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Automatic License Plate Recognition using the Deep Learning Networks

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Abstract—**According to today's statistics, more than half a billion vehicles are moving in the world and inspection and monitoring is one of the basic needs of any traffic system. All cars have an identification number or the same license plate as their primary ID, which today is one of the most suitable vehicle authentication tools. In this paper, the high capacity of deep neural networks in learning license plate identifiers is used. The proposed model of this paper has two stages of highlighting the license plate and reading the ID. In this regard, for highlighting, the combination of YOLO and XGBOOST network is used in encoder-coder network. The proposed model is evaluated on the FZU Cars dataset and based on the results of the experiments, the proposed model has a higher accuracy than the basic methods.**

Keywords: license plate detection; deep learning; Yolo algorithm; XGBoost; Encoder-decoder.

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I. INTRODUCTION (HEADING 1)

Automatic vehicle number plate recognition is a system for reading vehicle license plates using optical character readers. Vehicle license plate number is one of the most suitable information items for vehicle authentication. Automatic vehicle number plate recognition is a fully mechanized system that extracts their license plate numbers using image processing of vehicles passing through a location. To use this system, there is no need to install and equip cars with other devices (such as GPS or radio tags). Using special cameras, the system takes an image of the passing vehicle and sends it to the computer for processing by vehicle license plate recognition software. This system can be used in security and traffic fields. One of the most important parts of the automatic license plate recognition monitoring system is the OCR or character identification system, which is actually software that scans and processes the pixels of the license plates to convert them into one letter if they have the required size.

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In fact, after matching a set of photo pixels with a letter or number, OCR converts them into ASCII code understandable by computer systems and stores them in a file for later purposes [1, 2]. Automatic license plate recognition is one of the most important requirements of traffic control systems such as parking lots, toll terminals, taxi stations and automatic traffic control. Hundreds and perhaps thousands of traffic violations occur daily and are captured by special cameras, the image of the offending car. Investigation of these images by human resources with the aim of identifying vehicle license plate number requires a lot of time and manpower. Therefore, automatic identification of vehicle license plate position and identification of license plate number by software is important. In addition to traffic control, automatic license plate recognition can facilitate the entry and exit process of vehicles in institutions, organizations and terminals. In this way, the work of the guards is made easier and both the organization and the clients will feel more satisfied. Today, many cities have restricted vehicles to the central area of the city in order to control its traffic. Since the use of traditional methods (placing police forces in all areas) is both costly and low-precision, new solutions have been proposed to control and take the tolls of entering the densely populated areas of cities. One of these solutions is the use of vehicle license plate recognition technology. In this solution, vehicle license plate recognition cameras are installed at all points of the design and the entrance of each vehicle to the design area is recorded. Then, like the toll procedure, the driver is given an opportunity to pay the entry duties to the scheme until the due date. Otherwise, the driver will be required by law to pay a fine [3]. Intelligent transportation systems have a very long history of research on image processing [1, 2, 4]. However, the process of identifying the license plates is usually divided into two areas of ID and background in three stages: finding the location of the license plate in a view of the vehicle removed by the camera, zoning and extracting IDs and dividing the license plate image into two areas of ID and background, and finally categorizing and rereading the identifiers [5]. Various studies have been conducted in the field of machine learning and for reading IDs and vehicle license plate recognition.

For example, convolutional neural networks (CNN) are one of these networks that have been used in various applications such as recognition of letters, objects, etc. Since each image taken by the cameras has certain problems, the use of an upgrade method is not effective for all images [6, 7, 8]. To discount the above, it is suggested to use the high capacity of deep neural networks in learning license plate identifiers. One of the applications of deep learning that was able to achieve success in detecting successes were encoder-decoder structures or more generally the coders themselves. A self-encoder network in two steps first maps the input data into the property space, and then maps this property space into the primary space. The training requirement of this network is the reversibility of data in the decoder output, so the input information is not deleted in the encoder output, and according to the type and idea of the training, it is possible to extract information and features that are also suitable for other machine learning activities [9]. Other types of neural networks are widely used recursive networks that can be used to process a variety of sequences. In this network, unlike most neural networks where each learning unit is connected only to the neurons of the layer after itself, each neuron can also be connected to the units in the same layer. Of the famous types of this network, the short-term memory network is long [۱۰].

But the issue with these networks is that they do not have the ability to learn complex structures in images with high accuracy. In this regard, the purpose of this paper is to use YOLO learning networks and combine it with XGBoost for license plate recognition. The proposed model in this paper has three parts: coder, feature conversion and decoder. The encoder layer takes the binary image of the license plate and then highlights the license plate IDs in the new images. The purpose of highlighting vehicle IDs is to create an image of the license plate in which the black license plate IDs and other components of the license plate are closer to white as the background from the image.

The input of the proposed model is the image of the license plate and the target images are also binary images of the license plates that have already been tagged by users. The proposed model is evaluated on the FZU Cars dataset and based on the results of the experiments, the proposed model is more accurate. This indicates that the combination of yolo and XGBoost network, which is a round reinforced model, leads to increased categorization accuracy. Continue this article as follows organized. Section II of this article is dedicated to segmenting and reading vehicle license plate IDs. In Section III, the proposed method is described. The results of implementation and tests are detailed in section IV. Section V also includes conclusions.

II. SEGMENTING AND READING VEHICLE LICENSE PLATE IDS

In the process of finding the location of plaque, one of the methods used in most researches is to find areas with high edge density. Also, the use of moving window, the use of color space information and the extraction of tissue information using wavelet transform in order to find the location of the license plate have been considered [2-4]. The plaque separated from the locating stage due to problems such as variable lighting conditions, the presence of shadows on the plaque, contamination on the body of the plaque and deviation of the plaque from the horizon, does not have the proper quality to read the identifiers and it is necessary to be upgraded [11]. In order to convert the plaque image to binary image instead of the global threshold, the threshold method introduced in [12] is used. At this point, some areas with large area are removed. Finally, by aligning the remaining areas in the horizontal direction, the plaque deviation is also eliminated. The thresholding was performed using histogram information on lighting intensity and neural network. A neural network input is a vector composed of the number of pixels whose brightness intensity is placed in a range. Then the global threshold value in the output is calculated [13, 14]. The method thresholding in [15] is that for each pixel using the average and variance in the pixel neighborhood, a local threshold is calculated and by analyzing the connected components, the area on which the identifiers are located is extracted as a mask. After using this mask, the binary image of the plaque is filtered. In [16] the gray image of the plaque is used. In research [17], separates identifiers from the background using a hybrid method. In reference [18], using a homogeneous neural network with an encoder-decoder structure, a method for coding the license plate is presented.

However, after segmenting the license plate identifiers, they can be detected using conventional methods in recognizing optical letters. Typically, due to the change in distance between the imaging system and the license plate, the license plate image will have a deviation. Therefore, IDs separated from the plaque may be seen in different sizes. Methods of reading license plate IDs need to be able to recognize license plate IDs despite these problems. Considering that identifiers have similar shapes on plaques of the same nationality, each identifier can be categorized by matching the patterns of identifiers with predetermined patterns. Of course, rotation and deviation of the plaque can change the shape of identifiers. In [19], this problem has been tackled by taking into account different patterns of an identifier and changing their rotation angle. In order to match the separated identifiers and template images, a similarity criterion is required. Different categorization methods can be used to read the identifiers separated from the license plate. Therefore, general methods of categorization and machine learning for training and classification need to extract features from license plate identifiers. In reference [13] the skeleton of identifiers obtained using the morphological operator is used to extract the feature. In this way, the window containing the skeleton of the plaque ID is divided into 9 areas and in each area the angle of the skeleton sections is extracted as a feature.

Finally, an artificial neural network detects id using these characteristics. Perceptron neural networks have been used as a method to read identifiers separated from the vehicle license plate image in various researches such as [17]. This classification method also requires extracting appropriate features from vehicle license plate identifiers. In [20] the contour curve of identifiers is used as a feature independent of the shape and size of identifiers. Gabor filter is also used as one of the feature extraction methods for categorizing identifiers. In [21] the illumination intensity of normalized license plate identifiers was used as a feature in two categories of nearest neighbor and support vector machine. In [22], IDs are recognized using the geometric characteristics of identifiers and the distribution of brightness intensity. In [23], the gray image of identifiers in the neural network input is used to train the network. Reading license plate identifiers, in addition to being a final goal in researches, can also be used as a verification method in finding the location of plaque recognition. In [۲۴], the number of identifiers detected by a neural network has been used as a feedback for the plaque locating method.

The proposed model of this paper consists of two stages: highlighting the license plate identifier and reading the identifiers. The highlighting of license plate identifiers is performed using the combination of YOLO and XGBoost with the encoder-decoder structure.

In this paper, instead of reviewing and presenting common methods for plaque segmenting, deep learning methods that are more efficient have been used. The proposed model can learn the smoked image of the license plates in different conditions and then highlight the license plate IDs in the new images. The purpose of highlighting vehicle IDs is to create an image of the license plate in which the license plate IDs in black and other components of the license plate as the background disappear from the image and get closer to white.

Since the frequency of plaques with black identifiers is higher than those with white identifiers, the network will be less able to learn plaques with white identifiers. Therefore, plaques are painted inverted with white identifiers before training. In this layer, YOLO neural network is used for coding. In the next section, the details of the proposed model are explained in full.

III. THE PROPOSED MODEL

In this paper, the input of the proposed model of color images of vehicle license plates is from the FZU Cars dataset. Given that different optical conditions cause a lot of changes in the color of the license plate, so the color feature cannot be used as an efficient feature. On the other hand, in order to extract the characteristics from colored plaques, networks with more learning units are needed. On the other hand, increasing the input volume of the neural network reduces the computational speed and increases the estimation time of the network. For this reason, all images are grayed out and sent to the proposed model. The proposed model includes an encoder-decoder structure, changing the input structure to have features related to both the input image mode and it’s upside down. But what to keep in mind is the repetition of the feature extraction in the encoder, which will take time. Therefore, it is needed to use a method that also includes features related to the inverted image in the encoder output. The proposed method of this paper is the use of a small network that converts the output properties of the encoder into the properties related to the initial image inversion. In this article, the above network is called as property converter network. Given that the proposed network is too small to convert features, it will be time-efficient. Given that the property conversion network is applied to all input images, there is no need to categorize and separate the plaques before the encoder or feature converter input. With this method, different types of plaques can be identified using the same system.

TABLE I. RESULTS OF EXPERIMENTS ON TEST DATASET

Models	FZU Cars Dataset		
	Precision	**Recall**	**F-Score**
ZF	0.91	0.94	0.93
VGG16	0.92	0.95	0.94
ResNet50	0.93	0.95	0.94
Yolo	0.94	0.96	0.95
Proposed Model	**0.97**	**0.97**	**0.96**

This feature converter should convert the extracted features from the input image into features that are obtained from the image inverse. Therefore, to train this network, the features extracted from images with white identifiers have been used as training data in the input. The target data are the properties extracted in the encoder for the inverse of those images.

In the proposed model, YOLO is used as a teachable feature extractor to obtain features from input and XGBoost [8] as a high-level network identifier to produce results that can guarantee the extraction and classification of high-reliability features. Fig. 1 shows the series of steps of the proposed model.

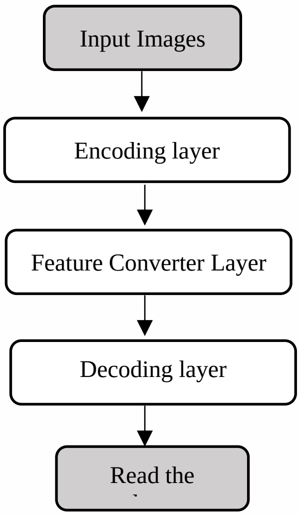

Figure 1. Stages of the proposed model

Then, in the feature transforming layer, a competitive generative neural network with two parts of producer and separator is used to generate new data, which aims to increase the number of educational data. In a competitive productive network with the manufacturer's section, adding noise can obtain new images from the images of the educational collection. After adding noise and producing images, the separator adapts the produced images to the educational data images. If the produced images do not match the original images, the separator rejects those images otherwise artificial images will be created. In this method, the network learns how to create new data from training data. The task of checking the insufficient of this similarity is the responsibility of the separator section, such as a game that if the separator section can guess that the main input of the network is different from the output made by the producer section or in other words not matched, wins and the producer part has to produce better output to the point that the producer part can select the separator part as a result of the game is finished. Trained competitive generating networks can create new photos that are true from the viewer's point of view and include many features of educational data.

IV. IMPLEMENTATION RESULTS AND TESTS

Considering that the emphasis of this paper is on vehicle license plate recognition, FZU Cars standard dataset has been used in tests. This dataset consists of 297 models of the machine with 43,615 images. In this paper, Python software is used to implement the proposed model. And the whole dataset is divided based on the cross validation method. Also, in order to evaluate the proposed model, the criteria for evaluating accuracy, accuracy and recall are used.

The results of the implementation of the proposed model show that the proposed model is more accurate on both data sets. Based on the evaluation results on the FZU Cars dataset, the proposed model has achieved precision, recall and F-score of 97%, 97% and 96%, respectively, which is more accurate than other previous models.

The idea of using a feature converter is to have features related to images and their upside downs at the same time in the decoder input. Therefore, the proposed decode-architecture needs to be designed in such a way that it can receive both sets of features in the input. Therefore, in order to highlight the license plate identifiers, it will act independently of the color of the identifiers. Using this method can be used to highlight license plate identifiers independent of input color. After highlighting the vehicle's license plate IDs, the next step is to read its IDs. In this article, you can read the license plate IDs from the image with prominent identifiers. The reason we use code breaker is that we need the input image to contain only a string of letters and numbers so that the network can read the text of the image.

For this reason, in the proposed model for reading image IDs, its identifiers are highlighted and the size of the background components are removed. Recursive neural network is also used to read image identifiers. The method works is that the input image is given to this network as a sequence. Then information from each location area is stored on the input image in the memory of its learning units. Finally, the input image is labeled as a sequence. This sequence is a combination of identifiers, and the dash mark indicates that the area of the identifier is empty. Finally, using the last layer of recursive neural network and using the combination and output connection method, a single sequence of plaque identifiers is returned. In common methods, the image of the license plate is first binary and then its identifiers are segmented for reading. However, reading vehicle license plate identifiers using recursive neural network is more efficient in dealing with some problems of license plate zoning. For example, some background components may still remain on the plaque image during the zoning process, or some identifiers may be broken and created in several parts. Considering that the recursive neural network receives the image of plaque IDs as a sequence, so it can show better performance when these problems occur.

V. CONCLUSION

Automatic vehicle number plate recognition is a system for reading vehicle license plates using optical character readers. Vehicle license plate number is one of the most suitable information items for vehicle authentication. Automatic vehicle number plate recognition is a fully mechanized system that extracts their license plate numbers using image processing of vehicles passing through a location. Considering the importance of number plate recognition systems in this paper, an improved deep learning model for automatic license plate recognition is introduced. The proposed model of this paper is based on the combination of YOLO network as a teachable feature extractor to obtain features from input and XGBoost as a high-level network identifier to produce results that can guarantee the extraction and classification of high reliability features.

The proposed model in this paper consists of two steps: highlighting vehicle license plate IDs and reading IDs. The proposed method of YOLO and XGBoost network with encoding-decoders structure has been used. This method highlights the plaque IDs independent of their color (white or black). Given that the coder does not have the ability to create a suitable image of the plaque with white identifiers, the encoder input must be changed in such a way that it has the characteristics of its two input image modes. In this regard, a small network is used in the property conversion layer that converts the output properties of the encode data into features related to the initial image inverse. The proposed model was tested on the FZU Cars dataset. Based on the results of the experiments, the proposed model on this dataset has 97% accuracy.

REFERENCES

[1] D. H. S. Dominguez, S. C. Q. Sandoval, and M. E. Morocho-Cayamcela, "End-to-End License Plate Recognition System for an Efficient Deployment in Surveillance Scenarios," in International Conference on Information Technology & Systems, 2022: Springer, pp. 697-704.

[2] A. Pattanaik and R. C. Balabantaray, "Licence Plate Recognition System for Intelligence Transportation Using BR-CNN," in Advances in Data Computing, Communication and Security: Springer, 2022, pp. 659-668.

[3] S. Saha, "A review on automatic license plate recognition system," arXiv preprint arXiv:1902.09385, 2019.

[4] I. Goodfellow, Y. Bengio, A. Courville, and Y. Bengio, Deep learning. MIT press Cambridge, 2016.

[5] N. Mufti and S. A. A. Shah, "Automatic number plate Recognition: A detailed survey of relevant algorithms," Sensors, vol. 21, no. 9, p. 3028, 2021.

[6] W. Weihong and T. Jiaoyang, "Research on license plate recognition algorithms based on deep learning in complex environment," IEEE Access, vol. 8, pp. 91661-91675, 2020.

[7] T. Vaiyapuri, S. N. Mohanty, M. Sivaram, I. V. Pustokhina, D. A. Pustokhin, and K. Shankar, "Automatic vehicle license plate recognition using optimal deep learning model," Computers, Materials and Continua, vol. 67, no. 2, pp. 1881-1897, 2021.

[8] V. Gnanaprakash, N. Kanthimathi, and N. Saranya, "Automatic number plate recognition using deep learning," in IOP Conference Series: Materials Science and Engineering, 2021, vol. 1084, no. 1: IOP Publishing, p. 012027.

[9] T. Naito, T. Tsukada, K. Yamada, K. Kozuka, and S. Yamamoto, "Robust license-plate recognition method for passing vehicles under outside environment," IEEE transactions on vehicular technology, vol. 49, no. 6, pp. 2309-2319, 2000.

[10] L. Xiaobo, L. Xiaojing, and H. Wei, "Vehicle license plate character recognition," in International Conference on Neural Networks and Signal Processing, 2003. Proceedings of the 2003, 2003, vol. 2: IEEE, pp. 1066-1069.

[11] Y. LeCun, Y. Bengio, and G. Hinton, " Deep learning," Nature, vol. 521, no. 7553, pp. 436-444, May, 2015.

[12] P. Angelov and A. Sperduti, "Challenges in deep learning," in Proc. European Symp. on Artificial NNs, 2016, pp. 485-495.

[13] L. Deng and D. Yu, "Deep learning: methods and applications," Foundations and Trends® in Signal Processing, vol. 7, no. 3–4, pp. 197-387, 2014.

[14] M. A. Wani, F. A. Bhat, S. Afzal, and A. I. Khan, Advances in deep learning. Springer, 2020.

[15] I. Giannoukos, C.-N. Anagnostopoulos, V. Loumos, and E. Kayafas, "Operator context scanning to support high segmentation rates for real time license plate recognition," Pattern Recognition, vol. 43, no. 11, pp. 3866-3878, 2010.

[16] F. Wang, L. Man, B. Wang, Y. Xiao, W. Pan, and X. Lu, "Fuzzy-based algorithm for color recognition of license plates," Pattern Recognition Letters, vol. 29, no. 7, pp. 1007-1020, 2008.

[17] S. Yu, B. Li, Q. Zhang, C. Liu, and M. Q.-H. Meng, "A novel license plate location method based on wavelet transform and EMD analysis," Pattern Recognition, vol. 48, no. 1, pp. 114-125, 2015.

[18] E. Rashedi and H. Nezamabadi-Pour, "A hierarchical algorithm for vehicle license plate localization," Multimedia Tools and Applications, vol. 77, no. 2, pp. 2771-2790, 2018.

[19] S.-L. Chang, L.-S. Chen, Y.-C. Chung, and S.-W. Chen, "Automatic license plate recognition," IEEE transactions on intelligent transportation systems, vol. 5, no. 1, pp. 42-53, 2004.

[20] D. Llorens, A. Marzal, V. Palazon, and J. M. Vilar, "Car license plates extraction and recognition based on connected components analysis and HMM decoding," in Iberian conference on pattern recognition and image analysis, 2005: Springer, pp. 571-578.

[21] I. Giannoukos, C.-N. Anagnostopoulos, V. Loumos, and E. Kayafas, "Operator context scanning to support high segmentation rates for real time license plate recognition," Pattern Recognition, vol. 43, no. 11, pp. 3866-3878, 2010.

[22] T. D. Duan, T. H. Du, T. V. Phuoc, and N. V. Hoang, "Building an automatic vehicle license plate recognition system," in Proc. Int. Conf. Comput. Sci. RIVF, 2005, vol. 1, pp. 59-63.

[23] B. Shan, "Vehicle License Plate Recognition Based on Text-line Construction and Multilevel RBF Neural Network," J. Comput., vol. 6, no. 2, pp. 246-253, 2011.
[24] C. A. Rahman, W. Badawy, and A. Radmanesh, "A real time vehicle's license plate recognition system," in Proceedings of the IEEE Conference on Advanced Video and Signal Based Surveillance, 2003., 2003: IEEE, pp. 163-166.

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