Creating a Formally Verified Neural Network for Autonomous Navigation

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1. Overview

Motivation:

- The increased reliance of self-driving vehicles on neural networks

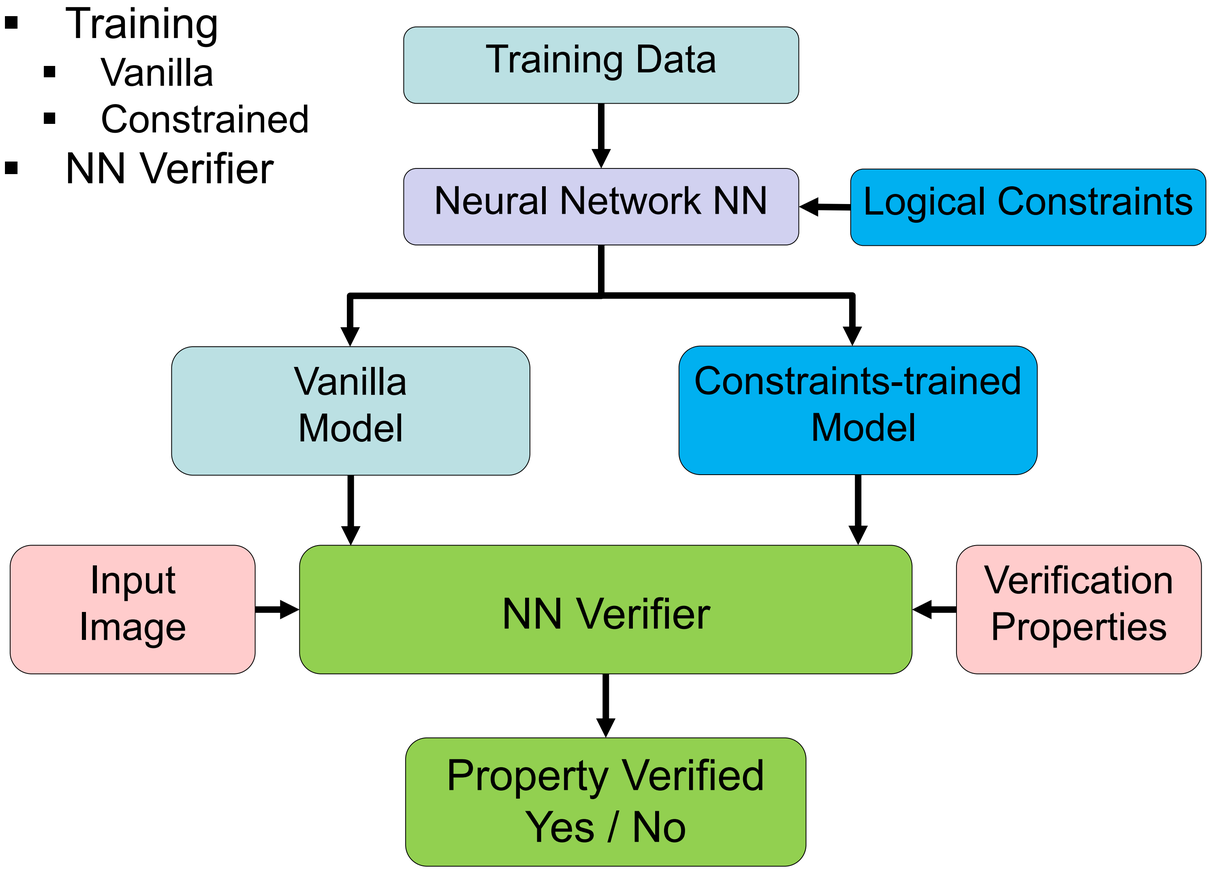
Must be formally verified before put to actual use !

Challenge:

- Design and training of a neural network on a custom dataset
- Use of machine learning with differentiable logics
- Obtaining formal guarantees of the neural network after training.

Suggested Approach:

- Training
  - Vanilla
  - Constrained
- NN Verifier



2. Case Study

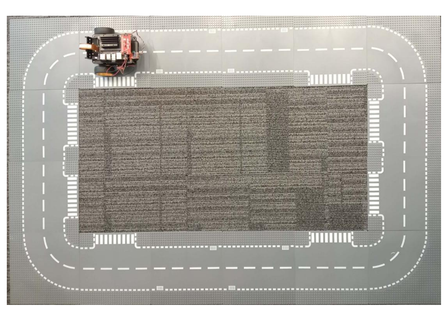
- Build a formally verified regression neural network that detects the centre of the track on which the vehicle is travelling.

Experimental Setup

- JetBot: an open-source AI robotic vehicle based on NVIDIA Jetson Nano.
- Reference track: built using readily available Lego road plates.

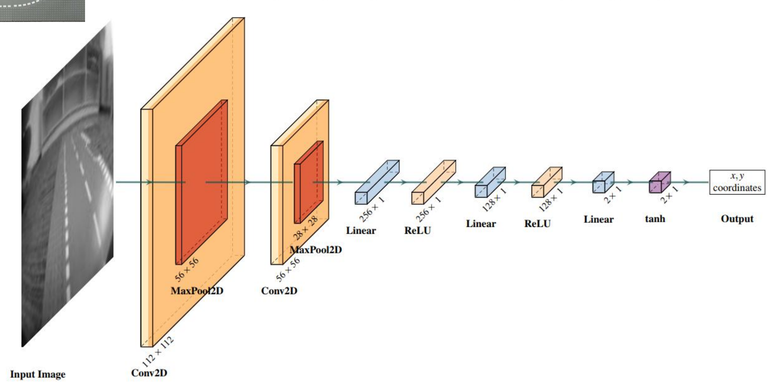
Data Collection

Data: Images from the onboard camera facing down on the track.
Labels: *x*, *y* coordinates indicating the centre of the track.
Total Samples : 385 images of size 224×224 pixels



Neural Network

Approximate the function
$\mathbb{N} : \mathbb{R}^{112\times112} \rightarrow \mathbb{R}^2$
Input : 112×112 image
Output: *x, y* coordinates



Funding

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3. Verification Property

Local Robustness:

$(x_0, \varepsilon, \delta) := \forall x. ||x_0 - x||_\infty \leq \varepsilon \Rightarrow ||\mathcal{N}(x_0) - \mathcal{N}(x)||_\infty \leq \delta$

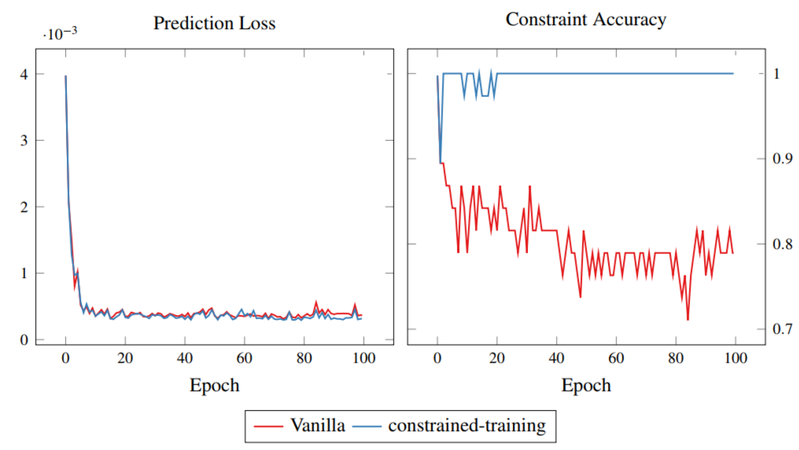
- This property checks that for slight perturbations *x* within some bound ε of a given input image x_0, the neural network $\mathcal{N}$ should give roughly the same output, i.e., difference between $\mathcal{N}(x_0)$ and $\mathcal{N}(x)$ should be within an acceptable threshold δ.

Property specification using DNNV:

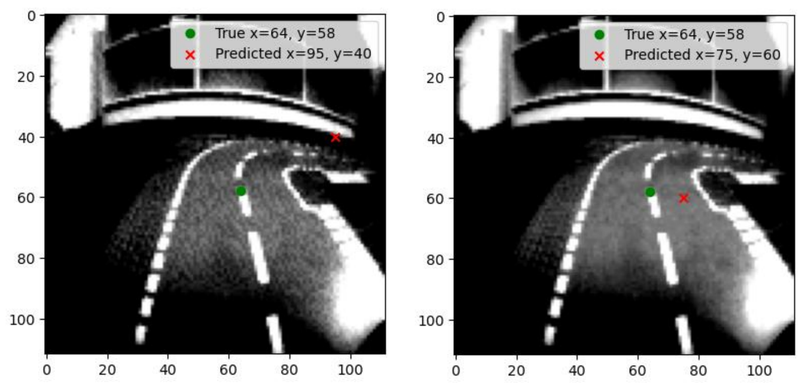
```
from dnnv . properties import *
N = Network ("N")
x = Image (" data / image_0 .npy ")
epsilon = Parameter (" epsilon ", float , default =(48. / 255))
delta = Parameter (" delta ", float , default =0.1)
Forall ( x_ ,
Implies (
((x - epsilon ) <= denormalise (x_) <= (x + epsilon )),
(abs(N(x_ )[0][0] - N(x )[0][0]) <= delta ) &
(abs(N(x_ )[0][1] - N(x )[0][1]) <= delta )
), )
```

4. Experimental results

Performance:



Prediction loss and Constraint accuracy of Vanilla vs Constrained-trained.



Vanilla (left) vs. Constrained-training predictions on an adversarial example.

Verification of Robustness Property:

- DNNV: A unified interface for NN verifiers
- Verifiers used: BAB, ERAN, Reluplex, nnenum, and MATLAB NNV

Output from DNNV:

```
dnnv . verifiers .bab
     result : BabTranslatorError ( Unsupported computation graph detected )
     time : 0.3495
dnnv . verifiers . eran
     result : unknown
     time : 4.9732
dnnv . verifiers . nnenum
     result : NnenumError ( Return code : 1)
     time : 0.7476
dnnv . verifiers . reluplex
     result : ReluplexTranslatorError ( Unsupported computation graph detected )
     time : 0.3622
```

5. Conclusion

Several insights were obtained including (but not limited to):

- Difference b/w traditional formal verification and verification of NN
  - NN verification limited to local properties in the available data.
- Effect of the neural network architecture on verification effort
  - Max-pooling vs. Average layers
- Efforts required in use of NN verification tools
- Tools focus more on classification rather than regression

Ref: **S. A. A. Bukhari**, T. Flinkow, M. Inkarbekov, B. A. Pearlmutter & R. Monahan, *"Creating a Formally Verified Neural Network for Autonomous Navigation: An Experience Report"*, Sixth International Workshop on Formal Methods for Autonomous System FMAS 2024, Accepted.