems, CCA is often applied to extract individual characters or groups of characters from the binary image obtained after thresholding. The term "connected component" refers to a set of foreground pixels that are connected in some way. Connectivity is defined by a neighborhood relationship, specifying how pixels are considered connected. CCA is to extract characters from the identified licensed plates. The CCA algorithm was employed by researchers for character segmentation, resulting in an impressive accuracy rate of 97.94%. This demonstrates the effectiveness of the CCA approach in accurately isolating characters within the background of the study [36].

Contour Analysis: Contour analysis is an influential tool for identifying and extracting objects with distinct boundaries, making it well-suited for character segmentation in ANPR systems. Combining contour analysis with other methods, like thresholding and connected component analysis, can enhance the overall accuracy and robustness of the segmentation process.

3.3. Character Recognition

Character recognition, or OCR, is the technology that enables ANPR systems to convert images of characters on license plates into text that can be handled and understood by computers. Optical Character Recognition (OCR) algorithms are employed to recognize each segmented character [36]. This involves pattern recognition and matching against predefined character templates. This step is vital for accurately retrieving and utilizing information from license plates, contributing to applications like traffic management, law enforcement, and parking systems.

3.3.1. OCR Techniques

Pattern Recognition: Traditional OCR methods use pattern recognition, where the system compares the shape and structure of characters against predefined templates.

Machine Learning (ML): Modern OCR often incorporates ML algorithms to improve accuracy. This involves training models on large datasets to recognize character patterns and variations.

Deep Learning (DL): Deep neural networks, particularly CNN, have significantly succeeded in character recognition tasks. They can automatically learn hierarchical features from images, making them well-suited for OCR.

4. Conclusion and Future Scope

ANPR systems have proven to be valuable tools in enhancing security, facilitating efficient traffic flow, and contributing to law enforcement. This paper conducts an in-depth survey of recent studies exploring Automatic Vehicle Number Plate Recognition (AVNPR) algorithms. Based on the specific features needed at each stage of the recognition process, AVNPR algorithms are categorized, and each stage is thoroughly discussed, including a performance summary and highlighting many associated issues and challenges.

The integration of advanced algorithms and computer vision techniques has substantially improved the accuracy and reliability of AVNPR systems, enabling them to handle diverse scenarios and challenging conditions. The efficiency of AVNPR systems relies not only on technological advancements but also on the value of the underlying datasets used for training.

A robust dataset ensures that the system can adapt to variations in LP styles, lighting conditions, and vehicle types. The review paper attempts to compile a selection of datasets that can assist researchers in their work. Many algorithms for the segmentation and recognition stages within the AVNPR system are also presented. These algorithms or methods are developed to enhance the accuracy and efficiency of the AVNPR process, offering diverse options for researchers to explore and implement in their work.

There is more scope to research improving the robustness of AVNPR algorithms in diverse environmental conditions, such as varying lighting and weather conditions, to ensure consistent performance. By focusing on AD in number plates, we aspire to contribute valuable insights and solutions that will shape the next generation of intelligent and adaptive ANPR systems.

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