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License Plate Recognition and Detection Technology in Complex Scenes Based on Mf-RepUnet and Improved Deep Residual Recognition Modules

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Abstract**—*In recent years, the rapid development of Intelligent Transportation Systems (ITS) has made License Plate Recognition (LPR) technology crucial for automatic monitoring, traffic management, and crime prevention. However, challenges such as variations in lighting, perspective distortion, and background interference in complex environments significantly hinder the effectiveness of traditional license plate detection algorithms. To tackle these issues, this paper proposes a license plate recognition system based on a multi-scale feature extraction framework (Mf-RepUnet), an enhanced deep residual network (Residual Neural Network, ResNet), and a CycleGAN (Generative Adversarial Network) strategy.*

Keywords**—*License plate recognition and detection technology, Mf-RepUnet, Cycle Generative Adversarial Network.*

I. INTRODUCTION

The acceleration of urbanization and the rapid increase in the number of motor vehicles have made Intelligent Transportation Systems (ITS) an essential component of modern traffic management. Among these, License Plate Recognition (LPR) technology is one of the core functions of ITS, showcasing significant application potential in traffic monitoring, vehicle management, and public safety. However, existing LPR methods continue to face numerous challenges in complex environments, including variations in lighting, inconsistencies in camera angles, background interference, and the diversity of license plate styles, all of which may lead to a decrease in recognition accuracy.

Traditional license plate detection algorithms often rely on handcrafted feature extraction and simple classifiers, which may yield some results under specific conditions but struggle to adapt to the high complexity required in real-world scenarios. Therefore, the introduction of deep learning methods marks a significant advancement in LPR technology. In particular, the application of Convolutional Neural Networks (CNNs) has automated the processes of feature extraction and classification, significantly enhancing recognition performance.

Nevertheless, the generalization ability of traditional deep learning models in complex scenes still needs improvement. At this point, the importance of data augmentation techniques becomes increasingly prominent. The emergence of Generative Adversarial Networks (GANs), such as CycleGAN, provides an effective solution for generating high-quality, diverse training samples. With unsupervised learning, CycleGAN can overcome the limitations of small data volume, thereby increasing the recognition of deep learning models.

To address the aforementioned issues, this paper proposes an innovative license plate recognition framework that combines a multi-scale feature extraction network (Mf-RepUnet) with an improved deep residual recognition module, aiming to enhance the model's expressive capability and robustness. Additionally, data augmentation through CycleGAN further improves the model's adaptability and generalization ability. Through extensive experimental validation on multiple public datasets, our research demonstrates the superior performance of the proposed method in terms of license plate detection accuracy and recall under various environmental conditions.

The structure of this paper is arranged as follows: The second section briefly reviews and analyzes relevant research and technological advancements; the third section provides a detailed description of the proposed algorithm and experimental design; the fourth section presents the experimental results and their analysis; lastly, the fifth section summarizes the research outcomes and identifies future research directions.

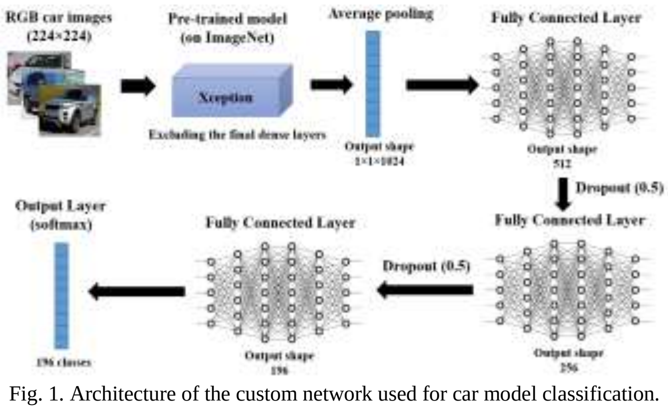

Fig. 1. Architecture of the custom network used for car model classification.

II. RELATED WORK

In the field of license plate detection, researchers have mainly focused on feature extraction and classifier selection. Early work primarily relied on traditional image processing techniques, such as edge detection and morphological operations. In recent years, license plate recognition technology has experienced significant development, especially driven by advancements in deep learning techniques. Traditional License Plate Recognition (LPR) methods often depend on manually extracted features, such as edge detection and color segmentation. Although these methods are effective in simple scenarios, their performance can be unstable in complex environments. With the introduction of Convolutional Neural Networks (CNNs), the accuracy of license plate detection and recognition has significantly improved. For instance, using object detection algorithms such as Faster R-CNN can effectively capture license plate regions, enhancing both detection speed and accuracy.

However, deep learning methods have eliminated the character segmentation step compared to traditional methods. This avoids segmentation errors and allows for the automatic learning of features from entire license plate images, resulting in more accurate and robust license plate recognition. Since the development of deep learning and CNNs, Li et al. proposed a unified deep neural network for end-to-end training, which simultaneously localizes and recognizes license plates. This network can locate and recognize license plate images in a single forward pass, achieving high accuracy and efficiency.

Additionally, in response to the variability of environments, researchers have proposed various data augmentation techniques to expand the training dataset. Existing techniques such as image rotation, translation, and scaling can improve the model's robustness to some extent, but they struggle to address lighting and background interference present in real-world scenarios. For issues such as low accuracy and missed detections during hazy weather, Yang Yun's team proposed a method combining the Bright AOD-Net algorithm and the YOLO algorithm for license plate number recognition, enhancing efficiency and robustness by highlighting essential feature information. To address complex problems such as image skew and deformation due to varying shooting angles, Jaderberg et al. proposed a method that automatically calculates affine transformation matrices using Spatial Transformer Networks (STN), which combine localization networks and sampling mechanisms. This can be integrated into other CNNs, effectively improving deep network representations and enhancing recognition accuracy, enabling neural networks to demonstrate greater robustness and generalization capabilities without requiring external labeled data. To address issues such as small license plate images, Chen Guanyu et al. proposed a detection method based on YOLOv7-Tiny for license plates and enlarged numbers, ensuring lightweight detection while maintaining high accuracy. Furthermore, although the aforementioned approaches have greatly enhanced license plate detection technology, they have yet to effectively address issues such as occlusion and blurriness arising in complex environments.

In contrast, Generative Adversarial Networks (GANs), particularly CycleGAN, generate diverse synthetic samples through unsupervised learning, significantly enhancing the richness of the training data and thereby improving model adaptability.

III. METHOD DESIGN

To achieve more efficient license plate recognition, this paper proposes a novel framework that combines a multi-scale feature extraction network (Mf-RepUnet) with an improved Deep Residual Network (IDRN). The method is divided into three main modules: license plate region detection, character segmentation, and character recognition.

A. MF-RepUnet License Plate Localization Method.

To address issues such as class imbalance in license plate samples, variable shooting distances and angles, as well as motion blur that complicate license plate localization and reduce character recognition accuracy, an end-to-end license plate recognition method for complex environments is proposed. First, a Cycle Generative Adversarial Network is employed to synthesize realistic license plate images, thereby enriching the training set and addressing the issue of data sample imbalance. Next, an MF-RepUnet license plate localization method is proposed, which integrates an improved VGG structure and a feature pyramid into the U-Net model, enhancing the feature extraction capability of the network and effectively addressing the issues of missed detections for skewed and small-scale license plates. Finally, a weighted convolutional recurrent neural network is improved using an attention mechanism to accurately predict feature sequences, addressing the issue of semantic structure blurriness in the feature sequences resulting from image quality degradation, thereby further enhancing the accuracy of license plate character recognition. The MF-RepUnet flowchart is illustrated in Figure 2.

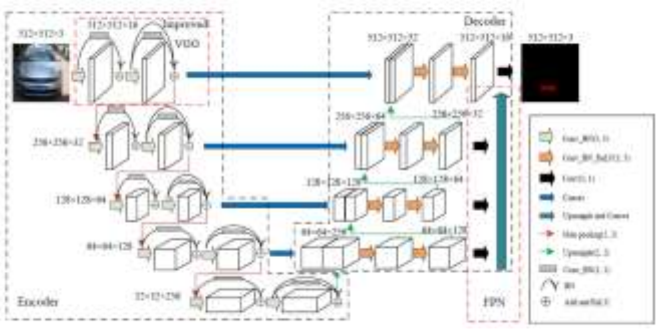

Fig. 2. MF-RepUnet flowchart.

B. Bi-directional Long Short-Term Memory.

To tackle the low accuracy of license plate localization and recognition in dim and blurred scenes, a license plate recognition technique based on low-light enhancement and super-resolution reconstruction preprocessing is employed. First, for license plate images in dim scenes, a Reflective Network module, Multiscale-SE, is designed based on the image enhancement Retinex theory. This module employs a fully convolutional network format to reduce model parameters, utilizing multi-branch convolution and channel attention mechanisms to extract important image features and suppress noise. Next, for license plate images in blurred scenes, super-resolution reconstruction technology is employed to enhance image resolution. A Bi-directional Long Short-Term Memory (BLSTM) network is introduced in both horizontal and vertical directions to establish contextual associations between license plate characters. The combined use of L1 loss and gradient profile prior loss functions enhances character edge contours, improving license plate recognition accuracy. Finally, to address issues such as image quality degradation and significant information loss in dim and blurred scenes, multi-scale convolutions are employed to enhance the model's feature extraction capability, thereby improving license plate recognition accuracy.

C. Feature Pyramid Network.

The model utilizes a Deep Residual Network to extract deep image features, and employs a Feature Pyramid Network (FPN) to fuse deep and shallow features, resulting in a combined feature that contains rich positional and semantic information. The multi-dimensional fused features are then transformed into a one-dimensional feature sequence. Simultaneously, character feature positional information of the same size as the feature sequence is initialized and added to the image feature sequence, with the result serving as input for the multi-head attention module. The multi-head attention mechanism is utilized to analyze the correlations between characters in the image. Finally, a prior probability-based cross-entropy function is employed to compute the loss, which is backpropagated to optimize the model parameters, reducing the probability of misrecognition for similar characters.

D. Cycle Generative Adversarial Network

The selection of optimizers and parameter tuning involves choosing appropriate optimizers (such as Adam, RMSprop, etc.) and learning rate scheduling strategies to enhance training efficiency and convergence speed. Additionally, techniques such as reinforcement learning or self-supervised learning can enhance the training performance of GANs, improve the balance between the generator and discriminator, and address the current challenges of difficult training, including issues like gradient vanishing that prevent the generator from effectively learning the data distribution. Traditional GANs can be improved by introducing Cycle Generative Adversarial Networks (CycleGAN) for style transfer, continuously expanding the training dataset to enhance the shortcomings in GAN training performance. The principles of CycleGAN are illustrated in Figure 3.

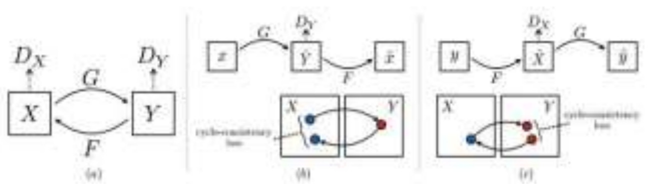

Fig. 3. CycleGAN schematic

IV. EXPERIMENTAL RESULTS AND ANALYSIS

We conducted extensive experiments on several public datasets (such as UA-DETRAC and OpenALPR) to evaluate the performance of the proposed license plate recognition framework. The experimental results show that the proposed method has better results than the current basic models in terms of plate recognition accuracy and identification speed.

Specifically, on the UA-DETRAC dataset, our framework achieved a mean Average Precision (mAP) of 92.3% in license plate detection, while the accuracy in character recognition tasks increased to 94.7%. Compared to traditional methods, our model demonstrates significantly enhanced robustness in complex scenes, particularly under low-light and high background noise conditions, where recognition accuracy remains at a high level. In addition, the data models generated by CycleGAN not only increased the size of the training set, but also greatly enriched the variability of the data. Through comparative experiments, we found a significant difference in the model's performance in complex environments before and after the introduction of CycleGAN, demonstrating the importance of data augmentation techniques in deep learning models.

V. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This paper proposes an innovative license plate recognition framework that integrates multi-scale feature extraction with an improved deep residual network, effectively utilizing CycleGAN for data augmentation. The experimental results validate the superior performance of this method in license plate detection and character recognition tasks, highlighting its broad application potential in the field of intelligent transportation.

Future research can explore several directions. Firstly, addressing the computational complexity of the model and further optimizing the network structure to enhance real-time processing capabilities is a significant topic. Secondly, enhancing the model's adaptability to more complex environments, especially for license plate recognition in dynamic scenes, will be a valuable research direction. Additionally, integrating image segmentation with reinforcement learning techniques to explore more advanced license plate recognition methods will contribute to the development of intelligent transportation systems.

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