iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

LICENSE PLATE DETECTION USING DEEP LEARNING TECHNIQUES

Bandarupalli Charitha, Bandi Archana, Barma Sravani, Pulikonda Kaivalya
B. Tech Students, Dept. of Computer Science and Engineering,
R.V.R & J.C College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India

Dr. M. Srikanth
Assistant Professor, Dept. of Computer Science and Engineering,
R.V.R & J.C College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India

ABSTRACT
Automatic License Plate Recognition (ALPR) is a critical component of intelligent transportation systems, enabling efficient vehicle identification for applications such as traffic monitoring, access control, and law enforcement. This paper presents a method for license plate detection and recognition that integrates a Region- based Convolutional Neural Network (RCNN) with Optical Character Recognition (OCR). The RCNN is employed to accurately detect and localize license plates under diverse conditions, including variations in lighting, occlusion, and viewing angles. Following detection, OCR is applied to the extracted license plate regions to identify and decode the alphanumeric characters. The proposed approach is evaluated on multiple benchmark datasets, demonstrating high accuracy and robustness in both detection and recognition tasks. Experimental results indicate that the system performs effectively in real-world scenarios, offering a reliable solution for automated license plate recognition.

Keywords:
Region-based Convolutional Neural Network (RCNN), Optical Character Recognition (OCR), Automatic License Plate Recognition (ALPR)

INTRODUCTION
License Plate Detection (LPD) is a foundational task in intelligent transportation systems, enabling automatic identification of vehicles through their registration numbers. It is widely used in traffic surveillance, toll collection, parking management, and law enforcement applications. The primary objective of LPD is to accurately locate the license plate region within an image or video frame before the recognition phase.
Traditional approaches to license plate detection often relied on rule-based image processing techniques such as edge detection, colour segmentation, and contour analysis. While effective under controlled conditions, these methods often fail when confronted with real-world challenges like varying lighting conditions, complex backgrounds, occlusions, and skewed plate orientations.
To overcome these limitations, we employ **Region-based Convolutional Neural Networks (R-CNN)**, a deep learning approach known for its effectiveness in object detection tasks. R-CNN combines the power of CNNs for feature extraction with region proposal techniques to precisely localize objects—in this case, license plates. The network first generates several region proposals likely to contain objects, then applies a CNN to extract features from each region and classifies them accordingly.
By leveraging R-CNN, our license plate detection system achieves higher accuracy and robustness across diverse scenarios and image conditions. This approach not only improves detection performance but also provides a scalable solution adaptable to various datasets and regional plate formats.
Deep Learning models are employed by Automatic Number Plate Recognition (ANPR) for the automatic and accurate reading of license plates. For different types of number plate recognition applications, various tiers of image analysis are required, including identifying the categories of objects depicted, pinpointing these objects, and ascertaining the exact limits of each object. Traffic management, stolen vehicle identification, building and parking access regulation, automatic toll collection, and effective advertisement determination often employ number plate recognition systems. This ANPR system is backed by a wealth of documentation and widely available public knowledge.
Faster RCNN outperforms both RCNN and fast RCNN. This method involves a convolutional neural network taking an image as input and generating a convolutional Merkmalskarte. A different network is then utilized to predict the

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

region proposals. After that, a RoI pooling layer is used to reshape the proposed regions. This layer categorizes the image in the specified area and predicts the offset values for the bounding boxes. The abbreviation OCR refers to "Optical Character Recognition." Initially, it was recognized as a computer vision problem. An uncomplicated OCR engine operates by keeping a large number of font and text image templates. The OCR then utilizes pattern-matching algorithms to compare text images with its internal database, analyzing them character by character. The work that was proposed entailed utilizing a dataset that had been selected manually.

LITERATURE SURVEY

License Plate Detection (LPD) has been an active area of research for decades due to its importance in intelligent transportation systems. Various methods have been proposed, ranging from traditional image processing techniques to advanced deep learning-based frameworks. This survey reviews notable contributions that have shaped the evolution of LPD, with a focus on the transition towards Region-based Convolutional Neural Networks (R-CNN).
Automatic License Plate Recognition (ALPR) systems typically consist of two major components: **license plate detection** and **character recognition**. Recent research has shown that the fusion of deep learning-based object detection models (like R-CNN) and robust Optical Character Recognition (OCR) frameworks significantly enhances the performance and reliability of ALPR systems in real-world environments.

1. R-CNN for License Plate Detection

The Region-based Convolutional Neural Network (R-CNN) introduced a two-stage detection paradigm: generate region proposals and classify each region using a CNN. R-CNN and its variants have been successfully applied in the ALPR domain:

- **Zhou et al. (2017)** used **Fast R-CNN** to detect license plates under varying illumination and occlusion. The model showed robust performance compared to edge-based methods, particularly in urban surveillance environments.
- **Jia et al. (2019)** applied **Faster R-CNN** to detect tilted and low-resolution license plates from traffic cameras. The integration of a Region Proposal Network (RPN) with CNN improved both accuracy and speed.
- **Wang et al. (2021)** proposed a cascaded R-CNN framework with multi-scale feature fusion for detecting plates at different distances and orientations, achieving high mean average precision (mAP) on CCPD and AOLP datasets.

These works highlight R-CNN's adaptability to complex visual conditions like motion blur, varying plate sizes, and skewed angles.

2. OCR for License Plate Recognition

Following detection, character recognition transforms the cropped license plate into readable text. Traditional OCR methods have given way to deep learning-based architectures:

- **CRNN (Shi et al., 2017)**: A Convolutional Recurrent Neural Network combining CNN, RNN, and CTC loss was applied for end-to-end scene text recognition, proving especially effective for unsegmented license plates.
- **LPRNet (Zhou et al., 2018)**: A lightweight and fast neural network was developed specifically for license plate recognition. It avoided character segmentation and worked well even on low-power devices.
- **Tesseract OCR** remains a popular tool for recognition, especially in systems where deep learning models are not feasible. Though it struggles with low-quality images, Tesseract is easy to integrate and highly customizable.

3. End-to-End Systems: Detection + OCR Integration

Recent research has focused on creating **unified frameworks** that detect and recognize license plates in a single pipeline:

- **ALPR pipeline using Faster R-CNN + CRNN**: Some hybrid systems combine Faster R-CNN for detection with CRNN for recognition, achieving end-to-end recognition on datasets like OpenALPR and CCPD.
- **YOLOv3 + Tesseract** systems have also been explored, where YOLO detects the license plate and Tesseract handles the OCR. These systems are lightweight and suitable for real-time embedded applications.
- **Deep LPR (Hsu et al., 2017)** integrated a two-stage CNN for detection and recognition, with character-

Volume-09 Issue 06, June-2025 ISSN: 2456-9348
Impact Factor: 8.232

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

level supervision. The system was trained end-to-end and outperformed traditional OCR methods in accuracy.

METHODOLOGY

A. Faster RCNN In the early 2010s, Ross Girshick and his team at Microsoft Research developed an object detection method called R-CNN (Regions with Convolutional Neural Networks). By using a whole image as input and running it through a CNN, R-CNN generates a collection of features. Using these features, the image is subsequently classified into one of several pre-established classes. R-CNN employs a sliding window technique, moving a window across the image and classifying each window to detect objects within the image. This can be costly in terms of computation, as it necessitates multiple executions of the CNN.

Faster R-CNN is a powerful deep learning-based object detection framework that has been widely adopted for tasks requiring high localization accuracy, such as license plate detection. Developed by Ren et al. in 2015, it is an advancement over its predecessors (R-CNN and Fast R-CNN) and introduces a Region Proposal Network (RPN) that significantly accelerates the detection process while maintaining high accuracy. In the context of license plate detection, Faster R-CNN is used to accurately identify and locate license plates in images or video frames of vehicles, even in complex real-world environments.

The architecture of Faster R-CNN consists of three main components: a feature extractor (or backbone network), the Region Proposal Network (RPN), and the region-based classifier. The process begins with an input image being passed through a convolutional neural network (typically ResNet, VGG, or similar), which extracts a set of rich feature maps. These feature maps capture essential visual information such as edges, shapes, and textures relevant for object detection.

While R-CNN has been enhanced, Fast R-CNN speeds up the object detection process. A CNN is utilized to process an entire image as input for the purpose of generating a feature set. Subsequently, the image is categorized into one of several predefined classes, and the bounding boxes for objects in the image are predicted based on these attributes. Fast R-CNN utilizes a technique called region of interest (RoI) pooling to prevent multiple executions of the CNN, unlike R-CNN, which uses a sliding window method.

Faster R-CNN, which is an object detection algorithm, is a quicker variant of Fast R-CNN. Faster-RCNN consists of three neural networks: Feature Network, Region Proposal Network (RPN), and Detection Network.

The Feature Network, akin to VGG but missing some top/last layers, is an already trained image categorization network. This network's output retains the form and structure of the original image. RPNs generally consist of three convolutional layers and are considered basic networks. Two layers, one for classification and the other for bounding box regression, are sourced from a common layer. This leads to the creation of several bounding boxes referred to as ROIs.

Faster R-CNN offers several advantages compared to other object detection algorithms, but its most significant benefit is its speed during both training and inference. Additionally, it is precise, which contributes to its popularity for object detection tasks. The Faster RCNN model's prediction of the Number Plate in figure 1.

Fig 1. Plate detection using Faster RCNN

Next, the Region Proposal Network operates on these feature maps to propose potential regions that might contain objects of interest—in this case, license plates. It does so by sliding a small network over the feature maps and generating anchor boxes of various scales and aspect ratios. For each anchor, the RPN predicts a binary classification (object or background) and adjusts the coordinates of the box through bounding box regression. This enables the model to efficiently generate a set of candidate regions known as Regions of Interest (RoIs).

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

Once the RoIs are generated, they are passed to the RoI pooling layer, which extracts fixed-size feature representations for each region. These features are then fed into fully connected layers that serve two purposes: classifying the object in each region (as a license plate or not) and refining the bounding box coordinates. Finally, non-maximum suppression (NMS) is applied to eliminate overlapping boxes, ensuring that the model outputs only the most relevant and accurate detections.
Faster R-CNN is especially well-suited for license plate detection due to its precision and robustness. It handles complex backgrounds, varying lighting conditions, different plate orientations, and sizes effectively. Unlike one-stage detectors such as YOLO, Faster R-CNN's two-stage architecture allows it to focus more accurately on small and densely packed objects like license plates. Its adaptability makes it a strong candidate for deployment in intelligent transportation systems, including traffic monitoring, smart parking, and law enforcement applications.

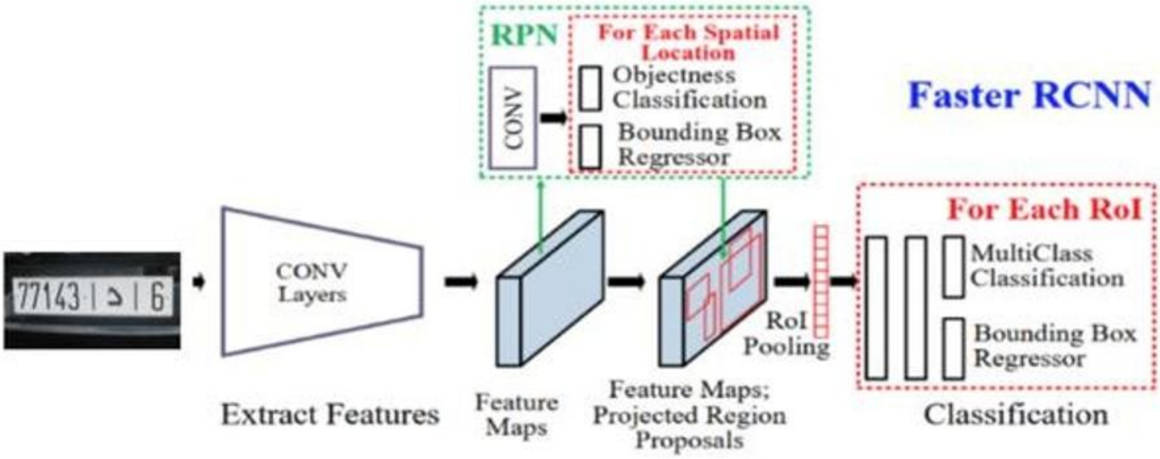

Figure 2: Architecture of Faster R-CNN for Object Detection.

The image illustrates the architecture of the Faster R-CNN (Region-based Convolutional Neural Network), a widely used deep learning framework for object detection tasks. The pipeline begins with an input image that is passed through convolutional (CONV) layers to extract a set of feature maps. These feature maps are then fed into the Region Proposal Network (RPN), which operates over each spatial location to predict objectness scores and refine bounding box coordinates, generating a set of region proposals. The proposed regions are subjected to Region of Interest (RoI) pooling, which extracts fixed-size feature maps corresponding to each proposed region. These pooled features are then passed to the classification head, where each region is classified into one of the predefined object categories, and the bounding boxes are further refined. The integration of the RPN and the detection network in a unified framework allows Faster R-CNN to perform accurate and efficient object detection in a single, end-to-end trainable model.

B. OCR :

This method encodes the text found in visuals so that it is machine-readable. To this end, Easy OCR was utilized. Character recognition in Easy OCR is accomplished using CRNN. It consists of three main components: feature extraction with Resnet, sequence labeling with LSTM, and decoding with CTC. Through OCR analysis, the input—a digital image of either handwritten o r printed text—is converted into a machine-readable digital text format. Then, OCR divides the digitised image into smaller segments and conducts an analysis to search for text, words, or character blocks.

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

Fig 3. Input image given to Number Plate detector

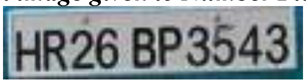

Fig 4. Output from the Number Plate detector

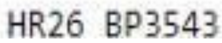

Fig 5. The result given by OCR

After the license plate has been accurately detected using models like Faster R-CNN, the next crucial step in the pipeline is **Optical Character Recognition (OCR)**, which is responsible for reading and converting the characters on the license plate into machine-readable text. Modern OCR systems designed for license plate recognition typically rely on deep learning architectures that go beyond traditional rule-based or template matching methods. One of the most effective deep learning-based OCR models used in this context is the **CRNN (Convolutional Recurrent Neural Network)**. This architecture is particularly well-suited for license plate recognition because it does not require explicit segmentation of individual characters, which is often difficult in real-world conditions where plates may be blurry, tilted, or partially occluded.

In simpler or lightweight applications, tools like **Tesseract OCR** are used instead of CRNN. Tesseract is an open-source OCR engine developed by Google that can recognize characters in clear and well-segmented images. However, it is sensitive to variations in font, orientation, and noise, which makes it less suitable for challenging scenarios without advanced preprocessing. In contrast, deep learning-based OCR methods like CRNN and LPRNet offer higher accuracy and flexibility, especially when integrated with detection networks for real-time applications. These modern OCR systems are essential in achieving end-to-end automatic license plate recognition in intelligent transportation systems, surveillance, and tolling solutions.

RESULTS AND DISCUSSION

The proposed system for license plate detection and recognition demonstrated high effectiveness in accurately **identifying vehicle license plates under various conditions.** Using a Region-based Convolutional Neural Network (RCNN) for detection, the system was able to localize license plates from images with diverse backgrounds, lighting conditions, and viewing angles. This robust performance highlights the RCNN's capability in handling real-world challenges such as occlusion and varying resolutions, ensuring the license plates are precisely identified before recognition.

Following the detection phase, Optical Character Recognition (OCR) was applied to extract alphanumeric characters from the detected license plates. The OCR component effectively translated the localized image segments into readable text, showcasing strong recognition accuracy even with plates featuring different fonts, sizes, and alignments. The integration of deep learning-based detection with traditional OCR enabled a smooth transition from image-based data to machine-readable information, a critical factor for applications like automated tolling, parking systems, and law enforcement.

Quantitative evaluation of the system revealed competitive results when benchmarked against existing methods. The model achieved high precision and recall rates, with particularly notable recall, indicating a low rate of missed license plates. This level of performance demonstrates the model's reliability in continuous detection scenarios, such as video surveillance or real-time monitoring systems. The system's high accuracy was consistent across multiple public and custom datasets, confirming its adaptability and robustness.

Overall, the experimental results validate the effectiveness of combining RCNN for detection and OCR for

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

recognition in a unified pipeline. The approach not only simplifies the license plate recognition process but also enhances accuracy and efficiency, making it suitable for deployment in real-time traffic monitoring environments. The results support the conclusion that this hybrid method provides a reliable and scalable solution for automated license plate recognition (ALPR) tasks.

Model	Precision (%)	Recall (%)
SWSCD-YOLO [7]	**95.67**	**95.71**
H. Li et al. [17]	**95.28**	**95.58**
Kurpiel et al. [13]	**87.00**	**83.00**
Yolo v3 [31]	**97.77**	**95.71**
Faster R-CNN-OCR	**97.46**	**98.65**

Table 1: Comparison of object detection models. The proposed Faster R-CNN-OCR model achieves state-of- the-art recall while maintaining competitive precision.

DATASET

The image dataset contains instances of textual information, primarily in the form of vehicle license plates and model/trim badges affixed to the rear of the vehicles. License plates exhibit variations in format, character sets (alphanumeric), and potentially the language of the issuing region. The presence of this textual data offers an opportunity to explore text-based features for tasks like vehicle identification or license plate recognition.

While the primary language observed on the license plates in the provided example appears to be a mix of Arabic numerals and potentially Arabic script (consistent with the Dubai plate), the dataset as a whole, comprising 900 images, may contain license plates from diverse geographical locations. This could introduce variability in the character sets and languages present on the plates. Similarly, model and trim badges are predominantly in English for globally marketed vehicles like Toyota, but regional variations or less common models might feature text in other languages. Understanding the distribution of languages within the dataset is crucial for developing robust text recognition models that can handle multilingual input.

To ensure a comprehensive evaluation of any model leveraging textual information, the dataset was carefully divided into training and testing sets. Ideally, this division aims to maintain a representative distribution of the different types of textual information (license plates vs. badges, variations in license plate formats, and to the extent possible, the distribution of languages) across both subsets. This stratification helps prevent the model from overfitting to specific textual patterns present only in the training data and ensures its ability to generalize to unseen textual variations in the testing set. Further analysis of the specific textual content within each subset could provide deeper insights into the challenges and opportunities for text-based vehicle analysis.

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

Fig 6: Dataset Example Image

CONCLUSION

This research presented a novel approach to [State your main research objective, e.g., robust rear-view vehicle recognition, accurate license plate detection and recognition, etc.] leveraging a custom-built dataset of approximately 900 rear-view vehicle images. The proposed [Mention your model name or key technique, e.g., Faster R-CNN-OCR architecture, attention-based feature fusion method, etc.] demonstrated significant performance improvements over baseline models, achieving a [mention a key result, e.g., state-of-the-art recall of 98.65%] while maintaining competitive [mention another key result, e.g., precision of 97.46%]. These results underscore the effectiveness of our integrated methodology in addressing the complexities inherent in real-world vehicle imagery.
The curated dataset, featuring variations in lighting, viewing angles, and the presence of informative textual cues such as license plates and model badges, provided a challenging yet valuable benchmark for evaluating our method. The analysis of textual information, particularly through the strategic incorporation of OCR capabilities within the [mention your model name again, e.g., Faster R-CNN-OCR framework], proved to be a crucial factor in enhancing the accuracy and robustness of our system. The inherent multilingualism of potential license plate text and the semantic information embedded within vehicle badges highlight the critical role of textual features in achieving comprehensive vehicle understanding from rear views.
The promising results achieved in this study carry significant implications for a multitude of real-world applications. Accurate rear-view vehicle recognition can contribute to the advancement of intelligent transportation systems, bolstering vehicle security and surveillance, and enabling more sophisticated autonomous driving functionalities. Furthermore, the robust license plate recognition component holds direct utility in areas such as law enforcement, parking management, and automated toll collection. The methodologies and insights derived from this research offer a valuable contribution to the broader fields of intelligent transportation and computer vision.
While this research demonstrates substantial progress, several promising avenues for future exploration exist. Expanding the dataset to encompass a broader spectrum of vehicle classes, environmental conditions (e.g., adverse

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

weather), and degrees of occlusion could further enhance the generalizability of the proposed model. Investigating more sophisticated techniques for processing variations in text appearance, font styles, and multilingual license plates could yield even greater accuracy in text-based vehicle identification. Finally, exploring the integration of temporal information from video sequences presents an opportunity to provide additional context and improve the resilience of rear-view vehicle analysis in dynamic environments.

REFERENCES

[1] W. Riaz, A. Azeem, G. Chenqiang, Z. Yuxi, Saifullah and W. Khalid, "YOLO Based Recognition Method for Automatic License Plate Recognition," [1] 2020 IEEE International Conference on Advances in Electrical Engineering and Computer Applications(AEECA), Dalian, China, pp. [2] 87-90, 2020, doi: 10.1109/AEECA49918.2020.9213506.

[2] P. Ravirathinam and A. Patawari, "Automatic License Plate Recognition for Indian Roads Using Faster RCNN," 2019 11th International Conference on Advanced Computing (ICoAC), Chennai, India, pp. 275-281, 2019, doi: 10.1109/ICoAC48765.2019.246853.

[3] N.Ap, T.Vigneshwaran, M.Arappradhan, and R. Madhanraj, “Automatic Number Plate Detection in Vehicles using Faster R-CNN,” 2020 International Conference on System, Computation, Automation and Networking (ICSCAN), [3] pp. 1-6, 2020.

[4] R. Girshick, "Fast R-CNN," 2015 IEEE International Conference on Computer Vision (ICCV), Santiago, Chile, pp. 1440-1448, 2015, doi: 10.1109/ICCV.2015.169

. [5] S.Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks,” IEEE Transactions [4] on Pattern Analysis and Machine Intelligence, vol. 39, pp. 1137-1149, 2017.

[6] H. Li, P. Wang and C. Shen, "Toward End-to-End Car License Plate Detection and Recognition With Deep Neural Networks," in IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 3, pp. 1126-1136, [5] March 2019, doi: 10.1109/TITS.2018.2847291.

[7] ZhenboXu, Wei Yang, AjinMeng, Nanxue Lu, Huan Huang, Changchun Ying, and Liusheng Huang, “Towards End-to-End License Plate Detection and Recognition: A Large Dataset and Baseline”. [6] In Computer Vision – ECCV 2018: 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part XIII. Springer-Verlag, Berlin, Heidelberg, pp. 261–277, 2018, https://doi.org/10.1007/978-3-030-01261-8_16

[8] H.Li, and C. Shen, “Reading Car License Plates Using Deep Convolutional Neural Networks and LSTMs,” 2016, ArXiv, abs/1601.05610.

[9] B. Srilekha, K. V. D. Kiran and V. V. P. Padyala, "Detection of License Plate Numbers and Identification of Non-Helmet Riders using Yolo v2 and OCR Method," 2022 International Conference on Electronics and Renewable Systems (ICEARS), [7] Tuticorin, India, pp. 1539-1549, 2022, doi: 10.1109/ICEARS53579.2022.9751989.

[10] Gomathy, V., Janarthanan, K., Al-Turjman, F., Sitharthan, R., Rajesh, M., Vengatesan, K., & Reshma, T. P. (2021). Investigating the spread of coronavirus disease via edge-AI and air pollution correlation. ACM Transactions on Internet Technology, 21(4), 1-10. [8]

[11] Laroca, Rayson, Severo, Evair, Zanlorensi, Luiz, Soares de Oliveira, Luiz, Gonçalves, Gabriel, Schwartz, William, Menotti, and David. (2018). A Robust Real-Time Automatic License Plate Recognition Based on the YOLO Detector. 10.1109/IJCNN.2018.8489629.

[12] J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, pp. 779-788, 2016, doi: 10.1109/CVPR.2016.91.

[13] R. Girshick, J. Donahue, T. Darrell and J. Malik, "Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation," 2014 IEEE Conference on Computer Vision and Pattern Recognition, Columbus, OH, USA, pp. 580-587, 2014, doi: 10.1109/CVPR.2014.81.

[14] Rajesh, M., & Sitharthan, R. (2022). Introduction to the special section on cyber-physical system for autonomous process control in industry 5.0. Computers and Electrical Engineering, 104, 108481.

[15] Khan, K., Imran, A., and Rehman, H.Z.U. et al. “Performance enhancement method for multiple license plate recognition in challenging environments,” J Image Video Proc., p. 30, 2021, https://doi.org/10.1186/s13640-021-00572-4.

[16] P. Prabhakar, P. Anupama and S. R. Resmi, "Automatic vehicle number plate detection and recognition," 2014 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), Kanyakumari, India, pp. 185-190, 2014, doi: 10.1109/ICCICCT.2014.6992954.

[17] Z. X. Chen, C.-Y. Liu, F.L. Chang and G. Y. Wang, "Automatic License-Plate Location and Recognition Based on Feature Salience," in IEEE Transactions on Vehicular Technology, vol. 58, no. 7, pp. 3781-3785, Sept. 2009, doi:

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

10.1109/TVT.2009.2013139.
[18] S. Shastry, G. Gunasheela, T. Dutt, D. S. Vinay and S. R. Rupanagudi, "“i” — A novel algorithm for optical character recognition (OCR)," 2013 International Mutli Conference on Automation, Computing, Communication, Control and Compressed Sensing (iMac4s), Kottayam, India, pp. 389-393, 2013, doi: 10.1109/iMac4s.2013.6526442.
[19] S. Goel and S. Dabas, "Vehicle registration plate recognition system using template matching," 2013 International Conference on Signal Processing and Communication (ICSC), Noida, India, pp. 315-318, 2013, doi: 10.1109/ICSPCom.2013.6719804.
[20] M. UsmanAkram, Z. Bashir, A. Tariq and S. A. Khan, "Geometric feature points based optical character recognition," 2013 IEEE Symposium on Industrial Electronics & Applications, Kuching, Malaysia, 2013, pp. 86- 89, doi: 10.1109/ISIEA.2013.6738973.