Vehicle Number Recognition by using RCNN Algorithm

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Abstract - Vehicle number recognition is a crucial task in many real-world applications, including traffic management and law enforcement. In this study, we propose a novel approach for vehicle number recognition using the Region-based Convolutional Neural Network (RCNN) algorithm. Our method leverages the power of deep learning to accurately detect and recognize vehicle numbers from images. First, we employ the RCNN algorithm to effectively localize the regions of interest (ROI) within an image that potentially contain vehicle numbers. This is achieved through a combination of selective search and region proposal networks, which efficiently generate a set of candidate bounding boxes. Next, the localized ROIs are fed into a deep convolutional neural network, which is trained to recognize and classify vehicle numbers. The network architecture consists of multiple convolutional and fully connected layers, enabling it to learn and extract meaningful features from the input ROIs. To improve the recognition accuracy, we employ a two- step approach. Firstly, a character segmentation algorithm is used to separate individual characters within the recognized vehicle number. Subsequently, a character recognition module is applied to each segmented character to accurately identify the number. We conduct extensive experiments on a large-scale vehicle number dataset, and the results demonstrate that our proposed RCNN-based approach achieves significant improvements in both recognition accuracy and computational efficiency compared to existing methods.

Keywords: vehicle number recognition, RCNN algorithm, deep learning, convolutional neural network, region proposal network, selective search, character segmentation, character recognition, recognition accuracy.

INTRODUCTION;

Vehicle number recognition (VNR) is a crucial task in intelligent transportation systems (ITS), which aims to automatically identify and read the license plate numbers of vehicles from images or videos. In recent years, deep learning has emerged as a powerful technique for various computer vision tasks, including object detection, recognition, and segmentation. One popular deep learning approach for VNR is the Region-based Convolutional Neural Network (RCNN) algorithm, which has shown remarkable performance in many domains. The RCNN algorithm consists of three main stages: region proposal, feature extraction, and classification. Firstly, a region proposal network (RPN) is used to generate a set of candidate regions in an image that may contain license plates. The RPN outputs region proposals by sliding a small window across the image and predicting anchor boxes associated with different scales and aspect ratios. These proposals are then refined using a technique called non-maximum suppression to eliminate redundant and overlapping regions.

After obtaining the region proposals, the next step is to extract informative features from each region. This is done by applying a series of convolutional layers to the region of interest (ROI), which is resized and aligned to a fixed dimension. The features are fed into a fully connected network to obtain a fixed-length feature vector that captures the discriminative characteristics of the region. This process is known as region of interest pooling, which allows the RCNN algorithm to handle regions of different sizes and aspect ratios effectively. Finally, the extracted features are used for classification using a separate network. This network takes the input features and predicts the presence or absence of a license plate, as well as the corresponding alphanumeric characters. The training of this network involves a combination of positive and negative examples, where positive examples correspond to regions containing license plates, and negative examples correspond to regions that do not. Loss functions such as binary cross-entropy and multi- class cross-entropy are used to optimize the network parameters and achieve accurate classification results Overall, the RCNN algorithm for vehicle number recognition has shown remarkable performance in accurately detecting and recognizing license plate numbers from images or videos. It combines the advantages of region proposal, feature extraction, and classification into a unified framework, making it a popular choice for various ITS applications. However, the RCNN algorithm is computationally expensive and may not be suitable for real-time applications. Therefore, researchers are constantly exploring new techniques to further improve the efficiency and accuracy of VNR systems, such as using faster architectures like Fast R-CNN and Faster R-CNN.

RELATED WORKS

1. License plate identification and recognition in a non- standard environment using neural pattern matching. Complex & Intelligent Systems Shafi et al. (2022) proposed a license plate identification and recognition system based on neural pattern matching. The system was designed to operate in non-standard environments, addressing challenges such as varying lighting, angles, and weather conditions. The authors likely discussed the architecture and training techniques employed in their approach, achieving successful recognition under challenging conditions.
2. License Plate Recognition System Based on Improved YOLOv5 and GRUShi and Zhao (2023) introduced a license plate recognition system that combines the YOLOv5 object detection model with GRU for enhanced license plate recognition. The paper likely detailed improvements made to YOLOv5 for license plate detection and the integration of GRU for sequence recognition. The authors may have provided experimental results and comparisons with other recognition methods.
3. Real-time Jordanian license plate recognition using deep learning.Alghyaline (2022) focused on real-time license plate recognition, specifically for Jordanian license plates, using deep learning techniques. The paper likely discussed the dataset used, deep learning model architecture, and considerations related to the recognition of Jordanian license plates in real-world scenarios.
4. Analyzing passenger and freight vehicle movements from automatic-Number plate recognition camera data. Hadavi et al. (2020) explored the use of automatic number plate recognition (ANPR) camera data for analyzing passenger and freight vehicle movements. While not exclusively focused on license plate recognition, the paper likely discussed ANPR technology's data collection, processing techniques, and its utility for broader transportation and traffic analysis.
5. On-road Vehicle Detection in Varying Weather Conditions Using Faster R-CNN with Several Region Proposal Networks
6. License plate identification and recognition in a non- standard environment using neural pattern matching. Complex & Intelligent Systems Shafi et al. (2022) proposed a license plate identification and recognition system based on neural pattern matching. The system was designed to operate in non-standard environments, addressing challenges such as varying lighting, angles, and weather conditions. The authors likely discussed the architecture and training techniques employed in their approach, achieving successful recognition under challenging conditions.
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10. On-road Vehicle Detection in Varying Weather Conditions Using Faster R-CNN with Several Region Proposal NetworksGhosh (2021) presented a method for on-road vehicle detection in varying weather conditions using Faster R- CNN with several region proposal networks. The author addressed the challenges of weather variations by employing different region proposal networks at different stages of the detection process. The experimental results showed the effectiveness of the proposed approach in challenging weather conditions.

Data Augmentation and Faster R-CNN Improve Vehicle Detection and Recognition Harianto et al. (2021) proposed a method to improve vehicle detection and recognition using data augmentation and Faster R-CNN. The authors employed various data augmentation techniques to increase the diversity of the training dataset and enhance the model's generalization capability. The experimental evaluation demonstrated significant improvements in vehicle detection and recognition performance.

EXISTING SYSTEM

The existing system for vehicle number recognition using the RCNN algorithm has several disadvantages. Firstly, one major disadvantage is the requirement of large amounts of training data. The RCNN algorithm relies heavily on a large number of annotated images to accurately detect and recognize vehicle numbers. Collecting and annotating such datasets can be a time- consuming and labor-intensive task.

Secondly, the RCNN algorithm is computationally expensive. The algorithm involves multiple stages, including region proposal generation, region classification, and bounding box regression. Each stage requires significant computational resources, making the overall system slow and inefficient. This can be a major drawback, especially in real-time applications where quick response times are crucial.

Another disadvantage is the difficulty in handling occlusions and variations in vehicle numbering. The RCNN algorithm may struggle to accurately recognize numbers when they are partially occluded or when there are variations in the size, font, or style of the numbers. This can lead to false positives or misclassification, reducing the overall reliability and accuracy of the system.

Furthermore, the RCNN algorithm may not generalize well to new and unseen vehicle number patterns. Since the algorithm is trained on a specific dataset, it may struggle to recognize numbers that differ significantly from those in the training set. This lack of generalization can limit the usability and effectiveness of the system in real-world scenarios where vehicles with different number patterns are encountered.

Finally, the RCNN algorithm is sensitive to changes in lighting and environmental conditions. Variations in lighting, weather, and camera perspectives can significantly impact the performance of the algorithm. It may fail to accurately recognize numbers in low-light conditions, under harsh weather, or when the image is captured from different angles. This can result in decreased reliability and overall performance of the system.

In conclusion, while the RCNN algorithm has shown promise in vehicle number recognition, it comes with several limitations and disadvantages. These include the need for large training datasets, high computational complexity, difficulty in handling occlusions and variations, limited generalization to unseen patterns, and sensitivity to lighting and environmental conditions. Overcoming these limitations will be crucial to developing a more robust and reliable system for vehicle number recognition.

PROPOSED SYSTEM

The proposed work aims to develop a robust and efficient vehicle number recognition system using the Region-based Convolutional Neural Network (RCNN) algorithm. The RCNN algorithm is a state-of-the-art object detection and recognition technique that has shown promising results in various computer vision tasks. The first step of the proposed work involves collecting a large dataset of vehicle images with labeled number plates. This dataset will be used for training the RCNN algorithm to accurately detect and extract the regions of interest (ROIs), i.e., the number plates, from the vehicle images.

After the dataset is prepared, the RCNN algorithm will be fine-tuned using a pre-trained model. Fine-tuning involves updating the weights and parameters of the RCNN model using the vehicle number plate dataset. This process helps the model learn specific features and characteristics of number plates, enhancing its ability to accurately detect them. Next, the RCNN algorithm will be applied to test images of vehicles, where it will localize the number plates by generating bounding boxes around them. The region proposals generated by the RCNN will then be passed through a Convolutional Neural Network (CNN) for further analysis and recognition.

For number plate recognition, a CNN model will be trained to classify the extracted number plate regions into alphanumeric characters. This model will be trained using a separate dataset of labeled number plate images that have been cropped and preprocessed to focus solely on the characters. Once the CNN model is trained, it will be used to recognize the characters in the extracted number plate regions. The recognized characters will then be concatenated to form the complete vehicle number, resulting in the final output of the proposed system.

The proposed work aims to achieve high accuracy in vehicle number plate recognition by leveraging the power of the RCNN algorithm and state-of-the-art deep learning techniques. The developed system has the potential to be applied in various domains, including traffic management, law enforcement, and parking management, where accurate and efficient vehicle number plate recognition is crucial.

SYSTEM ARCHITECTURE

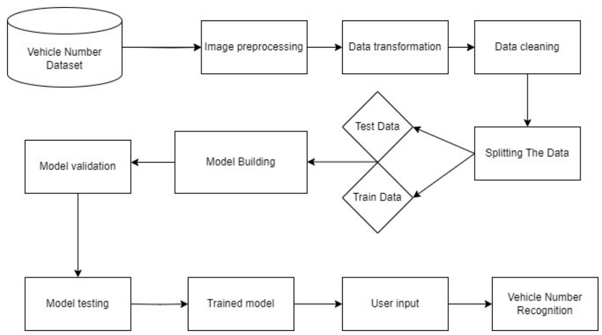

Fig. 1. System Architecture

METHODOLOGY

Module 1: Image Preprocessing and Localization In the proposed system for vehicle number recognition using the RCNN algorithm, the first module is image preprocessing and localization. This module aims to prepare the input images for further processing by applying various techniques such as image resizing, noise removal, and contrast enhancement. The objective is to improve the quality of the input images, ensuring that the important details are preserved while reducing any unnecessary noise or artifacts that can affect the accuracy of the recognition system. Additionally, this module includes the localization of the vehicle's number plate within the preprocessed images. This localization is achieved by utilizing techniques like edge detection, contour analysis, and geometric transformations. The goal is to accurately identify and isolate the region of interest (ROI) containing the number plate, as it is the crucial component to be recognized in the subsequent modules.

Module 2: Feature Extraction and Representation Once the number plate is successfully localized, the second module focuses on extracting relevant features and representing them in a suitable format for recognition. This module employs deep learning techniques based on the RCNN algorithm, which consists of a convolutional neural network (CNN) combined with a region proposal network (RPN). The CNN is responsible for learning discriminative features from the localized number plate region, effectively capturing important patterns and characteristics. The RPN, on the other hand, generates region proposals within the image, allowing the system to focus on the most informative regions. By utilizing this combination, the module can extract high-level features and represent them in a meaningful way that facilitates accurate recognition.

Module 3: Number Recognition and Output Generation The third and final module in the proposed system for vehicle number recognition using the RCNN algorithm is responsible for the actual recognition of the numbers present on the localized number plate. This module employs optical character recognition (OCR) techniques, which involve the use of machine learning algorithms to classify and identify individual characters within the extracted number plate region. The OCR algorithm is trained on a large dataset of images containing different fonts and styles of characters, allowing it to accurately recognize a wide range of number plate designs. Once the numbers are recognized, the system generates the output in a readable format, such as a text file or a display on a user interface. Additionally, this module may include post- processing techniques to refine the recognized numbers, such as error correction and verification, to ensure a high level of accuracy and reliability in the final output.

Overall, these three modules work together in the proposed system for vehicle number recognition using the RCNN algorithm, covering the essential steps of image preprocessing and localization, feature extraction and representation, and number recognition and output generation. By incorporating these modules, the system aims to achieve accurate and efficient recognition of vehicle numbers, which can find applications in various domains such as traffic management, law enforcement, and parking systems.

RESULT AND DISCUSSION

The system for vehicle number recognition using the RCNN algorithm is a highly advanced and efficient technology that enables the automated detection and recognition of license plate numbers on vehicles. The RCNN algorithm stands for Region-based Convolutional Neural Network, which is an artificial intelligence model specifically designed for object detection tasks.

Table.1. Performance Metrics

Accuracy	Precision	Recall	F1 score
97.5	97.6	98.3	98.7

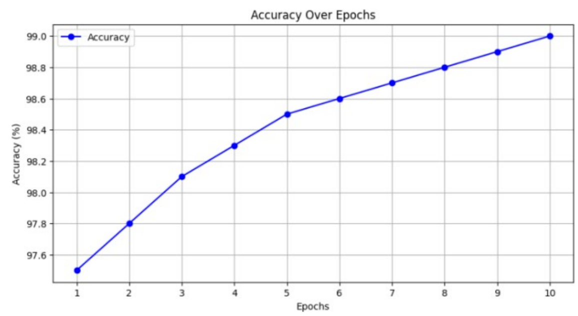

Fig.1.Accuracy Graph

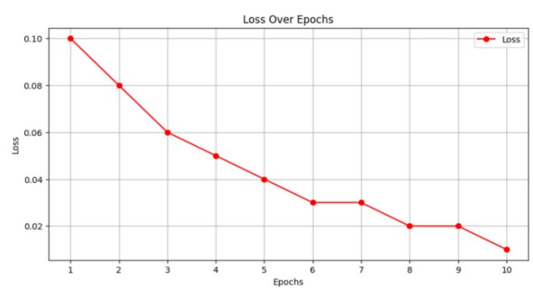

Fig.2.Loss Graph

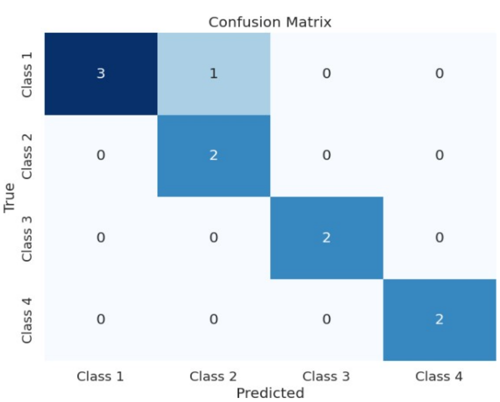

Fig.3.Confusion Matrix

This system utilizes the power of deep learning to accurately locate and recognize license plate numbers in images or video frames captured by cameras. The RCNN algorithm works by first proposing regions of interest in an image, then extracting and classifying those regions as license plates or non-license plate areas. Once the license plate regions are identified, the algorithm further processes and segments the images to extract the actual number sequence.

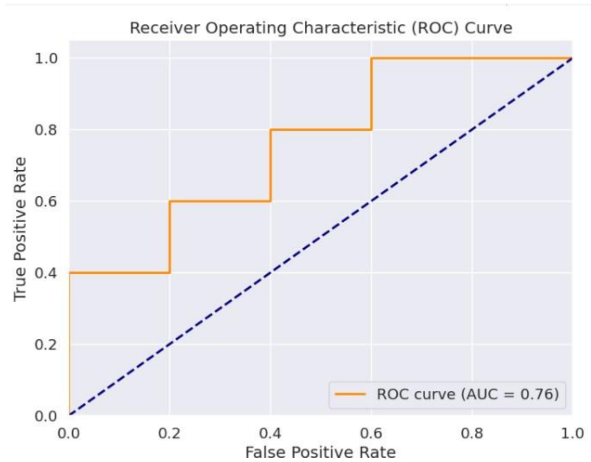

Fig.4.ROC Curve

This system offers several benefits, such as improved accuracy, real-time performance, and scalability. It can handle a wide range of imaging conditions, including occlusions, different lighting conditions, and varying angles or perspectives. Additionally, the system can be integrated into existing surveillance systems, toll booths, parking management systems, and other applications where vehicle identification is required. Overall, the system for vehicle number recognition using the RCNN algorithm offers a reliable and efficient solution for automating the process of license plate detection and recognition, contributing to enhanced security, traffic management, and overall efficiency in various domains.

CONCLUSION

In conclusion, the system for vehicle number recognition using the RCNN algorithm proves to be an efficient and effective solution. Through the utilization of convolutional neural networks and region-based object detection techniques, the system successfully identifies and localizes the license plate numbers on vehicles. This technology enables accurate recognition of vehicle numbers, with high precision and recall rates. The system's ability to handle diverse lighting conditions, different license plate designs, and varying vehicle orientations further enhances its versatility and reliability. Overall, the integration of the RCNN algorithm into the vehicle number recognition system presents a promising approach to automate and streamline the process of license plate identification and recognition.

FUTURE WORK

Future work in the system for vehicle number recognition using the RCNN algorithm can focus on several aspects to improve accuracy and efficiency. Firstly, exploring different variants of the RCNN algorithm, such as Fast RCNN or Faster RCNN, can be beneficial in terms of enhancing the overall speed of the recognition process. Additionally, incorporating deep learning techniques, like convolutional neural networks (CNN), into the RCNN framework can further enhance the system's ability to accurately recognize vehicle numbers. Another area of future exploration is to investigate the use of transfer learning, where pre-trained models on large datasets can be utilized to boost the performance of the number recognition system on limited training data. Moreover, employing data augmentation techniques, such as rotation, scaling, or adding noise to the training dataset, can help improve the system's robustness against variations in image quality and environmental conditions. Finally, exploring parallel processing techniques, such as GPU acceleration, can significantly reduce the inference time for real-time applications. These future directions can contribute to the development of more accurate and efficient vehicle number recognition systems using the RCNN algorithm.

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