Benchmark proposal: Object Detection for Maritime Search and Rescue

Executive summary: Collins Aerospace proposes a benchmark problem for the 2023 Competition on the Verification of Neural Networks (VNN). Current document contains problem background and the description of models and formal properties that are provided to the participants.

1. Background: Maritime search and rescue application

Generally, maritime surveillance has been conducted using satellites, manned aircraft, and other similar aircraft. These options have been limited in their ability to provide high-resolution, real-time video processing for various reasons. For example, satellite bandwidth is not ideal to handle large amounts of real time data, while rotorcrafts and fixed wing platforms can be very expensive. Current developments with quadcopters and other small drones have enabled additional options that are much cheaper than larger aircraft. Such unmanned vehicles can be equipped with various sensors and signal processing algorithms to enable automated identification of regions where search and rescue efforts may be focused, thereby reducing the time to rescue [1]. One of enabling technologies for this application is computer vision that is powered by state-of-the-art Machine Learning (ML) algorithms.

2. Benchmark model: YOLO object detection network

The object detection model chosen as a part of the benchmark is YOLOv5-nano[1]. The main objective of the benchmark is to assess current capabilities of VNN tools for verifying properties of deep neural networks of high complexity, such as YOLO. For the sake of an incremental approach, a “nano” version of YOLO has been selected. It contains much fewer learnable parameters compared to the original, full-scale YOLO versions. Furthermore, to make the model supported by VNN tools, SiLU activation functions have been replaced with (piecewise linear) Leaky ReLU activations.

The model has been trained on the SeaDronesSee Dataset[2] consisting of maritime search and rescue scenarios captured using a drone, generated by a team from the University of Tuebingen. The dataset consists of 8930 training Images and 1547 validation Images. All images are labelled. There are six classes in the dataset, such as Boat, Person, Jetski, Buoy. Intended function of the YOLO neural network is to detect objects of this type on the water surface, draw bounding boxes around them, and classify the objects. Model outputs can be provided to the operator at the ground station who can use this information to dispatch rescue missions/vehicles.

The YOLOv5nano model has 157 layers and ~1.8M learnable parameters. The training was done with an input image size of 640x640. The model has 3 output layers (“heads”). The total input size and output size of the model are, respectively, ~1.2M and ~277K.

3. Benchmark properties: Robustness

Current benchmark focuses on robustness properties. They are formulated by applying infinity norm perturbations to selected inputs and requiring that the predicted class remains unchanged (with possible bounded decrease of object existence confidence). The motivation is to keep the object detector robust, for example, to different lighting conditions and, possibly, to adversarial attacks. Robustness is particularly relevant to detection of swimmers on the water surface, because misclassifications and false negatives can have a significant safety impact (person not getting noticed

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[1] Neural network architecture is adapted from Ultralytics: https://github.com/ultralytics/yolov5. It is redistributed under AGPL-3.0.

[2] SeaDronesSee dataset: https://seadronessee.cs.uni-tuebingen.de/home. The dataset is used under license.

and, as a consequence, not rescued or rescued too late). This benchmark generates local robustness by applying L_∞ perturbations in the neighborhood of objects (e.g., persons, boats) on the image. The neighborhood is determined from the bounding box, which is the model detection of the object on an original, i.e., unperturbed image.

Mathematically, *local* robustness properties are defined in the "delta-epsilon" form:

$$\|x' - x\| < \delta \Rightarrow \left\|\hat{f}(x') - \hat{f}(x)\right\| < \varepsilon, \textit{ where } x,\ x' \in X \textit{ and } \delta,\ \varepsilon \in R_{>0}$$

The property requires that for an input perturbation bounded by δ the output must not deviate by more than ε (infinity norm is used to define perturbations). Provided robustness properties have different perturbation magnitudes, ranging from 0.1% to 10%.

Following steps are executed to formalize each property:

1. Randomly pick one of the provided images
2. Perform NN inference to compute bounding boxes and respective classes
3. Randomly pick one bounding box
4. Apply L_∞ perturbation to pixels inside the bounding box
5. Impose output constraint that (1) class confidence on the perturbed image is still the highest among all classes and (2) object existence confidence does not deviate by more than ε = 10%.

Key challenge: The main challenging aspect of the benchmark is the large number of inputs (on the order of 10^6) and outputs (on the order of 10^5). The former is due to the need of using a high-resolution image, because some objects (e.g., swimmers) are typically very small, therefore, further decrease of the input size of the YOLO model significantly hampers its prediction performance.

4. Closing Remarks

Robustness assessment of vision-based systems, such as object detection, is one of the key objectives to achieve *certification* of such ML-based functions. European Union Aviation Safety Agency (EASA) in their Concept Paper for Level 1&2 Machine Learning Applications [2] emphasizes Formal Methods as anticipated means of compliance for the verification of robustness of ML models. FM tools can become one of critical enablers of AI/ML trustworthiness [3], therefore, aviation industry is looking forward to maturation and improvement of relevant technologies. Current benchmark has the intent of being a motivating example of a realistic application in the aerospace domain.

References

[1] "Avalon - Aerial and vision-based assistance system for real time object detection in search and rescue missions," [Online]. Available: https://uni-tuebingen.de/fakultaeten/mathematisch-naturwissenschaftliche-fakultaet/fachbereiche/informatik/lehrstuehle/kognitive-systeme/projects/avalon/.

[2] EASA, "Concept Paper: Guidance for Level 1&2 Machine Learning Applications. Concept paper for consultation," Feb 2023.

[3] EASA and Collins Aerospace, "Formal Methods use for Learning Assurance (ForMuLA) - IPC project report," 2023.