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Car Image Classification and Recognition

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Abstract: Vehicle positioning and classification is a vital technology in intelligent transportation and self-driving cars. This paper describes the experimentation for the classification of vehicle images by artificial vision using Keras and TensorFlow to construct a deep neural network model, Python modules, as well as a machine learning algorithm. Image classification finds its suitability in applications ranging from medical diagnostics to autonomous vehicles. The existing architectures are computationally exhaustive, complex, and less accurate. The outcomes are used to assess the best camera location for filming, the vehicular traffic to determine the highway occupancy. An accurate, simple, and hardware-efficient architecture is required to be developed for image classification.

Keywords: Convolutional Neural Networks, Image Classification, deep neural network, Keras, Tensorflow, Python, machine learning, dataset.

I. INTRODUCTION

Keras is an open-source neural network library written in Python. It is compatible with Tensorflow. It is intended for rapid experimentation with Deep Learning Networks. Tensorflow is a library for developing and deploying neural networks for machine learning. A dataset is a list of mostly tabulated data. A dataset is the substance of a single database table. The Stanford University dataset was chosen because it contains images of cars with normal angles (front, rear, hand, and tilt) in which one could have images of these as seen in Figure 1. Deep neural networks analyze numerical and characteristic data. They extract characteristics and classify patterns. Since the deep neural network must learn on its own to identify a wide range of objects within an image, we will have a very large dataset; the more images we have for training, the better it will capture its characteristics, i.e. it will classify the objects. The classification problem is to classify all of the pixels in a digital image into one of the given groups. Image recognition is the most important use case of digital image processing. In supervised classification, we pick samples for each target class. Image classification refers to the task of extracting information classes from a multiband raster image. The resulting raster from image classification can be used to create thematic maps. There are two types of classification: supervised and unsupervised.

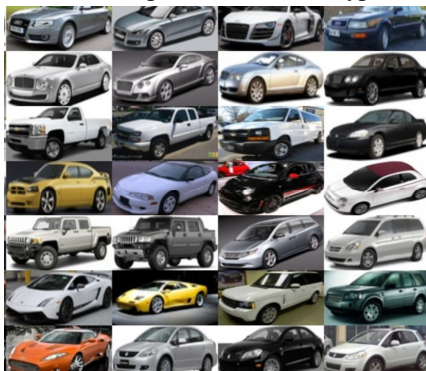


Fig. 1. Dataset from Stanford University[1]

II. MAIN IDEA OF THE PAPER

A. Paper I - Classification of Vehicle Images through Deep Neural Networks for Camera View Position Selections

This paper describes the License Plate Detection and Recognition techniques using Deeply Trained Convolutional Neural Networks that describes a fully automated license plate detection and recognition system. Deep convolutional neural networks are used by him (CNN). CNN's are educated and modified to work in a variety of environments. The idea is to have a range of license plates with various sizes, backgrounds, fonts, and so on.

They gather information for two purposes: license plate detection and character detection/recognition.

To detect license plates, they created a database of real-world photos with license plates that were visible in the background (vehicle, scene, etc.). As a result, for this mission, they gathered over 20,000 photos from various sources, capturing all of the requisite variations.

They collect highly cropped license plate image data for character recognition (without context). More than 25,000 photographs with various backgrounds and sources have been compiled. Following that, they use an automated method to segment, extract, and categorize characters, as well as samples of negative context graphics, before manually cleaning the data.

B. Paper II - Realization of Vehicle Classification System Based on Deep Learning

Vehicle positioning and classification is an important technology in intelligent transportation and autonomous driving. The system uses an SSD algorithm to achieve vehicle classification and positioning, from the picture collection, picture calibration, model training, model detection several aspects of the detailed introduction of the vehicle classification process. Pre-labeled can be adopted in image annotation to improve annotation efficiency. The SSD algorithm is a mainstream deep learning-based target detection algorithm in recent years. The algorithm has high detection efficiency and correct rate and is widely used in classification recognition and target positioning. The vehicle classification system based on deep learning uses TensorFlow as the experimental platform and python3 as the development language.

This system uses the SSD (Single Shot MultiBox Detector) algorithm during model training. The SSD algorithm is another very useful deep learning-based object detection algorithm after Faster RCNN and YOLO.

This system realizes the vehicle calibration, model training, model testing, and the whole process of deep learning detection targets. But there are still some problems, such as how to effectively detect vehicles in complex environments. Due to the limitations of hardware and time, in-depth research can be conducted in the future from the aspects of improving accuracy, improving detection accuracy, and improving calibration methods.

III. METHODOLOGY

A. Paper I - Classification of Vehicle Images through Deep Neural Networks for Camera View Position Selections

A dataset of 16,000 vehicle images from Stanford University was used to experiment with vehicle images to determine if the vehicle is in front, back, side, or tilted view. For training, 735 front images, 274 rear images, 1020 side images, and 13907 tilt images were used. Labels were developed as a next step in the process to be used for supervised learning.

When we load a sideways picture of a car, we already know what mark it belongs to, so when we give it entry, we already know what exit we expect. So, when training the network will adjust the weights of the neurons. Training sets were created with 80% of the images and 20% for tests. To begin training the neural network, the pixels of an image are used as inputs. If our images are 100x100 pixels, we will have 10,000 input neurons, even though we only have one color (grayscale). If we wanted a color picture, we'd need three channels, or 100x100x3, or 30,000 input neurons. The data must be normalized before entering the input values. The values of the colors of the pixels are in the range of 0 to 255, they must be transformed by dividing the value by 255. This will be in the range of 0 and 1. Convolutions will be performed, which means that the scalar product of a matrix of nearby pixels in the input image against the matrix known as the kernel will be computed mathematically. This kernel will have a dimension of 3 3 pixels, and it traverses all input neurons (left-right, top-down) to obtain a new output matrix, which would be a new layer of hidden neurons. The kernel will initially take random values and will be adjusted by backpropagation. Backpropagation is a gradient calculation method used in supervised learning algorithms used to train artificial neural networks.



Fig. 2. Folders with their classified images (front, rear, side, and tilt)[1]

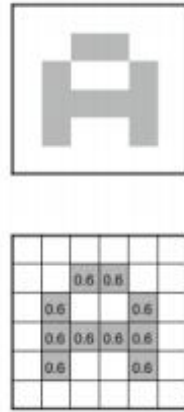


Fig. 3. Pixels of the image is displayed normalized[1]

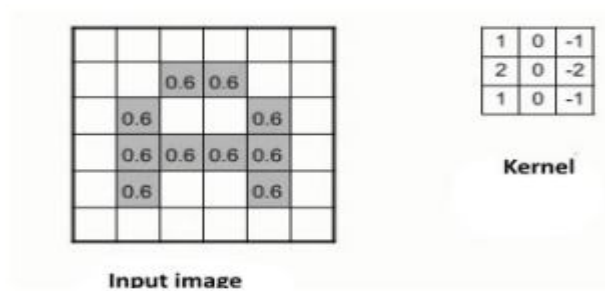


Fig. 4. Sample of the matrices to calculate the scalar product[1]

We began training with Python’s fit() feature. Next, we saved the qualified network with the save() function so that we could use it without having to retrain it, which saves time and unnecessary work.

After six epochs, an accuracy value of 88 percent is obtained, with the validation set hitting 87 percent. The neural network is already trained as a result of this.

B. Paper II - Realization of Vehicle Classification System Based on Deep Learning

1) *Experimental Data Set:* The number of data sets and accurate tagging is critical for deep learning and has a direct impact on model quality. Many useful data sets, such as PASCAL VOC, are available online. This experimental data set downloads JPG images from the Internet and marks them by themselves to systematically understand the entire mechanism of the deep learning classification model, as seen in Figure 6.

```

Train on 10198 samples, validate on 2550 samples
Epoch 1/6
10198/10198 [=====] - val_loss: 0.5036 - val_acc: 0.8608
Epoch 2/6
10198/10198 [=====] - val_loss: 0.4424 - val_acc: 0.8608
Epoch 3/6
10198/10198 [=====] - val_loss: 0.4146 - val_acc: 0.8627
Epoch 4/6
10198/10198 [=====] - val_loss: 0.3812 - val_acc: 0.8655
Epoch 5/6
10198/10198 [=====] - val_loss: 0.3736 - val_acc: 0.8627
Epoch 6/6
10198/10198 [=====] - val_loss: 0.3446 - val_acc: 0.8678

Test loss: 0.3306778106388718
Test accuracy: 0.8795105218887329

Found 2803 correct labels
Found 384 incorrect labels
    
```

Fig. 5. Training of the neural network of images[2]



Fig. 6. Vehicle dataset[2]

Collect 1000 vehicle images from the Internet and group them into eight categories: bus, family car, fire engine, heavy truck, jeep, minibus, taxi, trunk, each with at least 100 images. Since this page aims to demonstrate the experimental method, there aren't enough pictures to go around. You should gather more images if you want to improve your experimental performance.



Fig. 7. Picture annotation[2]

After the pictures have been collected, the next move is to mark them. The image represents a huge amount of work, and the basic work is continuously repeated. We can mark a portion of an image, use the pictures found by the model after training as pre-labeled pictures, and then manually inspect the pre-labeled pictures to convert them to labeled pictures.

Labelme, labelImg, yolo mark, Vatic, Sloth, and other resources are available for labelling data sets for deep learning. As seen in Figure 7, this article employs labelImg. After all of the images have been labelled, an XML file is created. The TensorFlow framework's data set format includes tfrecords files, and XML must be translated to tfrecords sort.

- 2) *Loss Function:* Model training is conducted after the data set is ready. Model training uses the TensorFlow framework and SSD model. The more important problem of the SSD model is the network structure and loss function. The network structure of the SSD has been introduced earlier. The loss function of SSD [1] is composed of two parts of loc (localization loss) and conf (confidence loss) weighted.

$$smooth_{l1}(x) = \begin{cases} 0.5x^2 & |x| < 1 \\ |x| - 0.5 & otherwise \end{cases}$$

3) *Model Training*: This experiment makes use of Windows 10, TensorFlow- GPU13.1, CUDA10.0, and Anaconda3.5. On the pycharm IDE, Python3 was used to build a deep learning system. Download the VGG16 model, change the parameters such as VGG, model storage route, and learning rate, and run the file after configuring the train SSDnetwork.py file that already exists in the SSD model. Due to time issues, this experiment only trained 10000 times, as shown in Figure 8:

```
INFO:tensorflow:global step 130: loss = 40.9667 (0.495 sec/step)
INFO:tensorflow:global step 140: loss = 38.1224 (0.504 sec/step)
INFO:tensorflow:global step 150: loss = 78.9224 (0.606 sec/step)
INFO:tensorflow:global step 160: loss = 47.5230 (0.464 sec/step)
INFO:tensorflow:global step 170: loss = 45.5651 (0.529 sec/step)
INFO:tensorflow:Saving checkpoint to path ./train_model/model.ckpt
INFO:tensorflow:global step 180: loss = 52.9261 (0.539 sec/step)
INFO:tensorflow:global step 190: loss = 49.9178 (0.498 sec/step)
INFO:tensorflow:global step 200: loss = 33.1039 (0.503 sec/step)
INFO:tensorflow:global step 210: loss = 45.4339 (0.479 sec/step)
INFO:tensorflow:global step 220: loss = 33.2440 (0.558 sec/step)
INFO:tensorflow:global_step/sec: 1.94793
INFO:tensorflow:Recording summary at step 229.
```

Fig. 8. Training process[2]

4) *Model Test*: Taxi and Jeep can be accurately detected by using the trained model detection, as shown in Figure 9.

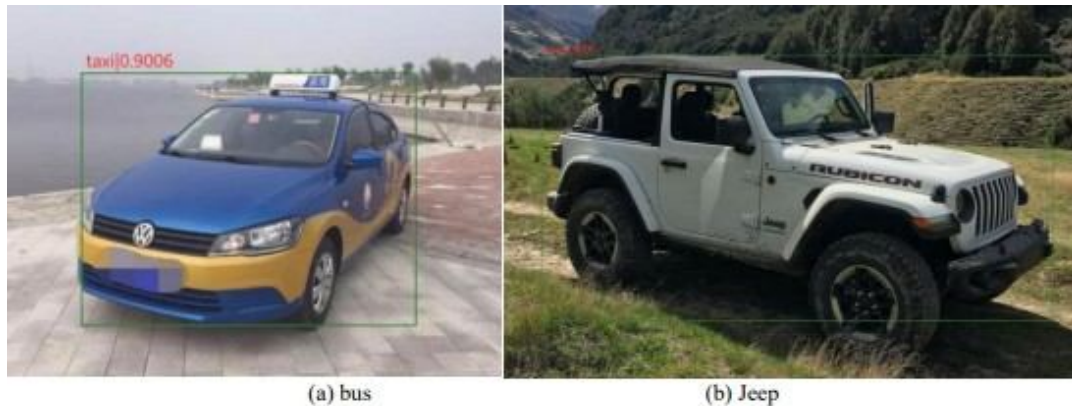


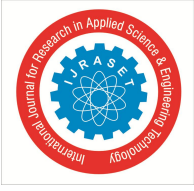
Fig. 9. Model test diagram[2]

IV. CONCLUSION

With the support of neural networks, machine learning, artificial vision, and Python, you can have applications in manufacturing in automated inspection systems with artificial vision (verifying containers or product classification that meets standards), and in the field of private security (in the detection of intruders). Some countries are already researching facial recognition access to aircraft, human resource administration (employees who enter work and therefore be able to register their entry, as well as its departure, access to restricted areas), autonomous vehicles, robotics, civil engineering (in the monitoring of structural health, etc.), verification of the displacements of a building, or in the bridge, displacements can be anomalies or structural failures, observed taking measurements in real-time).

With the results obtained in the experimentation section, it can be stated that the identification of the images of the vehicles displayed in the introduction section is favorable to be able to track vehicular traffic, traffic incidents, and to help civil structures monitor systems in determining the load of the bridge during the monitoring. This form of monitoring is continuous; it does not halt vehicular traffic, causing inconvenience to users of this structure; it also does not endanger the specialists' lives while inspecting under the bridge, which is difficult to enter for visual inspection; and it is non-destructive structure monitoring.

This system performs vehicle calibration, model preparation, model testing, and the entire deep learning detection target process. However, several issues remain, such as how to detect vehicles in complex environments. Owing to hardware and time constraints, in-depth research on improving accuracy, improving detection accuracy, and improving calibration methods. can be done in the future.



V. FUTURE SCOPE

Although imaging was previously synonymous with security and surveillance missions, the concept has come to reflect something broader in recent years. Image processing is now an essential component of AI systems, thanks to advances in science and technology. Various new types of processing systems that have recently emerged assist in chemical, thermal, and molecular imaging. Furthermore, the application of such systems has resulted in considerable progress in the field of space exploration. To collect useful information from space, most modern satellites employ a range of sensors. Furthermore, advances in broadband devices and mobile technology will help in the improvement of image processing systems in hand-held devices. To put things in perspective, the future of image processing looks bright and solid.

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