Improving benchmarks for autonomous vehicles testing using synthetically generated images

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Abstract—Nowadays autonomous technologies are a very heavily explored area and particularly computer vision as the main component of vehicle perception. The quality of the whole vision system based on neural networks relies on the dataset it was trained on. It’s extremely difficult to find traffic sign datasets from most of the counties of the world. Meaning autonomous vehicle from the USA won’t be able to drive though Lithuania recognizing all road signs on the way. In this paper, we propose a solution on how to update model using a small dataset from the country vehicle will be used in. It’s important to mention that is not panacea, rather small upgrade which can boost autonomous car development in countries with limited data access. We achieved about 10% quality raise and expect even better results during future experiments.

I. INTRODUCTION

Driver-less cars wildly use techniques based on neural networks to detect and classify traffic signs. To attempt well-tuned state such models need to be trained with a significant amount of data. In case of traffic signs that means photos taken in different weather and lightning conditions, actor speed etc. Many researchers working in autonomous car development are facing a lack of available qualitative datasets. Massive labeled datasets are publicly accessible for developed countries such as Belgium, Germany or China. However, for singe enthusiasts or private companies in smaller countries collecting and labeling data is too costly and time consumable. In this paper, we propose an alternative way to build a sizable benchmark for model training.

In order to prove our main idea that GAN[1] generated images of traffic signs perform better than classical data augmentation methods and artificial images synthesis allows us to achieve massive datasets, we have done following research milestones:

• Compiled road signs from Belgian Traffic Signs Dataset[5], The German Traffic Sign Benchmark[1], TSRD - which is part of Chinese Traffic Sign Database. Down below we are going to use a reference to this dataset as Superset. Superset consists of about 25000 images. Test dataset contains randomly extracted images from Superset. Test dataset counts 2500 images.
• GAN has been built using commonly used architecture and so has been built CNN[2] classifier.
• As the first step of our evaluation we are going to verify proficiency of Classifier which was pretrained on single GTSRB[3] by testing it Test dataset.
• Classical methods of data augmentation can boost Classifier performance and we prove it by re-train neural network with GTSRB extended with images we receive as a result of augmentation. Compare testing of outcome model on the same Test dataset.
• Next we are going to train our GAN and retrain Classifier on Superset extended with GAN-generated images.
• Last step is to test our newly trained Classifier on the same Test dataset.
• Later or we summarize conclusions and propose further improvement.

Important note: As traffic signs not precisely standardised and might differ crucially in different countries, we are going to use only those classes which consist similar essential features, more details provided in Table ??.

| TABLE I | USED TRAFFIC SIGN CLASSES |
|---------|---------------------------|
| 0       | Closed to all in both directions | circle, white, red |
| 1       | No entry                  | circle, white stripe, red |
| 2       | Stop and give way         | white text, red |
| 3       | Speed limit 30            | circle, white, red, black text |
| 4       | Speed limit 50            | circle, red, black text |
| 5       | Speed limit 70            | circle, white, red, black text |
| 6       | Speed limit 100           | circle, white, red, black text |
| 7       | End of restriction        | circle, white, black |
| 8       | Priority road             | diamond, white, yellow |
| 9       | Give way                  | triangle, white, red |

II. METHODS

A. Classifier

As far as we don’t aim in this experiment to built every neural network from scratch we took Classifier architecture from [2] as well as the idea to use a single grayscale channel instead of color images. Another reason is that the presented model achieves state-of-the-art using comparable simple and well-documented structure.
The process of training machine learning model might be simplified to adjusting of parameters and hyperparameters to reach the point where loss function approaches global minimum. The number of parameters proportionally depends on the complexity of the task in which the model tends to solve. Another words vast number of parameters demand a considerable amount of training data.

We can divide the training process into two stages:

**Stage 1**: Pretraining. We should pretrain the model using training dataset. Fortunately, from publicly accessible code repositories we can download already trained models.

**Stage 2**: Fine-tuning. Now we only have to retrain downloaded model using a decreased learning rate of 0.0001.

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**B. Classical Augmentation methods**

In spite of all the data available in Superset, we wish it to have good diversity as desired sign images need to be present in varying sizes, lighting conditions and poses to be sure that our Classificator achieves the best possible result. To overcome this problem scientists generate extended dataset based on the original one. This methodology is known as data augmentation. Commonly used techniques to increase the amount of available data are Scaling, Translation, Rotation, Flipping, Adding Salt and Pepper noise, Lighting condition, Perspective transform and many other. Which slightly modify existing images. This might help to increment items in the dataset by thousands, however, those images won’t be as variant as we want them to be. See an example of thee rotation method on Figure 2.

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**C. GAN**

The main contributor of this paper is Generative Adversarial Network, the idea of this neural network lays down in a special structure composed of two networks which are trained simultaneously, improving attributes of each other. It is especially interesting for researchers because of its robustness to overfitting. Another benefit is that the training process doesn’t require annotated training data. A generative model G captures the data distribution, and a discriminative model D estimates the probability that a sample came from the training data rather than G. The training procedure for G is to maximize the probability of D making a mistake. Data type we are going to manipulate is represented as an image, from this point of view using advantages of Convolutional Neural Networks seems to be a great idea. However, there are few architecture guidelines for stable Deep Convolutional GANs worked out in [6]:

- Replace any pooling layers with strided convolutions for discriminator and fractional-strided convolutions in generator.
- Use batchnorm in both the generator and the discriminator.
- Remove fully connected hidden layers for deeper architectures.
- Use ReLU activation in generator for all layers except for the output, which uses Tanh.
- Use LeakyReLU activation in the discriminator for all layers.

Using advises from our colleagues we end up with DCGAN architecture shown on Figure 3.

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**1) Regularization:** By definition regularizations are techniques used to reduce the error by fitting a function appropriately on the given training set and avoid overfitting. [8] Other words, it is used for tuning the function by adding an

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### Fig. 1. Performance comparison

### Fig. 2. Examples of augmented images

### Fig. 3. DCGAN Architecture

Training process simplifies to launching from the command line a Python script and providing desired parameters, for example:

```
$ python3 main.py --dataset superset
--input_height=28 --output_height=28 --train
```

The advantage of Using GAN for image generation is that it works for all sign classes, which is not true for data augmentation. For example, for “give way” sign, we can use a horizontal flip and slight rotation. For “Closed to all vehicles in both directions” all possible methods. Stop sign however can be flipped horizontally neither vertically, moreover, the rotation might cause problems with text detection if applies. Some mandatory signs after augmentation might totally change the meaning.

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4Deep Convolutional Generative Adversarial Network
additional penalty term in the error function. This is extremely important when the dataset is huge. \( L(X, Y) \) is loss metrics, where \( X \) is design matrix and \( Y \) - observation vector (wages). In the way to penalize loss function, we add norm of weights vector \( \omega \).

\[ L(X, Y) + \lambda N(\omega) \]

where \( \lambda \) is the tuning parameter that decides how much we want to penalize the flexibility of our model. \( L \) function is multiplication of so-called LASSO[3] and Ridge[4] norm.

### III. Results

In this section, we proceed to result which we receive during DCGAN training. Let's analyze graphs and numerical values we obtained during steps described in the introduction to understand if the hypothesis we claim matches the evidence.

First let’s analyze pictures generated by our DCGAN from Figure 6. Images look noisy and blurry, however we simply able to recognize data encrypted in the sign. Training process took 25 epochs, this is enough to teach model to generate signs, however not enough to make output realistic on the level, that we as humans won’t be able to identify which image is synthetic and which is real. Unfortunately for this experiment, we were limited by hardware, see Figure [5] for this reason we apply the minimal satisfying amount of epochs for proof-of-concept.

On Figure 7 we can see improvement which allows achieving augmentation, it’s notable, but not significant. The average accuracy of pre-trained classifier showed 77.61%, extended by augmented images increased this performance by 3%, which is a good result when we are speaking about the neural network model.

Our Classifier we trained on GAN-generated images perform on 87.42% accuracy. Received results successively prove our beginning statements, however, we still need to analyze and preprocess data. Although we know how to improve our dataset using DCGAN, up to the present time we have to upgrade phase of data preparation.

### IV. Discussion and Future Development

When it comes to explaining the trivial task to an Artificial Intelligence system we often face difficulties. For example, next improvement step in traffic sign recognition we might propose an automated decision which classes of signs can
be extracted from the dataset and augmented without losing meaning or accuracy, which method can be applied to the chosen class and which can not. This could be done using a simple decision tree.

To maximize proficiency of our Classifier we might extend or Superset not only with synthetically generated images but also apply augmentation to these images. For Generator we plan to use one of the regularization methods called cross-validation to achieve more realistic images on GAN output. Finally, the best crash test for this idea is real-time sign classification on the road.

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