Benchmarking Local Robustness of High-Accuracy Binary Neural Networks for Enhanced Traffic Sign Recognition

Andreea Postovan, Mădălina Erașcu

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Overview

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Steps for traffic sign classification:

- isolating the traffic sign in a bounding box
- classifying the sign into a specific traffic class.

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Well-know problem of the classifiers: the lack of robustness[1] [2].

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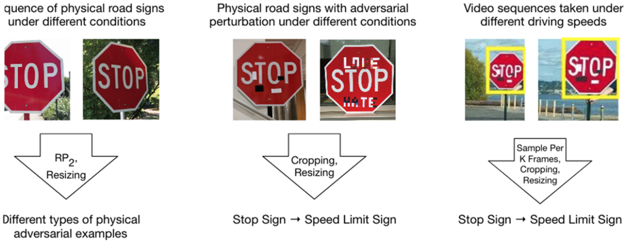

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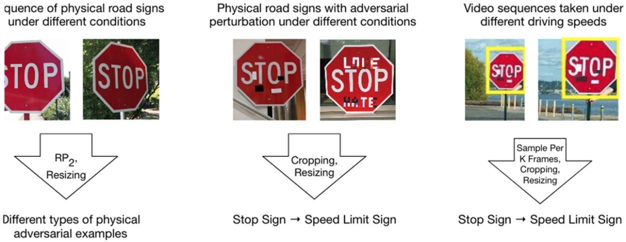

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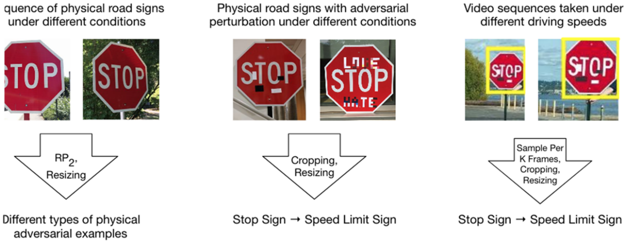

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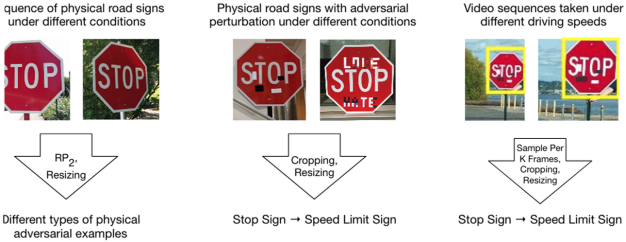

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- logical methods: recently explored, scalability issues ⇝ this presentation, our long time goal

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These models should have high accuracy while amenable for formal verification.

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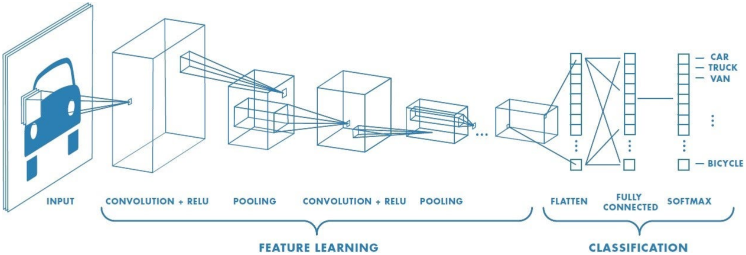

From https://saturncloud.io/blog/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way/

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Given a trained model and a property to be verified, does the model satisfy that property?

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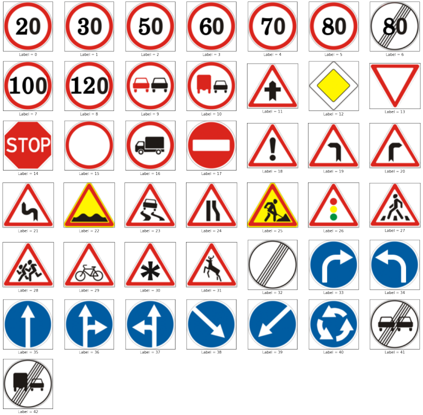
Data collection



Training:

- **GTSRB (German) traffic sign dataset.**
  - Classes: 43,
  - Size: from 25 $\times$ 25 to 243 $\times$ 225, and not all of them are square.
  - Each class: 210 - 2250 images
  - 39209 images used for training and validation with ratio 80:20

Testing:

- **GTSRB (German) traffic sign dataset.**
  - 12630 images used for testing
- **Belgium traffic sign dataset.**
  - Number of images = 4533.
  - Only 23 classes match the one from GTSRB.
- **Chinese traffic sign dataset.**
  - Number of images = 1818.
  - Only 15 classes match the one from GTSRB.

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Data analysis

Difference between Belgium (left) and GTSRB (right) dataset

Difference between Chinese (left) and GTSRB (right) dataset

Contents

BNNs Architectures with Best Accuracy[5]

The architectures below were obtained by a bottom-up approach, starting with simple layers (fully connected) and stacking new more complicated ones for higher accuracy.

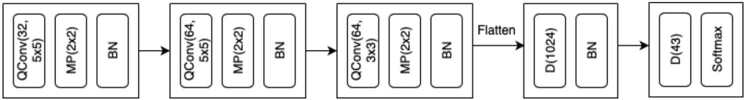

Figure: Architecture with Best Accuracy for GTSRB (96.45%) and Belgium (88.17%) dataset. Input: 64 px x 64 px

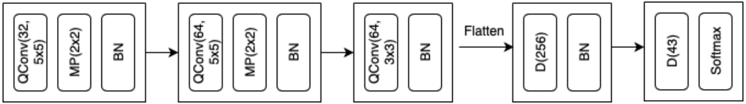

Figure: Architecture with Best Accuracy (83.9%) for Chinese dataset. Input: 48 px x 48 px

[5] More details in: A. Postovan, M, Erașcu. Architecturing binarized neural networks for traffic sign recognition. to appear in ICANN 2023

XNOR Architecture

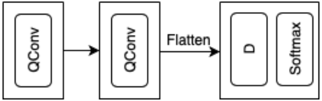

Figure: XNOR(QConv) architecture

Table: XNOR(QConv) architecture. Image size: 30px $\times$ 30px. Dataset for train and test: GTSRB.

Model description	Acc	#Binary Params	Model Size (in KiB)	
			Binary	Float-32
QConv(16, 3×3), QConv(32, 2×2), D(43)	81.54	1005584	122.75	3932.16

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- Local robustness ensures that for a given input x from a set χ, the neural network F remains unchanged within a specified perturbation radius ϵ, implying that small variations in the input space do not result in different outputs. The output for the input x is represented by its label l_x. We consider L_∞ norm defined as $||x||_\infty = \sup_n |x_n|$.

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Definition of local robustness useful in a computational setting. A network is ϵ-locally robust in the input x if for every x', such that $||x - x'||_\infty \leq \epsilon$, the network assigns the same label to x and x'.

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   ```
   (assert (or (>= Y_0 Y_38)
               ...
               (>= Y_37 Y_38)
               (>= Y_39 Y_38)
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               (>= Y_42 Y_38)))
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Our benchmark was used for scoring the competing tools but different images were chosen in order to avoid tuning of the solvers for precise instances.

Experimental Results of the VNN-COMP 2023

Table: VNN-COMP 2023 Results for Traffic Signs Recognition Benchmark

#	Tool	Verified	Falsified	Fastest	Penalty	Score	Percent
1	Marabou	0	18	0	1	30	100%
2	PyRAT	0	7	0	1	-80	0%
3	NeuralSAT	0	31	0	4	-290	0%
4	alpha-beta-CROWN	0	39	0	3	-60	0%

- **Verified** is number of instances that were UNSAT (no counterexample) and proven by the tool.
- **Falsified** is number that were SAT (counterexample was found) and reported by the tool.
- **Fastest** is the number where the tool was fastest (this did not impact the scoring in this year competition). Penalty is the number where the tool gave the incorrect result or did not produce a valid counterexample.
- **Score** is the sum of scores (10 points for each correct answer and -150 for incorrect ones).
- **Percent** is the score of the tool divided by the best score for the benchmark (so the tool with the highest score for each benchmark gets 100) and was used to determine final scores across all benchmarks.

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