Proceedings of the 3rd International Conference on Signal Processing and Machine Learning
DOI: 10.54254/2755-2721/4/20230442

License plate classification based on MobileNetV2

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Abstract. In China, there are various colors of license plates which represent different kinds of vehicles and we construct a model on Edge Impulse platform to deal with problems in actual engineering programs like parking, traffic flow control, city planning, etc. Lots of researchers have proposed different techniques about license plate classification but most of them have difficulties maintaining the balance between the size of the dataset and a decent accuracy. In order to achieve that, this research would combine transfer learning and MobileNetV2 to build a model on edge impulse. Transfer learning, as our model's learning method, decrease the size of dataset under the precondition of maintain decent accuracy. MobileNetV2 is a lightweight CNN architecture, developed by Google and it allows our model applying on mobile devices so that our model would have more application prospect. In the process of model designing, the SoftMax function was utilized as the activation function and the Adam optimization algorithm was also applied to optimize the neural network. Training the model with a modest scale of data selected from the CCPD dataset and PKU vehicle dataset, our best-trained model based on MobileNetV2 gives the highest accuracy of 99.0 %.

1. Introduction

License plate is the vehicle's "identity", license plate recognition technique helps identify vehicles on inspected roadways and automatically extract license plate data for processing. Parking lot management, traffic flow control, vehicle location detection, auto-control traffic light, highway automation supervision plus toll station control, and other tasks can be accomplished by such technique [1]. It has already shown its great power in automatic traffic control and maintaining urban security. It can also be applied to detect the number and type of vehicles passing through a certain area, so as to plan the construction of charging piles, gas stations, and commercial complexes to improve the advancement of the economy. It is clear that license plate recognition is of great significance to our daily life, so there are many researchers have investigated them [2].

However, there are still some problems that occur in current researches about license plate color recognition. Usually, the modeling process requires a large-scale sample size and the model can hardly be applied to movable miniature devices as they require a lot of training time and are unable to achieve personalized application.

In order to reduce the dependence on a large number of samples, our study selects transfer learning as the machine learning method. This learning method uses the similarity among data, models, and tasks

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to apply the already trained content directly to the new task. The reason why this method can be achieved is that the first few layers of the convolutional neural network are extracting classification features, and the classification begins in the full connection layer. The process of extracting features is very similar, only the first few layers of the classification of cats and dogs need to be taken over, and the full connection layer can be modified to classify apples and pears. This method can greatly save training time and achieve better results on a small sample basis.

At the same time, in order to improve the personalized application ability of the model, this study applies MobilenetV2, which is developed by Google, in the process of model construction. It is born for the terminal equipment computer vision application. Compared to the mainstream research used in the model, this model is characterized by configurable parameter quantity, low latency, small consumption, efficient operation, and accuracy that will not be inferior too much. It belongs to the lightweight model which can be applied in mobile and embedded devices.

2. Related work

For the topic of license plate recognition, the current researches can be divided into two categories, namely the recognition of license plate numbers and the recognition of license plate colors.

In the research about the recognition of license plate colors, a number of researchers proposed the method of manually setting thresholds and rules [3-6]. Although this method is simple to operate and small in cost, the license plate recognition system will be affected by many factors in the actual application scenario, such as weather, blur degree, chromatic aberration, etc., so it can hardly adapt to complex environments. Once the environment is switched, the threshold must be manually reset to adapt the model to the new environment. In order to improve its adaptability and accuracy, many people have proposed the method of immune data [7-8]. By simulating cloning selection and mutation, immune tolerance, immune memory, and other mechanisms combined with the KNN algorithm for license plate color recognition, the efficiency of the KNN algorithm and the adaptability of the license plate recognition system is improved. At the same time, in order to improve the adaptability of the system, the other group of researchers proposed the method of combining fuzzy logic with learning algorithms. [9] This method improves the accuracy of the results by introducing fuzzy logic, and in the meantime, parameters such as thresholds and weights in the process are obtained through learning algorithms, thus strengthening the adaptability of the model [10-11]. Although adaptability and accuracy are improved through this approach, the process is cumbersome, time-consuming, and requires large samples to maintain accuracy, making it costly and difficult to apply to some microdevices.

Therefore, in order to solve the defects of these two types of methods at the same time, this study will apply a license plate recognition method that combines transfer learning and the MobilenetV2 model together. The transfer learning proposed by this research can be well adapted to the license plate recognition system in different environments, effectively improving its accuracy and adaptability, and reducing the required sample size. And also, by introducing mobile V2, a lightweight model, the results can be easily applied to micro mobile devices and many embedded terminals.

3. Methods

In this study, the license plate classification is developed based on a machine learning image classification method called MobileNetV2. This work can be subdivided into the following steps: (1) data collection, (2) data processing, (3) model building, and (4) model evaluation. The complete steps as shown in Figure 1.

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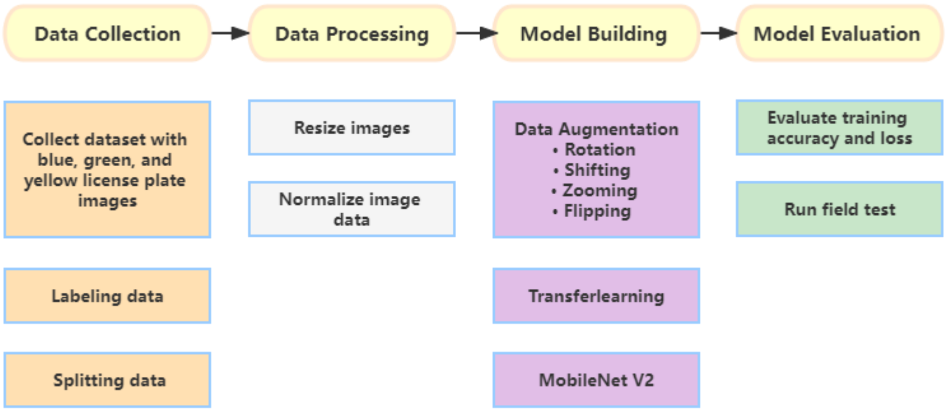

Figure 1. Steps to build the model.

3.1. *Data collection*

The License Plate Classification model starts with collecting the data. According to the License plates of motor vehicles of the People's Republic of China, different colors on the license plates (LPs) are used to distinguish different types of vehicles.

For example, the white-on-blue LPs are issued to regular vehicles, the black lettering on gradient green LPs are issued to regular EV vehicles or regular plug-in HEV vehicles, and black-on-yellow LPs are issued to vehicles longer than 6m or certified to carry 20+ passengers. The CCPD open-source dataset and PKU vehicle dataset provide us with images that have been divided into three categories: blue, green, and yellow. This model will distinguish the color of the license plate.

For building the model, we randomly selected 900, 947, and 743 images from blue, green, and yellow color groups, and all these images were labeled and uploaded to the Edge Impulse platform. The Edge Impulse platform automatically split these images between training and testing data. The dataset has been divided into training sets and testing sets with a 79:21 ratio. Examples of the data are shown in figure 2.

Figure 2 Examples of the data.

3.2. *Data processing*

The data processing phase is of great necessity before the model training and testing phase. All the images were resized to fit the longest axis and became160x160 pixels. The Image processing block from Edge Impulse is dedicated to computer vision applications. It helps normalize image data and optionally reduces the color depth. The Image block performs normalization, converting each pixel's channel of the image to a float value between 0 and 1. In this model, all the image data were processed in RGB color.

3.3. *Model building*

By working on a specific problem in one domain and gaining knowledge from it, transfer learning has become an effective method that transfers those existing knowledge to help solve problems in different but similar domains when there is limited data for training. In recent years, this method has become a

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powerful tool for classification problems in multiple industry domains. There are various models for transfer learning, and we chose a general transfer learning model for images from the Edge Impulse platform.

The MobileNetV2 model is used as the CNN architecture in our real-time license plate classification system. MobileNetV2 is a classification model (distinct from MobileNetSSDv2) based on Convolutional Neural Network (CNN) architecture developed by Google. It is particularly suitable for mobile devices as it substantially reduces the memory footprint required during inference by keeping the large intermediate tensors never fully materialized. This strategy reduces the need for main memory access in many embedded system designs [4], allowing devices like single-board computers or smartphones to run real-time classification under limited computing performance and memory resources. As the Residual Block (shown in Figure 3) has been proved useful to help improve the accuracy and build a deeper network in ResNet, MobileNetV2 introduces a similar block called the Inverted Residual Block (shown in Figure 4), which leverages the shortcut architecture of ResNet and a combination of lightweight depthwise convolutions and 1×1 point convolution. Small size, high processing speed, and remarkable accuracy allow this FER task to maintain a good balance between speed and accuracy.

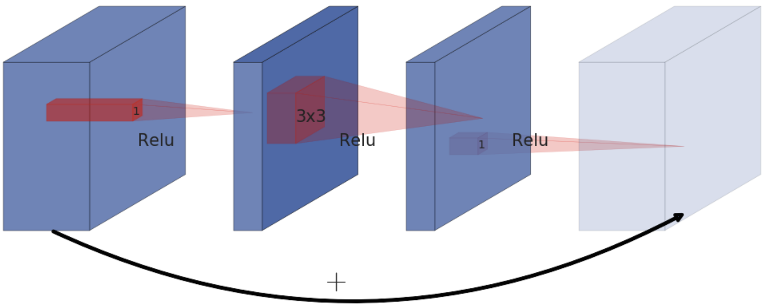

Figure 3. Residual Block applied in ResNet.

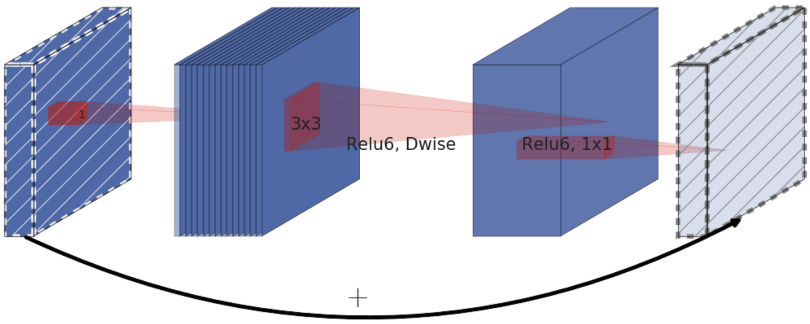

Figure 4. Inverted Residual Block applied in MobileNetV2.

Data augmentation technique was applied to our transfer learning model. By randomly rotating, shifting, zooming, or flipping data during training, it allows users to run more training cycles without overfitting, which can improve accuracy with a limited dataset. The Adam optimization algorithm was used in the training and the SoftMax function is applied as the activation function. The learning rate is 0.001 and 20% of the samples from our training set were held apart for validation. Some hyperparameters like epoch 10 and dropout layer with a rate of 0.1 are also set to train. After the model is completed, it will be packaged to a file so that it can be easily deployed on micro devices like Raspberry Pi, ESP32, or even a smartphone to carry out the classifying task from cameras or images.

For some simple testing work, the Edge Impulse platform provides users with a solution that directly deploys the model on a mobile browser without the need for additional apps. By scanning the QR code with a smartphone from the specific webpage, the platform will transmit a packaged lite app to the browser through its own server. For advanced developers' further mobile software development needs,

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EdgeImpulse Inc. also provides developers with an open-source mobile client which is open-sourced on GitHub(edgeimpulse/mobile-client).

4. Results & discussion

This study conducted its experiments on three open-source datasets. The first dataset is taken from a GitHub project called the Chinese City Parking Dataset (CCPD). It is a large and comprehensive open-source project for license plate detection and recognition on GitHub. In this dataset, over 250k unique car images are taken manually by workers of a roadside parking management company with an Android POS and are annotated with license plate locations carefully. To our best knowledge, CCPD is the largest publicly available LP dataset and the only one that is annotated with vertices location [1]. The second is a plus version of CCPD, which was contributed by community contributors. It is used to supplement the absence of yellow license plate data in the original CCPD dataset. The third dataset is the PKU vehicle dataset, which contains 3983 Chinese license plate images captured in different scenarios. All the images are divided into five groups (from G1 to G5) by their capturing environment, and images in G4 were captured during nighttime while images in other groups were captured during daytime [2].

4.1. The comparison of performance

The entire training process takes 40 minutes on average. Thanks to the MobileNetV2 architecture which has already been pre-trained on the ImageNet dataset simplified and accelerated training procedures, as it has been shown in Figure 5 below, our best-trained model based on MobileNetV2(with no final dense layer) achieves a fairly high accuracy of 90.84% from the very beginning of training and reached the highest accuracy of 99.0% at last. From the confusion matrix (Table 1), we can see that the recognition rate of our algorithm is above 97.9, and the overall performance is good

Table 1. Confusion Matrix of the Model.

Color	Blue	Green	Yellow
Blue	99.3%	0.7%	0%
Green	2.1%	97.9%	0%
Yellow	0%	0%	100%
F1 SCORE	0.99	0.99	1.00

The main objective of this paper is to train a license plate classification model within a few limited training samples. Although we have achieved a satisfactory result through our tiny model, in some cases, the model misrecognized the red car with a blue LP as a truck with a yellow LP or misrecognized a blue Tesla with a green LP as a gasoline car with a blue LP. The examples of misrecognition are shown in Figure 6.

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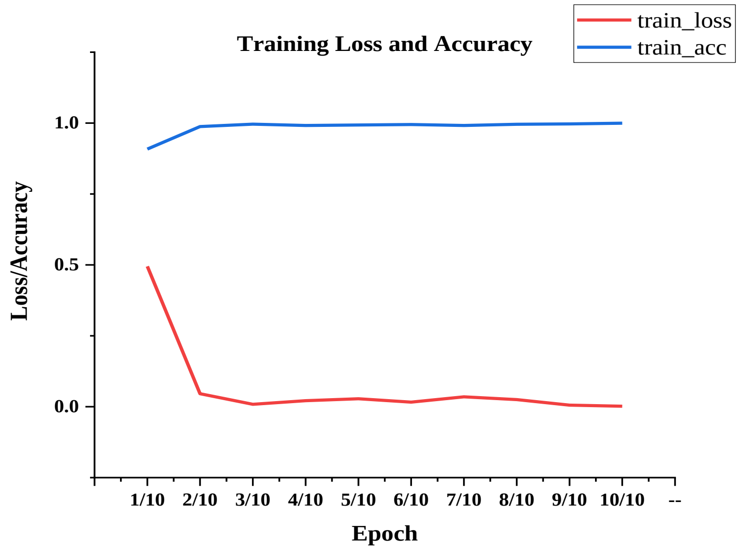

Figure 5. Image of Loss and Accuracy vs Epoch.

(a) (b)

Figure 6 (a) shows the model misrecognized the red car with a blue LP as a car with a yellow LP, (b) shows the model misrecognized a blue Tesla with a green LP as a gasoline car with a blue LP.

4.2. Analysis of misrecognition

We can safely come to the conclusion that it is the defects of the dataset that led to such results by checking the data explorer and analyzing those misrecognized images (Figure 7).

Concerning the Example of Misrecognition 1, over 70% of the yellow LP images we uploaded to the platform are trucks, and most of them are red. As in Chinese culture, red is a popular color that symbolizes luck, joy, and happiness, and it is also a widely used safety color, so it is commonly used by truckers, which led to our lack of color diversity and thus caused such misrecognition.

Concerning the Example of Misrecognition 2, the blue body of the Tesla takes up more space than the green LP, so although it should be an EV vehicle with a green LP, it is easily be misrecognized as a gasoline car with a blue LP.

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Figure 7. Sampling results for the yellow license plate dataset.

4.3. Application

This model that is trained on the Edge Impulse platform can be easily deployed on some small single-board computers like ESP32 or Raspberry Pi etc. And this platform provides an easy way to turn the impulse into optimized source code that can run on any device. It can even directly run on any smartphone or computer without any app required. Therefore, it provides a simple solution for road traffic counting in areas such as urban planning, road construction, and infrastructure construction to any potential customers. For instance, by counting the traffic flows, urban road designers are allowed to determine how many lanes a road should have and which level of the construction requirements of the road should reach. Another application of this model is that it helps gas and electric energy suppliers decide how many gas stations and charging points should be built in the area.

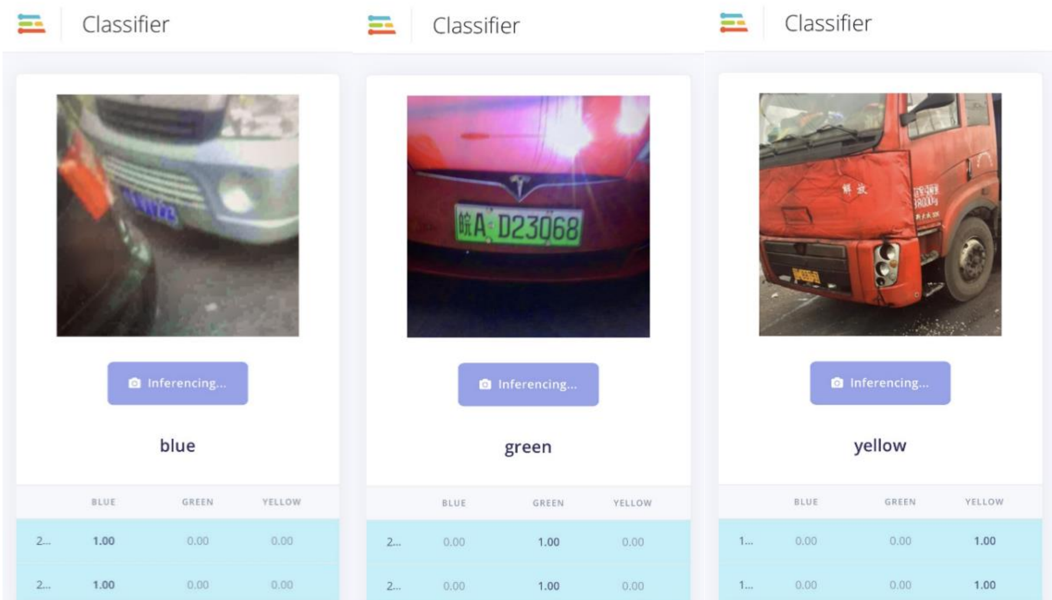

Figure 8. Field test result running on the smartphone browser.

By scanning the QR code with a smartphone from the Edge Impulse platform, the model can be easily deployed on a smartphone browser (Figure 8). The platform invokes the built-in camera of the smartphone and reads video from frame to frame. The packaged lite application running on the browser will resize the image, normalize the image data and convert it to the array. Then it will predict input data from the previously built model. The license plate color will be labeled below the viewfinder with a real-time predicted percentage.

We have done some field tests using a smartphone that runs the model directly on the browser and the results are satisfactory, it's quite surprising that we can come up with a decent accuracy rate with such a small dataset, but there will still be some room for further improvement.

5. Conclusion

This research is mainly about the recognition of license plates' colors by using the Edge Impulse platform. In order to solve the problems which, occur in similar researches, we use transfer learning as the learning method. Transfer learning greatly reduced our training time and achieved better results on a small sample basis. During the construction of the model, we choose MobileNetV2 as our training model and it is a lightweight model which can be applied in mobile and embedded devices. It helps our model achieve personalized application easily. As for the results, the best train model gets a pretty good accuracy of 99.0 % and we successfully limit the processing time to around half an hour. Finally, we are fully convinced that our model can be applied to actual engineering programs successfully and promote the advancement of the new economy.

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