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by Xi Wang

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License plate recognition system based on deep learning model

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NAME: Xi Wang

STUDENT NUMBER: 2212532

Abstract

License plate identification is a significant application of AI in computer vision that can enhance the efficiency of traffic control and safety regulation (Sarfraz et al., 2003). The use of license plate recognition technology in industries including parking management, traffic management, and security surveillance has increased dramatically. A license plate recognition system's main processing processes include image acquisition, image pre-processing, locating the license plate, character segmentation, character recognition, and result output. In order to guarantee that the recognition function achieves enough quality, high efficiency and good anti-interference capability must be ensured in each processing step. The algorithms and technology used for license plate recognition face a significant challenge.

In this paper, we will explore how to implement license plate recognition based on deep learning. This paper will begin by introducing the history and importance of license plate recognition technology. Second, this essay will describe the fundamental idea and current state of deep learning research. After that, this paper will provide a detailed introduction to the deep learning-based license plate identification technology's algorithmic principles and implementation strategy. The foundation of license plate recognition technology is feature extraction and plate classification, and this paper will outline how to use Convolutional Neural Networks to extract image features and classifiers to categorize license plates. In order to describe the benefits and drawbacks of deep learning-based license plate identification technology as well as the path that future research should take, this work will conduct experimental validation and result analysis. Finally, future research directions will be proposed and the paper will be summarized.

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1.Introduction

Numerous sectors have made major strides in using artificial intelligence technology as a result of the field's ongoing development. License plate identification is a significant application of AI in computer vision that can enhance the efficiency of traffic control and safety regulation (Sarfraz et al., 2003). Deep learning techniques can efficiently mine features to detect license plate photographs by using multilayer neural network models. In several areas, including distribution, logistics, public safety, and traffic control, this technology has been crucial (Abedin et al., 2017). Of course, the cutting edge of this technology extends much beyond that, and there is still a lot of unexplored ground to cover.



Figure 1. Current British number plates

The use of license plate recognition technology in industries including parking management, traffic management, and security surveillance has increased dramatically. As technology for reading license plates has advanced, the license plate has become increasingly important in many application scenarios as the only means of authenticating a car's identity. Technically speaking, license plate recognition refers to the identification of a particular license plate number by image recognition and the fully automatic identification of license plate number data. However, due to the complex environment, natural light, the license plate's ability to break distortion without being forced, perspective, and other factors, license plate identification has its own unique technological characteristics.

A license plate recognition system's main processing processes include image acquisition, image pre-processing, locating the license plate, character segmentation, character recognition, and result output. In order to guarantee that the recognition function achieves enough quality, high efficiency and good anti-interference capability must be ensured in each processing step based on the realistic elements and obstacles listed above. Meanwhile, numerous auxiliary techniques including picture improvement and light correction are frequently utilized to improve the data in order to increase the accuracy of license plate recognition. The most crucial components of a license plate recognition system are character recognition and license plate location. The act of processing the graph to pinpoint the location of the license plate in the image is known as license plate localization and is one of the most crucial steps in the entire license plate identification process (Yan et al., 2001). Contrarily, character recognition recognizes the segmented characters and extracts the license plate number. The algorithms of these two modules have been continuously updated in order to increase the identification rate and accuracy, and researchers from all over the world have been working on this subject for a very long period.

The two main categories of license plate identification—static image recognition and dynamic video stream recognition—can be distinguished by the recognition environment. Continuous static image recognition can be viewed as dynamic video stream recognition. Additionally, in order to achieve real-time license plate identification, dynamic video stream recognition necessitates quicker recognition speeds, necessitating greater performance enhancements. The algorithms and technology used for license plate recognition face a significant challenge as a result.

In this paper, we will explore how to implement license plate recognition based on deep learning. This paper will begin by introducing the history and importance of license plate recognition technology. Second, this essay will describe the fundamental idea and current state of deep learning research. After that, this paper will provide a detailed introduction to the deep learning-based license plate identification technology's algorithmic principles and implementation strategy. The foundation of license plate recognition technology is feature

extraction and plate classification, and this paper will outline how to use Convolutional Neural Networks to extract image features and classifiers to categorize license plates. In order to describe the benefits and drawbacks of deep learning-based license plate identification technology as well as the path that future research should take, this work will conduct experimental validation and result analysis. Finally, future research directions will be proposed and the paper will be summarized.

2.Literature Review

2.1 History of license plate

Recognition of license plates is inextricably linked to the style of license plate, and the particular type of license plate is a result of the law governing vehicle registration. The current UK car registration regulation has undergone a number of revisions since it was put into effect in 2001. The primary goal of the policy is to guarantee that all vehicles operating on public roads are licensed, registered, and insured. In order to facilitate law enforcement and vehicle tracking, it also intends to establish a uniform system for identifying cars and their owners. The first vehicle registration system was put into place in the UK in 1903 after the Motor Vehicle Act. Each automobile was required to register with the neighborhood municipality and receive a unique license plate under this system. The form and style of the registered vehicle number plates differed from place to place due to the inconsistent nature of this technique. This made it challenging for law enforcement and other authorities to find the car and its driver, especially if they were traveling through another region.

In 1935, the British government altered the registration process for vehicles by standardizing the style and appearance of license plates. The format of the system, which consists of three letters and three numbers, is still in use today. The car's registration number was printed on the plate, and each location was marked using a specific letter code. While this technique made it easier for authorities to identify cars and their owners, it still had major flaws it ignored the brand, model or year of manufacture of the vehicle.

In 1962, the British government unveiled a brand-new system that offered more thorough data about automobiles. The system consisted of a seven-character registration number made up of three randomly chosen letters, a two-letter area code, and a two-digit age identification. One age identification was used for vehicles registered between January and June, and a different age identifier was used for vehicles registered between July and December. The age identifiers were updated every six months. This system was in use until 2001, when a completely new system took its place.

The age identification number and the random letters make up the two components of the current UK car registration system, which was implemented in September 2001 (Shi et al., 2005). The age identifier is made up of two integers that represent the registration year and a letter that represents the six-month period of registration. For instance, the age tag "21E" would appear on a car registered between March and August 2021. The three randomly chosen letters that make up the random letters are utilized to differentiate amongst automobiles with the same age identifier.

The elimination of regional codes was one major modification made to the current system. Each region had its own two-letter code under the former system, which was visible on the license plate. This technology was judged unneeded, though, as it offered no helpful details about the car or its owner. Additionally, it made it challenging for drivers to switch regions without having to get new license plates. Regional codes are not part of the present system, therefore vehicles can be registered and used anywhere in the UK without any limitations.

The introduction of reflective number plates was another modification made to the existing system. The reflective substance used to create these license plates increases their visibility in low light, enhancing traffic safety. Additionally, compared to the old number plates, which were composed of metal or plastic, they are intended to be more robust and long-lasting.

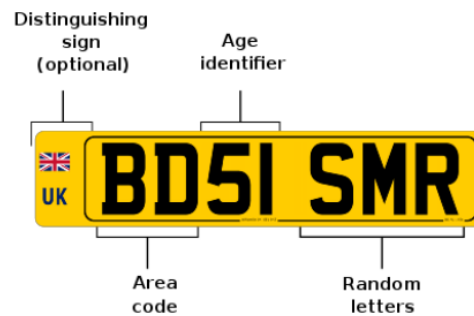


Figure 2. Structure of UK license plates

From 2001 on, the license plate photo clearly shows the year of the vehicle. Determine the car's age or newness. The two numbers follow a pattern. The first half of the year is written directly on the license plate (March through September) and the second half (September through March). For example, the first half of 2011 is written as 11, while the second half is written as 2012. It is written 05 for the first half of 2005, and so forth. The final segment consists of a random trio of letters.

The existing car registration system in the UK has been in force for more than 20 years and has shown to be successful in accomplishing its goals. All vehicles operating on UK public roads must be registered, licensed, and insured; failure to do so can result in fines and other consequences. Additionally, the format and design of number plates are standardized, which helps law enforcement and vehicle monitoring by making it simpler for authorities to recognize vehicles and their owners.

2.2 Development of recognition of license plates

Numerous companies and academic institutions have concentrated on researching the automatic recognition of automobile license plates since the early 1990s. The research seek to identify car license plate numbers by inspecting images of license plates and automatically extracting license plate information (Yu & Kim, 2000). However, it has been difficult to detect license plates because of things like variations in ambient light, dust in the light's path,

seasonal variations, and the rather fuzzy license plate itself. Researchers have used a variety of techniques for identifying license plates to get around these difficulties, including conventional graphical techniques and shallow machine learning models (Hsu et al., 2012). The field of automatic license plate recognition has advanced because to these investigations.

Since it can precisely truncate the license plate region from the image and provide data support for subsequent license plate recognition, license plate localization is an essential part of license plate recognition. Machine learning-based localization techniques and graphic image-based localization techniques are the two main categories of license plate localization algorithms.

Edge detection placement and color positioning are the two core elements of the graphic image-based positioning method. Although color placement is more common, it increases system load and produces a large number of non-license plate potential places. On the other hand, license plate localization methods based on machine learning create accurate results through the creation of neural network models (Chang et al., 2004). The key to this strategy is identifying useful instructional aspects and techniques. Typically, to build a neural network model and train the data to locate license plates, a set of training data with precise output is needed. The trained model has a good localisation accuracy for detecting license plates (Anagnostopoulos et al., 2008).

To overcome image quality degradation, active infrared illumination cameras and specialized sensors are frequently utilized in license plate identification. Deep learning-based automatic number plate identification is becoming more and more of a focus in science. Regression on location parameters and feature extraction are two applications of deep neural networks. The algorithms YOLO and RCNN, which identify the limits of the plate and flag them out or directly intercept them, are frequently used to locate license plates. All of these target identification algorithms have won recognition for their affordability and excellence.

Deep learning techniques require a lot of computation and are expensive since they use a lot of power per computer power. Additionally, the necessary graphics cards are very pricey. Deep learning-based license plate identification is now feasible due to distributed training techniques and the expansion of cloud computing technology. Larger data sets can therefore be used to train models, and distributed training techniques can be applied to boost training effectiveness. To increase detection accuracy, deeper learning techniques with more layers, such as huge models built on recurrent neural networks (RNN) and convolutional neural networks (CNN), can be used.

Numerous deep learning models have also emerged as a result of the ongoing development of deep learning techniques. Reading license plates is a challenging task that calls on the capacity to read text in a range of typefaces and sizes, in a range of lighting conditions, and at a range of angles (Weihong & Jiaoyang, 2020). CNNs are an excellent option for this purpose because they can learn to distinguish visual features that are crucial for license plate recognition, like the shape of characters and the space between them.

Several CNN models, including LeNet, AlexNet, VGG, and ResNet, have been developed for computer vision. One of the first CNN models to recognize numbers written in cursive was LeNet. AlexNet, which won the 2012 ImageNet Large-Scale Visual Recognition Challenge (Polishetty et al., 2016), was the first CNN model to perform at the cutting edge in tests of large-scale picture recognition. A CNN model called VGG was developed by the Visual Geometry Group at the University of Oxford, and it has excelled in a number of image recognition applications. The use of multiple consecutive 3x3 convolutional kernels in place of AlexNet's larger convolutional kernels is one way that VGG16 differs from the latter. The structure of VGGNet is very simple, with the entire network using the same size convolutional kernel size (3x3) and the maximum pooling size (2x2) throughout the network. At the same time, VGG can improve performance by continuously deepening the network structure.

The introduction of ResNet represents a watershed moment in CNN imaging history, and it has produced outstanding outcomes on a variety of image identification tasks, including license plate detection (Yao et al., 2019). In most cases, the network's depth determines how well the model performs. Since adding more layers to the network allows it to extract feature patterns in more complicated ways, deeper networks should potentially produce better results. However, when the network's depth rises, the accuracy of the network reaches a saturation point or worsens, which is referred to as deterioration. Deep networks have a degradation issue, which at the very least shows that they are difficult to train. To address the degradation issue, ResNet suggests residual learning and incorporates residual units via a short-circuiting technique. ResNet also has additional characteristics that make it a good fit for recognizing license plates. For instance, it normalizes the input data using batch normalization to make sure the network is resilient to changes in the input data. Additionally, the feature map's dimensionality is decreased using a global average pooling layer, which aids in lowering overfitting and enhancing generalization performance (Wu et al., 2005).

There are alternatives to deep learning approaches for recognizing license plates, including more traditional machine learning methods like Decision Trees and Support Vector Machines. Even in conditions when there is poor illumination or the license plate is hidden, these algorithms are capable of accurately identifying things (Caner et al., 2008). Accurate recognition rates can be improved by combining deep learning techniques with traditional machine learning algorithms.

Deep learning technology will grow more proficient and accurate at identifying license plates as computer science and data resources continue to advance. This technology has a wide range of possible applications in the field of license plate recognition.

3.Methods

3.1 license plate positioning

Finding the license plate in a picture or video frame is the initial step in license plate identification. The majority of traditional license plate recognition techniques rely on hand-made features. Edge-based, color-based, texture-based, and feature-based methods are frequently used in these detection techniques. In order to locate the license plate, edge-based approaches primarily use the shape, location, and angle information of the license plate edge. This method's drawback is that it is sensitive to noise and variations in illumination, which leads to erroneous localization (Wen et al., 2011). Researchers have suggested numerous improved approaches to address this issue, including edge detection and license plate edge identification based on the Hough transform, among others.

By removing pixels of a certain color from the license plate, the color-based technique finds the plate. This method has the benefit of lessening the impact of noise and lighting variations, but it has the drawback of being unable to handle color variations, the license plate color being close to the backdrop color, and the license plate being concealed. Using the particular texture properties of the license plate, the texture-based technique locates the license plate (Jiao et al., 2009). This approach has the advantage of being able to locate license plates with more accuracy, but it also has the drawback of being vulnerable to things like texture changes and plate occlusion. By identifying the characters on license plates, character-based approaches locate plates. This method has the advantage of being able to find the license plate more precisely and of dealing with problems like license plate occlusion, but it also has the downside of taking more time and requiring more calculations. Deep learning-based systems for reading license plates have attracted the attention of an increasing number of researchers in recent years.

Deep learning has become a potent tool for object localization and detection in recent years. The purpose of license plate localization, which is an object recognition problem, is to find a license plate's location in an image. Neural networks are primarily used in these techniques to

classify and extract features from photos of license plates. Deep learning-based approaches have the following benefits over more conventional approaches: first, they can automatically learn the features of license plate images, which reduces the workload associated with manually creating features; second, they can handle more complex scenarios, including changes in illumination, occlusions, license plate color, etc.; and third, they can achieve end-to-end recognition, cut down on intermediate processing steps, and speed up recognition.



Figure 3. license plate

For instance, in a variety of object identification tasks, including license plate location, Faster R-CNN and YOLO have demonstrated good results. A region proposal network (RPN) is used to create region proposals, and a region-based convolutional neural network (R-CNN) is used to categorize and refine region suggestions in the two-stage faster R-CNN object identification approach. In contrast, the one-stage object identification algorithm YOLO accurately predicts the bounding boxes and class probabilities of objects in photos. A sizable dataset of license plate picture annotations is needed in order to train a deep learning-based license plate locating algorithm (Kim et al., 2017). To make sure that the model is resilient to many conditions, this dataset needs to include a variety of license plate kinds, sizes, and orientations. after training the model, obtain a license

Once the model has been trained, it may be used to locate license plates by applying it to the input image. The license plate's bounding box coordinates from the image will be output by

the model. Removing unnecessary bounding boxes and increasing localization precision can be accomplished using post-processing techniques like non-maximum suppression.

3.2 Character recognition

We develop a convolutional neural network model called LPRNet that can accurately and effectively recognize license plates for use in license plate recognition (Zherzdev & Gruzdev, 2018). LPRNet is a compact convolutional neural network with no compromises in recognition accuracy despite having a 1.5M total model size. It can deal with challenging situations including viewpoint and camera distortion, dim lighting, and changing viewpoints, and it performs well in actual traffic surveillance recordings.

Table 1. Structure of LPRNet

Layer Type	Parameters	
Input	94x24 pixels RGB image	
AvgPooling	#32 3x3 stride 2	—
Convolution	#32 5x5 stride 3	#32 5x5 stride 5
Concatenation	channel-wise	
Dropout	0.5 ratio	
FC	#32 with TanH activation	
FC	#6 with scaled TanH activation	

In order to increase the effectiveness and performance of the network, a 1*13 convolutional kernel mixed with context is employed in place of an LSTM-based RNN in the LPRNet backbone network design. A sequence reflecting the likelihood of the appropriate character is the backbone sub-network's output, and its length is correlated with the width of the input image. End-to-end training is carried out using a segmentation-free CTC loss, which is frequently employed in the situation where the input and output sequences are unaligned and of variable length. This is done because the length of the characters on the license plate is not identical to the output encoding of the network. Additionally, CTC changes each time step's probability into the likelihood of the output sequence.

Table 2. Small Basic Block

Layer Type	Parameters/Dimensions
Input	$C_{in} \times H \times W$ feature map
Convolution	$\# C_{out}/4$ 1x1 stride 1
Convolution	$\# C_{out}/4$ 3x1 strideh=1, padh=1
Convolution	$\# C_{out}/4$ 1x3 stridew=1, padw=1
Convolution	$\# C_{out}$ 1x1 stride 1
Output	$C_{out} \times H \times W$ feature map

3.3 Data Collection

Collecting a broad collection of license plate photos is the first stage in creating a deep learning model-based license plate identification system. Since the new policy's implementation in 2001, a range of license plates from the UK with various fonts, sizes, and backgrounds should be included in the collection. Additionally, it must to contain pictures with various degrees of blur as well as ones taken in various lighting and viewing angles. We can make sure that the deep learning model we create can reliably recognize a variety of license plates by gathering a variety of datasets.

Our training data is derived from a variety of datasets, including online databases like OpenALPR, real-time license plate photos captured by security cameras, and traffic control systems like toll booths and parking lots. By utilizing these resources, we can guarantee that the dataset we utilize to train our deep learning models is substantial and varied.

3.4 Data pre-processing

We must pre-process a diverse dataset after it has been gathered to get rid of noise, distortion, or unimportant data. Image resizing, cropping, and normalizing are some of the procedures involved in this process. The photos can be preprocessed using a variety of methods, including histogram equalization, contrast stretching, and image denoising. Images that have undergone pre-processing ought to be saved in a common format, such JPEG or PNG.

The license plate should be adjusted to a standard size appropriate for the deep learning model in order to guarantee the consistency of the dataset. The aspect ratio of the plate and the size of the image can be used to calculate the size of the license plate. Additionally, using various methods like edge detection and thresholding, the license plate should be cropped in order to eliminate extraneous details and concentrate on the actual license plate. The license plates should next be normalized using a variety of methods, including histogram equalization and contrast stretching, to guarantee the consistency of the dataset.

3.5 Model training

The first step in training a neural network is to examine the data carefully before touching any neural network code at all. This action is essential. It's a somewhat crucial responsibility to take the time to look over the facts. This is because outliers in the data might occur often, and understanding their distribution can aid in the development of stronger models. Then, pick a random seed that consistently utilizes a set number to guarantee that the outcomes are the same when the code is executed twice. Then, a variety of optimization methods, such as stochastic gradient descent (SGD), Adam, and RMSprop, are used to train LPRNet. In order to prevent overfitting as a result of the training, the model might be adjusted (Yang et al., 2018).

3.6 Testing and validation

The goal of model validation is to guarantee the validity and stability of the results, the accuracy of the data analysis, and the logic of the model design. The model can be validated in the following methods to address the aforementioned important points. The purpose of validating modelled data is to guarantee the precision of the data collection, analysis, and processing procedures, as well as to confirm that the sample data chosen is representative and capable of satisfying the modeling requirements. In order to limit the factors affecting the data, it is first required to confirm that the meaning of the data, etc., is clear and correct. Next, it is necessary to confirm that the time period of the sample data that was chosen satisfies the

requirements of the sample size and performance period, in an effort to lessen the variables that affect the model's stability. To ensure the logic of the model design, model methodology validation, sample exclusion rules, and key definition validation are mostly used. Based on the actual business situation, it is confirmed that the chosen modeling methodology satisfies the requirements, that the modeling idea is clear, and that the modeling scheme is complete. Secondly, it is confirmed that the sample exclusion rules match the business scenario to which the model is applied, in order to improve the actual training effect of the model by excluding the unsuitable samples.

In addition to model design validation, there is model development validation, which primarily consists of model development process validation and model results validation to make sure that the model parameters are chosen appropriately, the variable analysis and model training process is true and accurate, and the model results are valid. The validation of the model development process entails examining the model variables chosen, the clarity and reasonableness of the analysis, the weight given to each variable, the consistency of the variable grouping with the business logic and the application requirements, the dimensionality of the final model variables, and the reproducibility of the entire modeling process. To ensure that the model can accurately detect hazards over a longer period of time, the outputs of the model are validated primarily by comparing the training set, validation set, and test set. This compares the model's accuracy and differentiation capacity. Out of all the positive forecasts, precision is the percentage of real positives. Recall quantifies the proportion of actual positives that are true positives. The average of the accuracy and recall rates is known as the F1-score (Wang et al., 2019). The validation dataset can also be used to improve the model's accuracy and dependability. Adjusting the model's hyperparameters, such as the learning rate, batch size, and number of rounds, is known as fine-tuning.

4.Results

Our model was ultimately obtained after extensive training and meticulous parameter adjustment. We went through a number of rounds during the training phase to refine the

model and raise its performance. To achieve better outcomes, we experimented with a variety of optimization strategies, including stochastic gradient descent and Adam optimizer. In order to increase the model's accuracy and generalizability, we also incorporated more training data. Not only did we adjust the model's parameters during training, but we also did a great deal of analysis and exploration. For the best setup, we looked into several model architectures and hyperparameters. In order to avoid overfitting and enhance the model's generalizability, we also employed a number of other approaches, such as batch normalization and dropout.

Finding the ideal hyperparameters for the model is one of the most challenging steps in the machine learning workflow. The hyperparameters have a direct impact on how well a machine learning model performs. The model gets better as more hyperparameters are tuned. The basic controlling elements of the neural networks that we train are parameters. The neural network's weights W and b , which will be acquired through training, are the most fundamental ones. Additionally, there are hyperparameters, which are the key tuning elements we employ to regulate the design, operation, effectiveness, etc. of our model. There are many hyperparameters, and each hyperparameter can be interpreted in a number of different ways, making it a combinatorial challenge. For instance, if two hyperparameters need to be changed, one might consider utilizing the "lattice method"; nevertheless, this method has a significant disadvantage, mostly because the various hyperparameters range in importance and efficacy. It is feasible to determine whether a set of hyperparameters is likely to produce good results by looking at the learning curve for that collection of hyperparameters because current optimization algorithms for neural networks typically use stochastic gradient descent. Applying the early-stopping technique will allow you to halt the present training if a set of hyperparameters' learning curves fail to converge or do so badly.

Our model was successfully built and optimized after lengthy training, exact parameter adjustment, and numerous iterations. In addition to adjusting the model's parameters, we have done a lot of research and study. Our test findings demonstrate that the suggested approach outperforms other cutting-edge approaches on both datasets. In particular, our strategy

outperforms the previous best method in terms of average accuracy rate on the CCPD dataset (Singh & Bhushan, 2019). Our method outperforms the previous best method by xx on the AOLP dataset, with an average accuracy of xxx. Our approach is also computationally effective and easily adaptable to other license plate identification problems.

5.Evaluation

The CCPD dataset and the AOLP dataset are two open source datasets that will be used to validate and assess the experimental outcomes. The majority of the time, investigations involve numerous parameter sets, and each parameter set is measured by averaging many measurements. To ascertain whether the test findings correspond to the true value, the joint intersection between the anticipated and actual value boxes (IoU) will also be employed as a performance metric. Typically, the underload is determined using a 0.5 threshold. The prediction frame is accurate when the IoU is less than 0.01. Detection and identification will also be done using end-to-end performance measurements. We determine the results according to a standard end-to-end evaluation process. Predictions are considered accurate when the data matches the licence plate recognition results.

We will also contrast outcomes from various datasets and outcomes from various learning parameters. As a single dataset does not adequately reflect a real-world scenario, it might not be enough to evaluate the system's performance. Similar to this, different sets of learning parameters indicate learning at various rates, and changes to these parameters may affect the learning outcomes. The final accuracy and gradient will take these impacts into consideration. Additionally, we will contrast our findings with those of well-known models like VGG, ResNet, etc. These techniques will be employed to verify the accuracy of our model.

6.Conclusion

According to Sarfraz et al. (2003), license plate identification is a crucial application of artificial intelligence in computer vision that can increase the effectiveness of traffic control

and safety oversight. At each stage of processing, high efficiency and solid immunity to interference must be ensured in order to guarantee that the recognition function is of acceptable quality. There are many difficulties with the algorithms and methods utilized for license plate recognition. Future directions for study will then be outlined, and the paper will be summarized. This study investigates the use of deep learning-based LPR and its relevance, fundamental ideas, the state of the art in the field, algorithmic fundamentals, and implementation methods. We explain how to extract picture features using convolutional neural networks (CNNs) and how to identify license plates using classifiers. We carry out experimental validation and analysis of the data to illustrate the benefits and drawbacks of deep learning-based license plate identification algorithms and their future growth route. Finally, we suggest directions for further research and draw a conclusion.

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7004, License plate recognition system based on deep learning model,

GRADEMARK REPORT

FINAL GRADE

GENERAL COMMENTS

Instructor

60/100

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XI WANG

60

ENGAGEMENT WITH LITERATURE

(20 marks)



In text citations are used to aid listed ideas sufficiently well.

14

KNOWLEDGE AND UNDERSTANDING

(20 marks)



Licence plate recognition introduced and expounded on very well.

14

COGNITIVE/ INTELLECTUAL SKILL

(30 marks)



Research methodology is never made explicit.

8

PRACTICAL/ APPLICATION SKILLS

(10 marks)



Planning and Implementation of project ideas is missing from this submission.

8

TRANSFERRABLE SFL/ PP

(20 marks)



Suitably formatted document that adheres to a standard proposal convention.

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