# Vehicle License Plate Detection Using Deep Learning

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2022 International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT) | 978-1-6654-7013-1/22/$31.00 ©2022 IEEE | DOI: 10.1109/ISMSIT56059.2022.9932852

***Abstract*— This study focuses on using a Deep Convolutional Network trained with data from license plates to automatically categorize and geolocate vehicles (DCNN). Toll collection, accident reconstruction, and the identification of suspicious vehicles are just some real-world applications that use license plate readers. The study recommended using a vehicle classifier based on deep learning to pinpoint the location of license plates and license numbers simultaneously. Bounding quadrilaterals are provided by the classifier instead of bounding rectangles, which provides a more accurate indication for vehicle registration estimation to license plate localization. This task was accomplished using the Python programming language and various deep learning libraries. Since the training of the proposed DCNN model began with a weight that had already undergone a certain number of iterations in a model without a classification head, the total number of training iterations will be close to 10,000 when taking into account the transfer learning component of DCNN. Because of transfer learning, the DCNN model could begin at a good place, making it simpler to enhance functional heads at once. According to the study's characterization of the task at hand—vehicle number estimation as well as license plate segmentation and vehicle—the DCNN achieved 98.8% accuracy in classification.**

**Keywords— Vehicle, deep learning, detection, DCNN, license plate, segmentation, optimization.**

## I. INTRODUCTION

This research examines how neural systems can stay resistant to insufficient information when utilized for vehicle categorization and position prediction via license plate localization. As mentioned in [1], people possess a natural ability to acquire information and make decisions with limited information. There is no doubt that this ability would have been a boon to evolution, but it is still unknown how human brains are able to perform it. These subject piques the curiosity of every engineer attempting to develop more durable intelligent systems [2], and it has significant consequences for our knowledge of learning and information processing in the brain. Focusing on artificial neural networks as described in [3] enables us to preserve the second perspective that is crucial to this inquiry. Target challenge is car detection in partially covered photos. Classical vehicle recognition has been researched extensively in both the brain and artificial systems, making this a good issue for investigation. Before digging deeper into the paper's major emphasis, it will be useful to provide a summary of the field's current situation and explain essential theoretical concepts.

### A. PROBLEM STATEMENT

In the vehicle number estimation stage, most existing systems are based on the frontal view of vehicle. The open-source version of commercial software struggles to find the vehicle number estimation and license plate with transformation, like a tilted license plate or the license plate which belongs to the car in an oblique view as mentioned in [11]. This problem states a critical performance bottleneck for machine learning based systems since the vehicle position estimation and detection failure means the total inability to comprehend a specific position. Here, we conclude the problems of vehicle classification and number estimation with license plate localization that’s would be solved:

1. Real-time vehicle images captured at an angle cannot be estimated.
2. Having to deal with more generic vehicle classification and position estimation causes a loss of contextual knowledge.
3. Can training data be generated from a vehicle image and an average vehicle categorization with a known ground truth?
4. Does the method of using (DCNN) to automate vehicle recognition and location estimation measures using live photos work?
5. If similar studies are conducted in the future, what factors should be taken into account?

### B. ALGORITHM AND SOLUTION

In contrast to DCNN-based vehicle detectors, the training process for our model requires no heuristic decisions; all we need to do is let our model naturally learn the ability of detection using an anchor-free deep convolutional neural network (DCNN) for our head network. In addition, after planar rectification by perspective transform, we may run further OCR on a more accurate region because our model regresses the four vertices of a quadrilateral individually, not just the bounding rectangle. It's not easy to figure out which of the many possible head designs is causing the model to fail to converge. To ensure that the initial single-head design concept was implemented appropriately, we added additional functional heads to the model one by one during the design process.

### C. *Aim of Contribution*

The research aims to solve the four sub-tasks in the vehicle classification and vehicle number estimation with license plat localization process, our research focuses on the vehicle number estimation with license plate localization after vehicle classification task, aiming to accurately locate the vehicle position in various scenes with single or multiple vehicles inside. As to maintain the contextual information when dealing with higher vehicle classification performance, the license plate localization will be detected as well, the pose of the car, on which side (front or rear) does the license plate lay on will also be classified. The research will show a detection example; the vehicle numbers with license plate localization missing problem mentioned in the problem statement can be solved by our proposed method. The research conclude our main contributions as followed:

- Research has designed a DCNN-based network for vehicle classification and number estimation vertices with a variety of angles in real-world scenes.
- Along with vehicle number estimation and the license plate localization, vehicle's number information will also be given.
- Our model will detect and classify the region of the car's front part and the rear part where a vehicle position is onto.
- To train our model, research proposed a new dataset with manually annotated front-rear bounding boxes.
- The classification process is based on a novel anchor-free method presented in methodology, no manually decided anchor-box size is needed; it might be an inspiration for other vehicle classification and detecting applications.

## II. Related work

To generate final vehicle detection results, an encoding method for image information is necessary, and this is often called feature extraction in the vehicle detection task, lots of convolutional neural network architectures are designed for this purpose, the CNN architecture used for feature extraction is then viewed as backbone architecture as given in [5]. On top of the backbone architecture, how to utilize the feature map generated in different inner layers of the network has been studied widely in recent years. In the convolutional neural network, a sequence of down-sampling process will be performed, in this process, early layers with high resolution often have richer spatial information and weaker semantic information, deeper layers with lower resolution often have less spatial information but more semantic information [6]. This leads to a property that early layers are good at detecting small vehicles but lack of the ability to recognize and classify vehicle categories, on the other hand, deeper layers are short of finding small vehicles but more capable of categorizing vehicles and more robust on different translation, illumination, and transformation of a vehicle. Vehicle classifier like Faster R-CNN and YOLO, they detect the vehicle by only utilizing the final output feature map, to overcome the spatial information-lacking problem, a method is to intuitively, train one classifier with different scales of images or to train several classifiers with each classifier handling different sizes of images and then combine the results as mentioned in [7]. This process is called Image Pyramid and shown at the top left. This method could be computationally expensive since we need to feed the image several times at the training and testing stage as given in [8].

Since the classic deep learning pipeline is divided into four sub-tasks, the optimization process is quite tricky as each of the processes links to and counts on each other as mentioned in [9]. An overall and end-to-end optimization strategy is needed if we want to push the performance of deep learning to another level. Recently, deep learning technics aid the deep learning a lot especially with the help of Convolutional Neural Network (CNN). Researchers in [10] proposed a network named Warped Planar Vehicle Detection Network, their method is to find a license plate inside a single vehicle using DCNN, with obtaining not only rectangle bounding boxes, but also parallelograms after the model learned the affine transform parameters and applied to rectangle bounding boxes, their model can transform the license plate back into the rectangle easily by inverse affine transform and further do the DCNN.

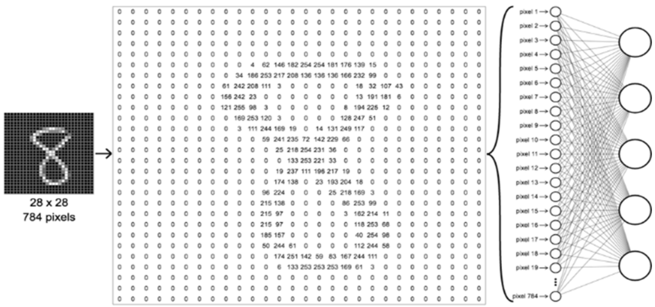


Fig. 1. *(The depiction of deep learning based DCNN network while learning the digits though hidden layers) [10]*

## III. Methodology

For those curious, the suggested model is abbreviated as "DCNN" (Deep Convolutional Neural Network). The DCNN classifier uses deep learning to make a determination with no intermediate steps or anchors. Figure 2 depicts the entire model. An input RGB image will have its width and height halved before being processed by two layers of Hourglass Network to obtain the final, high-resolution version used for feature extraction from the image's backbone. Using these features as inputs, three concurrent processing nodes will independently deal with localization, region regression, and classification. In Figure 2, on the right, we see an example of our model's output showing that the license plate region has been located, and in addition, we are provided the front-to-rear region of the owner car, as well as its pose information.

### 2.1 *Deep Convolutional Neural Network*

Since a DCNN is a multi-stage classifier, its speed comes at the expense of accuracy, and notably for smaller vehicles, accuracy suffers. Imagine a license plate on a small vehicle and you'll get an idea of the scale difference between the two. This means that the feature extraction ability of the spine network infrastructure becomes significant, and that spatial information that needs to be fruitful to prevent losing detections for small vehicles. Research developed DCNN Network as our core design after being inspired by the widespread use of the Hourglass Network in modern, one-stage detectors. This architecture outperformed a standard, straightforward DCNN by a significant margin. After verifying that our unique anchor-free technique for region regression is performing as expected, we incorporated the heads for license number recognition to the original architecture of our DCNN model for license plate detection. We trained weights for the license plate heads and the backbone architecture, and then we trained the car posture heads that were incorporated in the new research. Once we were satisfied with the quality of our model's license plate detection training, we added the final piece: a system to classify plates.

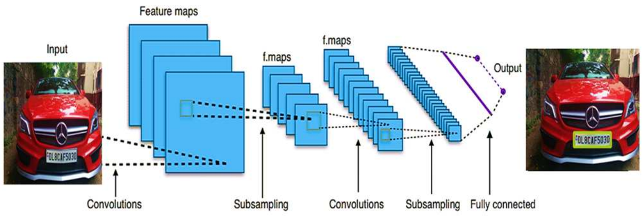


Fig. 2. *(The architecture of deep convolutional neural network for license plate classification)*

## 2.2 Detection and Classification using DCNN

Figure 2 provides a clear understanding of the architecture, and we will illustrate each of the four parallel DCNNs that serve as our head networks outside the backbone network. A deep convolutional neural network with filter size 3x3 is used for the localization head; the resulting feature map has dimensions of 64x64x1, with a single output channel per pixel indicating the pixel's likelihood of carrying a license plate. Since the background class was not incorporated into our design, we have a single-class problem, and the sigmoid activation function met our needs, so that's what we went with.

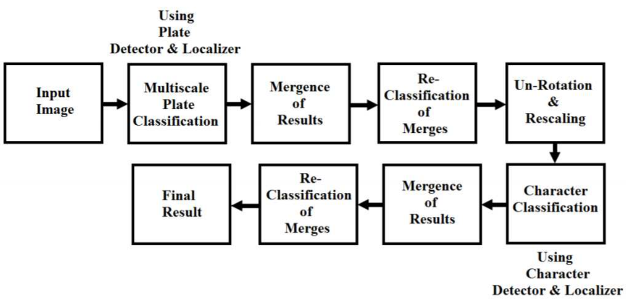


Fig. 3. *(The block diagram for character classification using deep learning classifier with multi-scaling and emergence of plates).*

A 3x3 convolutional neural network is used to do the region regression, with an output feature map of 64x64x8 pixels, eight output channels per pixel, with these channels taking care of the region proposal for vehicle number estimate and license plates localisation. The study employs four sets of unit vectors in the same four-quadrant arrangement as scalars to expand these unit vectors; then, after expanding a set of unit vectors, the researchers perform a vector addition of the horizontal vector and the vertical vector in the set to obtain a final destination point. This study obtained four points by repeating the previous step on each of the four pairs of unit vectors, and these points will serve as the vertices of a quadrilateral representing the license plate's territory. We utilized a linear activation function (equal to no activation function) for the DCNN layer because our research requires the expansion factor for unit vectors and so requires accurate scalars. Car pose (front-rear) area regression follows the same procedure as license plate region regression, except that the vertices now represent the front-rear portion of a vehicle. This is a multi-class classification job with three possible categories: foreground, middleground, and backdrop. A convolutional neural network with filter size 3x3 performs the classification process, and the resulting feature map is 64x64x3, where each channel in each pixel reflects the probability for the foreground class, the background class, or both. Because of its adaptability to multiple classes, character classification with activation function was chosen here.

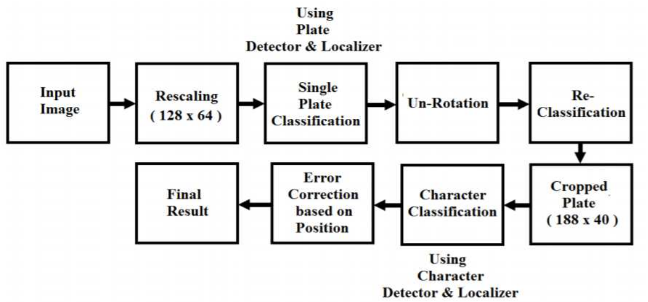


Fig. 4. *(The block diagram for character classification using deeplearning classifier with rescaling and error correction)*

## 2.3 details of training

In this section, we'll explain how our training process is put together, from the online data augmentation technique we utilize to the transfer learning technique we employ to avoid an unstable training state, and finally, how we tune the hyperparameters for various iteration durations. Kaggle dataset was used for both training and testing in this study. Many different kinds of augmentation were chosen at random before the training images were fed into the algorithm. With 10-fold cross-validation, 80% of the data is used for training, and the remaining 20% is used for testing.

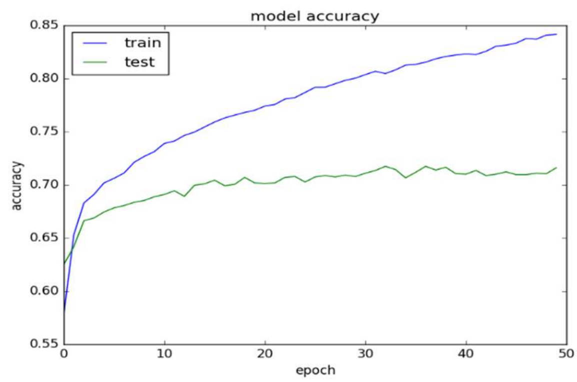


Fig. 5. *(The training and testing accuracy with total 50 number of epochs)*

There was a random order to the one-time execution of each technique for each image. Because to online data augmentation, the variety of the original training data is maintained. The research uses random parameters in all of the augmentation methods, which means that after applying all of the methodologies, a single actual image would be transformed into an infinite number of augmented images. This increases the training data scale as well as protects the prototype from overfitting too soon.

## IV. RESULTS

Ubuntu 16.04 LTS was used for both development and testing, together with an Intel i7-6500 CPU, a GeForce GTX1080 graphics processing unit, and 16GB of RAM. The system was developed in Python 2.7, and TensorFlow and Keres were used as deep learning frameworks. All of the codes may be found on the internet. We also made the codes available for Windows and python 3.7. The research shows some examples of the classification results on the Kaggle dataset, the text above the bounding quadrilaterals of car's front-rear gives the classification results, Front, Rear, or Unknown for background class. The number followed by class is the output of the SoftMax activation function. The license plate probability is also written at the bottom of the bounding quadrilateral.


*(a) Input Image* *(b) Detection* *(c) Classification*

Fig. 6. *(The input image, detection and classification of sampled license plate on vehicle)*


*(a) Input Image* *(b) Detection* *(c) Classification*

Fig. 7. *(The input image, detection and classification of sampled license plate on vehicle)*


*(a) Input Image* *(b) Detection* *(c) Classification*

Fig. 8. *(The input image, detection and classification of sampled license plate on vehicle)*

## V. DISCUSSIONS

This gave us an insight that a proper design of the labeling strategy can undoubtedly have a massive effect on the performance of a supervised learning vehicle detector. The classification task is relatively easy for our DCNN model to learn; the classification had already reached high accuracy in the early iterations as mentioned in [14]. Nevertheless, the accuracy is quite low before multiple iterations, that was due to the wrong label strategy in our early design, we labeled the front-rear region by the same method used in region regression, which led to a limited region for ground-true labels. Observing the situation, we modified the label encoding strategy immediately and solved the issue.

TABLE I. COMPARISON OF PROPOSED TECHNIQUE WITH EXISTING LITERATURE

| Article | Technique | Accuracy |
|---|---|---|
| [15] | Recurrent Neural Network | 97.71% |
| [16] | Support Vector Machine | 89.26% |
| [17] | Convolutional Neural Network | 96.87% |
| Proposed | Deep Convolutional Neural Network | 98.8% |

## VI. CONCCLUSION

The devised DCNN based vehicle number estimation with license plate localization model showed the ability to detect license plates under different vision angles. Our system also detects bounding quadrilateral instead of bounding rectangles, yielding a more precise indication for vehicle number estimation and license plate localization compared to conventional systems. Another main contribution is providing the vehicle information while performing vehicle number estimation and license plate localization detection, we called this kind of information contextual information, which provides the relation comprehension between the vehicle number estimation and license plate localization and the vehicle, we got the pose classification accuracy 98.8%. Applications like traffic scene analysis, we may utilize contextual information for enhancing the interpretation of the vehicle number estimation and license plate localization. Since we have obtained the area of the owner car, by further analyzing, research can get; for instance, car brand, model, and color information. In addition, some parking lots tell users to park their cars in a consistent direction, the pose information given by our system might help the management of those parking lots.

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