Vehicle Number Plate Recognition Using Optical Character Recognition

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ABSTRACT

Optical Character Recognition (OCR) is one of the key technologies in Automatic Number-Plate Recognition (ANPR).

In this study, our team is building a machine learning model that implements the OCR system to complete the character recognition tasks on the vehicles number plate images.

More specifically, our group is applying the concept of both a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) over Recurrent Neural Network (RNN) to build a model that can accurately recognize characters in the image of a number plate.

ANLY-590
Final Project

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INTRODUCTION

Optical Character Recognition (OCR):
[1] The mechanical or electronic conversion of images of typed, handwritten or printed text into machine-encoded text, whether from a scanned document, a photo of a document, a scene-photo or from subtitle text superimposed on an image.

This automation is hugely successful in processing a large number of works in a very short period of time, but never be more accurate than the works that are carefully done by humans. As an instance, **Automatic Number-Plate Recognition (ANPR)** still have the following difficulties: [2] blurry images caused by a motion blur, poor lighting, an object obscuring part of the plate, and many others, which still requires humans attention to complete the recognition process. Further researches and studies are essential to overcome that flaws.

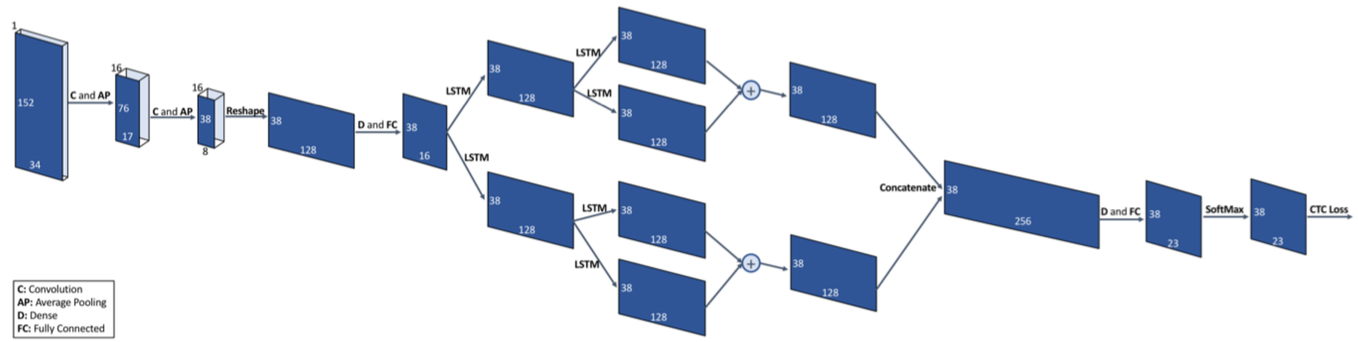
In this project, our group mainly focuses on **applying OCR in recognizing the characters in the image of vehicle number plates** and targeting to get the accuracy of over 90%. Contrary to the previous approaches, our team is implementing the concept of both Convolutional Neural Network (CNN) with two convolution layers and an average pooling operation, and Long Short-Term Memory (LSTM) over Recurrent Neural Network (RNN).

DATASETS

An artificially generated dataset that are very similar to the real world vehicle number plates.

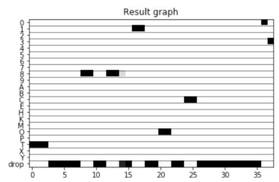
- **Source**: downloaded from 'Supervisely' website.
- **Size**: total of 22,764 data (JSON format + PNG format).
- **Split**: use 11,382 data to train the models, and the other 11,382 data to test the models.
- **Data structure**:
  - *TrainTestDataSet*: DataSet object for both training and testing datasets.
  - *DataSet:* DataElement object for a single dataset
  - *DataElement:* Contains variables for each attribute obtained from a single data file.
- **Cleaning logic**:
  - Check if the given data has any missing attribute values (label and size of the given number plate).
  - The number of characters in a label must be eight, and the size of the plate must be 152 by 34 (width by height).
  - Check if the given data already exists in the dataset.

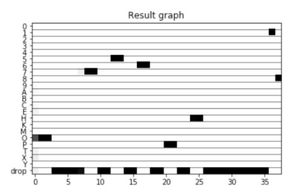
STRUCTURE OF OUR MODEL



RESULT

- **There are total 22,764 dataset and we split it half and half.**
- **Training**: 11,382 dataset.
- **Testing**: 11,382 dataset
- **Accuracy**: 11,344 of 11,382 are correct. (99.67%)
- **Examples of result**





CONCLUSIONS

The most challenging and important part on building our model was **making pairs of the LSTM in RNN process**, since one of them is forward and the other one is backward. Our team then added them up or performed concatenation. We would have gotten a very different result with a low accuracy if we did not insert the backward LSTM layer to our model.
As our **future work**, we will put more effort on simplifying our model design to enhance the overall performance on training the model especially to reduce to total execution time. In addition, we want to test our model with various kinds of RNN models and other activation functions to verify whether we can come up with the model that can increase the accuracy on recognizing the characters on the number plate.

DISCUSSION

There is 4 kind of loss. Most of the misclassified license plate containing M in the beginning. Our model will misclassify it to H or K. We also misclassified some O to C.

1) M-H case (Showing 2 cases out of 33 cases)

Actual	Predict
M811CO23	H811CO23
M485PX01	H485PX01

2) M-K case (2 cases)

Actual	Predict
M152KY86	K152KY86
M155EP17	K155EP17

3) O-C case (2 cases)

Actual	Predict
O611AK84	C611AK84
O611HC07	C611HC07

4) Etc. (1 case)

Actual	Predict
K645TA74	K445TA74

Below is the comparison table for the experiments. The different choices of the number and the size of pooling affect the accuracy of the 1-2-1-2-1 structure a lot. However, it doesn't affect 1-2-4-2-1 that much. For filters equal to 64, 128, or 256, the accuracy for 1-2-4-2-1 is equal to 99

Layer Structure		1-2-1-2-1	1-2-1-2-1	1-2-4-2-1	1-2-4-2-1	1-2-4-2-1	1-2-4-2-1
CNN	filters	16	16	16	16	16	16
	Pooling times	2	1	2	2	1	2
	Pooling size	(2, 2)	(4, 4)	(2, 2)	(2, 2)	(4, 4)	(2, 2)
RNN (LSTM)	filters	128	128	64	128	128	256
Accuracy		97%	86%	99%	99%	97%	99%

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