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RoHNAS: A Neural Architecture Search Framework with Conjoint Optimization for Adversarial Robustness and Hardware Efficiency of Convolutional and Capsule Networks

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ABSTRACT Neural Architecture Search (NAS) algorithms aim at finding efficient Deep Neural Network (DNN) architectures for a given application under given system constraints. DNNs are computationally-complex as well as vulnerable to adversarial attacks. In order to address multiple design objectives, we propose *RoHNAS*, a novel NAS framework that jointly optimizes for adversarial-robustness and hardware-efficiency of DNNs executed on specialized hardware accelerators. Besides the traditional convolutional DNNs, *RoHNAS* additionally accounts for complex types of DNNs such as Capsule Networks. For reducing the exploration time, *RoHNAS* analyzes and selects appropriate values of adversarial perturbation for each dataset to employ in the NAS flow. Extensive evaluations on multi - Graphics Processing Unit (GPU) - High Performance Computing (HPC) nodes provide a set of Pareto-optimal solutions, leveraging the tradeoff between the above-discussed design objectives. For example, a Pareto-optimal DNN for the CIFAR-10 dataset exhibits 86.07% accuracy, while having an energy of 38.63 mJ, a memory footprint of 11.85 MiB, and a latency of 4.47 ms.

INDEX TERMS Adversarial Robustness, Energy Efficiency, Latency, Memory, Hardware-Aware Neural Architecture Search, Evolutionary Algorithm, Deep Neural Networks, Capsule Networks

I. INTRODUCTION

Among the Machine Learning algorithms, Deep Neural Networks (DNNs) have shown state-of-the-art performance in a wide variety of applications [1] [2]. Finding an efficient DNN architecture for a given application through a Neural Architecture Search (NAS) is a very complex optimization problem, which involves a huge number of parameters

and typically extremely long exploration time [3]. The search space becomes even bigger when employing NAS algorithms for new brain-inspired types of DNNs, such as the Capsule Networks (CapsNets) [4]. Such CapsNets, and more in general advanced DNN models, aim at providing high learning capabilities. However, these advancements in DNN architectures come with multiple design challenges:

- 1) *High computational complexity*: DNNs need specialized hardware accelerators to be deployed and executed at the edge, where the resources are constrained [5].
- 2) *Security*: DNN classifiers can be fooled by adversarial attacks, which are small and imperceptible perturbations added to the inputs [6]. Such a threat is extremely dangerous for safety-critical applications [7]. Furthermore, integrating means for security during NAS is a challenging problem, but can enable robust DNN designs [8] [9], as compared to the regular DNN design flow.

Hence, the problem is: *how to design complex DNNs in an energy-efficient and robust way through an automated multi-objective NAS framework?*

A. LIMITATIONS OF STATE-OF-THE-ART AND SCIENTIFIC CHALLENGES

Traditionally, the adversarial robustness of a given DNN is investigated a posteriori, i.e., once the DNN is already designed. The hardware efficiency of a DNN implemented on a given hardware accelerator is also a metric that is typically analyzed a posteriori, thus challenging the feasibility of its implementation on resource-constrained neuromorphic and/or IoT devices. We perform a motivational case study to analyze the adversarial accuracy¹ and memory footprint of different DNNs, illustrating their adversarial robustness and complexity. We apply the Projected Gradient Descent (PGD) attack [10] with $\epsilon = 0.0001$ to the LeNet [11], the ResNet-20 [12], the CapsNet [4], and the DeepCaps [13], trained for the CIFAR-10² dataset [14]. The results in Fig. 1 show that the LeNet [11], which is relatively small and shallow, is hardware efficient due to its low memory footprint, but relatively more vulnerable to attacks. A more complex DNN such as the ResNet-20 [12] has a higher memory footprint but it also exhibits higher adversarial accuracy than the LeNet. Interestingly, the DeepCaps [13], despite having a smaller memory footprint than the ResNet-20, is also relatively more robust against adversarial attacks. *The goal of this paper is to integrate these diverse yet important objectives in a NAS framework to obtain Pareto-optimal solutions that explore the potential tradeoffs between different design objectives like computational complexity, memory, energy, latency, and/or security.*

Including the DNN security into the optimization goals of the NAS is a challenging task, because, besides the challenges in its representation in the design framework, it might lead to a massive search space explosion due to

¹We refer to the *adversarial accuracy* as the DNN test accuracy obtained when applying the adversarial attacks to every test example, i.e., by giving adversarial examples as input to the DNN.

²Performing numerous experiments for analyses and evaluation, constituting many NAS rounds on complex DNNs with CIFAR-10 dataset already took several weeks to months on our multi-GPU HPC node. Therefore, testing for bigger dataset is out of our currently available computational power and memory resource. Nevertheless, we believe that these findings are highly valuable, and would scale to bigger datasets as well.

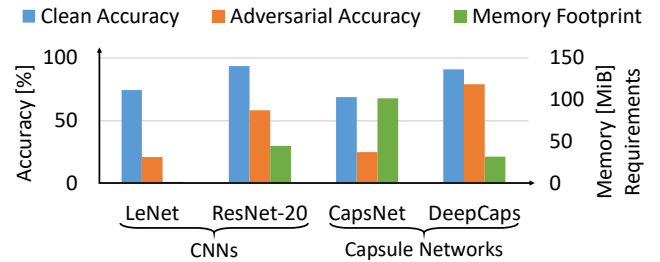


FIGURE 1: Adversarial robustness to the PGD attack vs. memory footprint of LeNet, CapsNet, ResNet-20, and DeepCaps for the CIFAR-10 dataset.

several additional factors and extremely time-consuming training and evaluations of numerous candidate solutions. A wide variety of adversarial attacks have been proposed in the literature [15], and it is extremely complex to evaluate the adversarial robustness to different attack algorithms. A recent study in [16] proposed a method evaluating the DNN robustness to the PGD attack [10] as the optimization goal of the NAS. *On the contrary, our work performs joint optimizations for the adversarial robustness and hardware efficiency both, thereby leading to the increased complexity of the optimization problem, as well as large training time for evaluating the DNN robustness.* Moreover, it is challenging to model, implement and evaluate the hardware execution of different DNNs and CapsNets (including convolutional layers, fully-connected layers, and dynamic routing) in the NAS design flow.

B. OUR NOVEL CONTRIBUTIONS

To address the above-discussed challenges, we propose the novel *RoHNAS* framework (see Figure 2) that integrates multiple optimization objectives (like hardware efficiency and adversarial robustness) for diverse types of DNNs, like Convolutional Neural Networks (CNNs) and CapsNets. *RoHNAS* employs the following key mechanisms:

- 1) For architectural model flexibility and fast hardware estimation, we deploy analytical models of the layers and operations of DNNs and CapsNets, as well as their mapping and execution on specialized accelerators (**Section III-A**).
- 2) To speed-up the robustness evaluation, we analyze and choose the values of the adversarial perturbations, which provide valuable differences when performing the NAS with DNNs subjected to such adversarial perturbations (**Section III-B**).
- 3) We develop a specialized evolutionary algorithm, based on the principles of the Non dominated Sorting Genetic Algorithm II (NSGA-II) method [17], to perform a multi-objective Pareto-frontier selection, with conjoint optimization for adversarial robustness, energy, memory, and latency of DNNs. (**Section III-C**)
- 4) To reduce the overall training time, we devise a fast evaluation methodology for DNNs trained for a limited

number of epochs (Section IV-C), while the Pareto-optimal solutions are evaluated after full-training, to obtain the exact results (Section IV-D).

Implementation and Validation Contributions: We have implemented our *RoHNAS* using the TensorFlow library [18], and evaluated more than 900 DNNs for the MNIST, Fashion-MNIST and CIFAR-10 datasets. Extensive validations are performed on Nvidia's multi-V100 Graphics Processing Unit (GPU) High Performance Computing (HPC) Nodes requiring weeks to months of experimentation time.

Open-Source Contribution: For reproducible research, we will release the code of the *RoHNAS* framework and the pre-trained models of the Pareto-optimal DNNs upon acceptance.

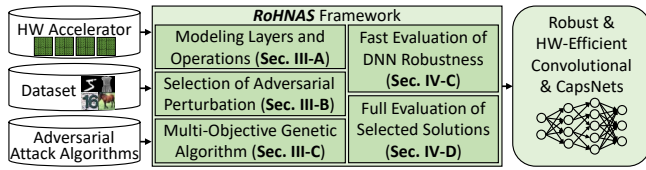


FIGURE 2: Overview of our *RoHNAS* framework.

II. BACKGROUND AND RELATED WORKS

A. ADVERSARIAL ATTACKS

DNNs are now deployed for a wide variety of applications, including safety-critical ones such as Autonomous Driving [2], Medicine [19], and Finance [20]. Despite their performance, DNNs have severe security flaws, as adversarial attacks can fool DNNs with small input perturbations [6]. Many studies [21] [15] have shown that DNNs are vulnerable to carefully crafted inputs designed to fool them. Very small imperceptible perturbations added to the data can completely change the output of the DNN model [22].

It is essential for the attacker to *minimize the added adversarial perturbation to avoid its detection*. Formally, given an original input x with a target classification label c with a DNN model $m(\cdot)$, the problem of generating an adversarial example x^* can be formulated as a constrained optimization problem [15]:

$$\begin{aligned} x^* = \arg \min_{x^*} \quad & \mathcal{D}(x, x^*), \\ \text{s.t.} \quad & m(x) = c, m(x^*) = c^*, c \neq c^* \end{aligned} \quad (1)$$

Where \mathcal{D} is the distance between two images and the optimization objective is to minimize this adversarial perturbation to make it stealthy. x^* is considered as an adversarial example if and only if $m(x) \neq m(x^*)$ and the perturbation is bounded ($\mathcal{D}(x, x^*) < \epsilon$, where $\epsilon \geq 0$).

Goodfellow et al. [23] proposed the fast gradient sign method (FGSM) to generate adversarial examples by exploiting the gradient of the model w.r.t. the input images, towards the direction of the highest loss. Afterward, Madry et al. [10] and Kurakin et al. [24] proposed two different versions of the projected gradient descent (PGD) attack, an

iterative version of the FGSM that introduces a perturbation α to multiple smaller steps. After each iteration, the PGD projects the generated image into a ball with a radius ϵ , keeping the perturbation size small. It is a white-box attack and has both the targeted and untargeted versions. The algorithm consists of the following iteration:

$$x_i^* = x_{i-1}^* - \text{proj}_\epsilon(\alpha \cdot \text{sign}(\nabla_x \text{loss}(\theta, x, t))) \quad (2)$$

Further details about different types of adversarial attacks and defenses can be found in comprehensive surveys such as [6] [15]. Moreover, recent works attempted to improve the DNN robustness against adversarial attacks by hash-based deep compression [25] or approximate computing [26], thus requiring significant hardware design overhead.

B. CONVOLUTIONAL AND CAPSULE NETWORK HARDWARE

A wide variety of hardware architectures has been proposed for accelerating the execution of DNN inference [27] [28], focusing on improving the performance and energy-efficiency through compression, dedicated operation mapping, and specialized hardware design. Recently, hardware architectures for CapsNets have been proposed [29]. CapsNets layers require the execution of operations, such as dynamic routing, that are not supported by traditional DNN accelerators but crucial to detect changes in the compositional structure of the inputs [30].

CapsNets, firstly proposed by the Google Brain's team [31], are elaborated DNN models in which the neurons are grouped together in vector form to compose the *capsules*. Each neuron of a capsule encodes spatial information, while the vector's length encodes the probability of the entity being present. While the first architecture proposed in [4] is composed of only three layers, recently deeper CapsNet models were proposed [13] [32]. The main components of a CapsNet are the following:

- **Convolutional (Conv) Layer:** The CapsNets need one or more traditional Conv layers to be applied at the beginning of the network.
- **Convolutional or Fully-Connected (FC) Capsule Layers:** A generic CapsNet can contain some Conv capsule layers, whose principle of operation is identical to that of traditional Conv layers. However, the convolution is performed between the capsules rather than neurons, and the activation function needs to be the *squash* operation (Eq. 3), which constraints the length of the capsule vectors in the range $[0, 1]$.

$$y = \frac{|x|^2}{(1 + |x|^2)} \frac{x}{|x|} \quad (3)$$

A CapsNet needs necessarily to be ended by a FC capsule layer, which mimics a traditional FC layer, but operating with capsules.

- **Dynamic Routing:** It is possible, but not necessary, to perform a *dynamic routing* between two adjacent

capsule layers. The dynamic routing [4] is an iterative algorithm which associates *coupling coefficients* to the capsules predictions. The coupling coefficients of the capsules predicting the same result with greater confidence are maximized.

Figure 3 shows a simple three-layers CapsNet, as presented in [4]. CapsNets need to be completed by a *reconstruction network*, consisting of FC layers or Transposed Conv layers, to reconstruct the input image.

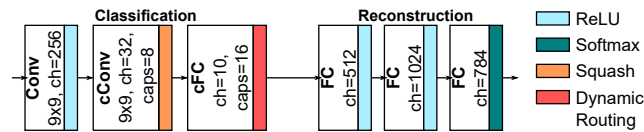


FIGURE 3: Architectural diagram of the CapsNet model of [4].

The aforementioned CapsAcc [33] accelerator (see Figure 4) has been proposed to efficiently deploy the CapsNets in hardware, adapting to the specific needs of the dynamic routing and the squash operation. CapsAcc differs from other DNN accelerators for its Activations unit, which can apply the squash function in addition to the traditional Rectified Linear Unit (ReLU) and Softmax functions. Moreover, a Routing Buffer is inserted to store the partial results generated during the execution of the dynamic routing algorithm. Dedicated scratchpad memories are employed to minimize the energy consumption at runtime [34].

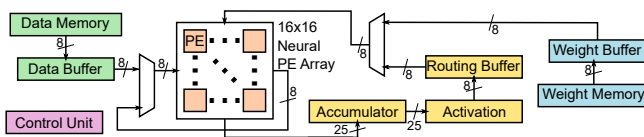


FIGURE 4: Architectural diagram of the CapsAcc accelerator of [33].

C. HARDWARE-AWARE NAS AND ROBUST NAS

Traditional NAS algorithms [3] [35] [36] have aimed at finding a high accurate DNN model for a given task, i.e., the DNN model which provides the highest accuracy on a given dataset. For example, the Efficient Neural Architecture Search (ENAS) algorithm [3] has generated a new architecture with 55.6 perplexity on the Penn Treebank [37] dataset. Recently, the interest in hardware efficiency has been growing, leading to designing Hardware-Aware NAS (HA-NAS) methodologies [38]. The main difference between traditional NAS and HA-NAS algorithms is that the latter also consider the hardware-deployment efficiency of candidate models, e.g., in terms of energy consumption, latency, or memory footprint. Among the related works, there exist mainly three types of heuristic search algorithms for the HA-NAS, which are (1) evolutionary algorithms, (2) reinforcement learning, and (3) differentiable NAS. The Accuracy-and-Performance-aware

Neural Architecture Search (APNAS) [39], which is based on reinforcement learning, extends the ENAS algorithm by including the performance of DNNs executed in hardware in the optimization objectives of the NAS. AttentiveNAS [40] jointly optimizes the DNNs' accuracy and the computational complexity in terms of Mega Floating Point Operations (MFLOPs). MnasNet [41] takes as an objective the inference latency and measures it by executing the candidate models on mobile phones. In [42], an extended search space is used, which includes architecture parameters, quantization, and hardware parameters, precisely the tiling factors. Targeting the Field Programmable Gate Arrays (FPGAs), the FPGA-implementation aware Neural Architecture Search (FNAS) algorithm [43] uses an analytical model to consider the latency only. HotNAS [44] targets energy efficiency by including model compression in the search space and supporting hardware for compressed models. During the candidate selection, the Single Path One-Shot (SPOS) NAS [45] applies latency and Floating Point Operations (FLOPs) constraints. HURRICANE [46] generates a search space tailored to a specific hardware platform, considering the FLOPs and number of parameters, and their effect on the latency. The Differentiable NAS (DNAS) framework [47], in which the search space is represented by a stochastic super net, explores a layer-wise space where each layer of the CNN corresponds to a different block, and the learning is conducted by training the super net. These works are primarily for the CNN models, and cannot handle Capsule Networks.

On the other hand, recent works have also proposed NAS methodologies to achieve high robustness against adversarial attacks. In [16], a *supernet* containing all the possible architectures in the search space is trained. Then, subnetworks are sampled from the supernet and evaluated in terms of accuracy and robustness to adversarial attacks. In [48], the search space is expanded to include some combinations of layers that have been proven to be particularly effective against adversarial attacks. However, all the works that focus on NAS for adversarial attacks have not yet considered the hardware efficiency aspects as conjoint optimization objectives. Moreover, these works are primarily for the CNN models, and cannot handle CapsNets. Recently, NASCaps [49] has proposed a NAS methodology for CapsNets based on an evolutionary algorithm, but it cannot handle robustness challenges, and does not explore the tradeoffs between hardware efficiency and adversarial robustness.

Our RoHNAS framework distinguishes from the previous works because it combines for the first time hardware efficiency and robustness to adversarial perturbations as joint optimization goals for the NAS, and targets both CNN and CapsNets models.

III. ROHNAS FRAMEWORK

Our evolutionary algorithm-based NAS methodology performs a multi-objective search. It automatically searches

for inherently robust yet hardware-efficient DNN models by selecting Pareto-optimal candidates in terms of robustness, energy, latency, and memory footprint. The search space comprises both CNNs and CapsNets. The workflow of our *RoHNAS* framework is shown in Figure 5, and is explained in detail in the following subsections.

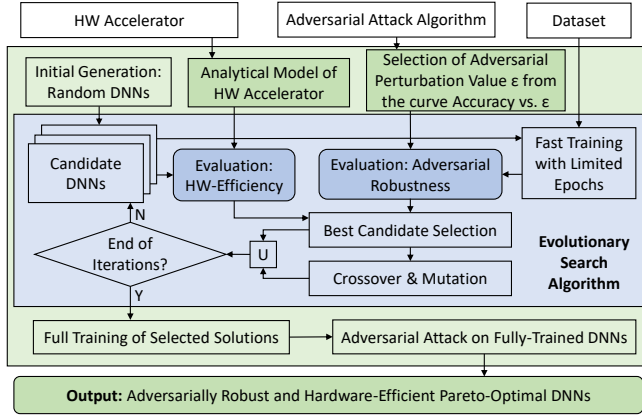


FIGURE 5: Overview of our *RoHNAS* framework and its key functionalities.

The framework's inputs are the hardware accelerator, the algorithm for generating the adversarial attack, and the dataset. After modeling analytically the hardware accelerator, the appropriate values of the adversarial perturbation to employ in the search are selected. This process, as will be described more in detail in Section III-B, consists of analyzing the accuracy vs. adversarial perturbation curve, and focusing on the high variation region which corresponds to the highest slope of the curve. After selecting the values of the adversarial perturbation to employ in the search, the evolutionary search algorithm (based on the principles of the NGSA-II genetic algorithm [17]) performs an iterative exploration through crossover, mutation, and best DNN candidate selection based on the objectives. To speed up the process, during the evolutionary algorithm, the adversarial robustness is evaluated after a fast training, i.e., for DNNs trained with a limited number of epochs, where its number is determined based on the Pearson Correlation Coefficient [50]. Towards generating exact robustness results, the set of Pareto-optimal DNN models are fully-trained, and the robustness against the adversarial attack on fully-trained DNNs is evaluated.

A. LAYER AND OPERATION MODELING

The *RoHNAS* framework models each layer through a *layer descriptor*, which contains all the relevant architectural parameters necessary to describe a generic DNN layer using a position-based representation. As shown in Figure 6, a layer descriptor contains all the information to construct its related layer, such as layer type, input feature map (IFM) size, input channels, input capsules, kernel size, stride size, output feature map (OFM) size, output channels, and output capsules. Using these parameters, it is possible to build many

different types of CNN or CapsNet layers. Moreover, such a modular representation can easily be extended to support different layer types. Multiple layer descriptors, together with information on extra skip connections and resizing of the inputs, form a *genotype*, which allows describing various CNN and CapsNet architectural models.

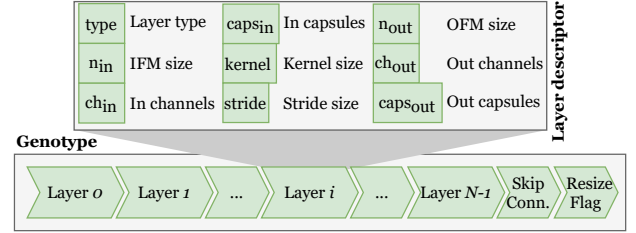


FIGURE 6: Genotype structure. IFM stands for Input Feature Map, while OFM means Output Feature Map.

To estimate the execution requirements of a DNN model on a specialized DNN hardware accelerator (e.g., CapsAcc [33] or Tensor Processing Unit (TPU) [51]), it is necessary to know its underlying hardware characteristics, for instance:

- T , the clock period;
- $Load_Weights$, the number of clock cycles necessary to load the weights into the Processing Element (PE) array;
- $P_{PEarray}$, the power consumed by the PE array, here estimated with the Synopsys Design Compiler tool;
- E_{memory} , the energy required for one memory access, here estimated with the CACTI-P tool [52];

Knowing these parameters makes it possible to estimate the latency, energy consumption, and memory footprint of a DNN model analytically. From the dimensions of the layers of a given DNN, we assess:

- w_l , the number of weights in a layer;
- s_l , the number of values to be summed to obtain an output value, for each layer;
- f_l , the number of feature maps to be multiplied by the same weight, for each layer;
- c_l , the number of clock cycles needed to process a layer.

Given the model and the hardware features, the number of groups of weights loaded into the array ($w_{PEarray}$) and the number of memory accesses (m_{acc}) can be determined through Equations 4 and 5, respectively. By computing the clock cycles (see Eq. 6), it is possible to estimate the latency and energy consumption, which, in conjunction with the memory footprint, form the set of hardware parameters computed through Eq. 7.

$$w_{PEarray} = \left\lceil \frac{w_l}{16 \cdot \min(16, s_l)} \right\rceil \quad (4)$$

$$m_{acc} = \begin{cases} 256, & \text{if } f_l = 1 \\ 16 \cdot \max(s_l - 15, 1), & \text{otherwise} \end{cases} \quad (5)$$

$$c_l = w_l \cdot w_{PEarray} + f_l \quad (6)$$

$$\begin{aligned} latency &= \sum_{l \in L} c_l \cdot T \\ energy &= \left\lceil \frac{m_{acc}}{128} \right\rceil \cdot E_{memory} + \sum_{l \in L} c_l \cdot T \cdot P_{PEarray} \quad (7) \\ memory \text{ footprint} &= \sum_{l \in L} w_l \end{aligned}$$

The model has been validated by comparing the results with the hardware implementation of the CapsAcc [33]. Recent studies in [49] have also shown that the above-discussed parameters and such analytical models are sufficient to accurately estimate the latency, energy, and memory footprint of a given DNN model. In the following, we discuss the efficacy of our analytical models by comparing the estimated values with the real values of latency, energy, and memory requirements. By comparing our analytical model with the real implementation of the CapsNet [4] on CapsAcc [33], our model provides accurate estimations of latency and memory footprint, and underestimates the energy consumption by around 25%. Such a difference might be due to other elements of the hardware implementation (e.g., interconnection overhead) that are not considered by the analytical model. Despite this underestimation, the fidelity of our models is high, i.e., all candidates have similar underestimation trend, so the selection of the candidates would not be affected by this underestimation of analytical models. Please note that our main focus was to have fast estimation with high fidelity.

B. DESIGN SPACE REDUCTION BY SELECTING AN APPROPRIATE ADVERSARIAL PERTURBATION VALUE

Since the design space can potentially explode by considering several types and strengths of adversarial perturbations, the *RoHNAS* framework restricts the design space by automatically selecting the values of adversarial perturbations to be used in the NAS for a given dataset. Algorithm 1 summarizes the proposed procedure. For each element of the testing dataset, the adversarial example is generated through the PGD algorithm [10] (line 4). Note, here we use PGD for illustrative reasons, and other adversarial attack algorithms can be integrated into our *RoHNAS* framework. The parameter ε determines the amount of adversarial perturbation. When considering the variation of the accuracy w.r.t. ε , as we will show in Section IV-B, the region in which the slope is highest is in the middle of the graph, which corresponds to half of the clean accuracy, i.e., $\frac{Acc_0}{2}$ when considering that Acc_0 is the clean accuracy. By exploiting this intuition, our algorithm selects ε_{NAS} , which is the value of adversarial perturbation that provides the closest accuracy to the desired value of $\frac{Acc_0}{2}$. The selected value of ε_{NAS} is employed in the *One EPS* search, which optimizes for the robustness against one value of

perturbation. Moreover, aiming at covering a wider spectrum of adversarial perturbation range, the *Two EPS* search is devised. ε_{low} and ε_{high} are selected (lines 10-11), and the NAS is conducted by optimizing for the adversarial accuracy with both values.

Algorithm 1: Adversarial Perturbation Selection.

Input: Deep Neural Network: N ;

Test Dataset: $\mathcal{D} = \bigcup_j X_j$;

Adversarial Perturbation Budget:

$\varepsilon_i \in \mathcal{E} = [\varepsilon_{MIN}, \varepsilon_{MAX}]$;

Output: Perturbation to apply for the NAS: ε_{NAS} ;

```

1  $Acc_0 = Accuracy(N(\mathcal{D}))$ ;
2 for  $i \in \mathcal{E}$  do
3   for  $j \in \mathcal{D}$  do
4      $X'_{ij} = PGD(N, \varepsilon_i, X_j)$ ;
5   end
6    $\mathcal{D}'_i = \bigcup_j X'_{ij}$ ;
7    $Acc_i = Accuracy(N(\mathcal{D}'_i))$ ;
8 end
9  $\varepsilon_{NAS} = \varepsilon_i : Acc_i \approx \frac{Acc_0}{2}$ ;
10  $\varepsilon_{low} \approx \frac{\varepsilon_{NAS}}{10}$ ;
11  $\varepsilon_{high} \approx 3 \cdot \varepsilon_{NAS}$ ;
```

C. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM

The selection of the Pareto-optimal solutions in the *RoHNAS* framework is based on the principles of the NSGA-II algorithm [17]. The main core of the search algorithm is iterated for g times, where each iteration g_i represents a generation. Each generation g_i consists of a set of *parent candidates* P_i , from which the *offspring candidates* Q_i are generated.

At each generation g_i , the offsprings are generated from the parents via *crossover* and *mutation*. To perform the crossover operation, two parents P_a and P_b are randomly selected from the whole set of parent candidates. The genotypes of P_a and P_b are then pseudo-randomly splitted in two parts, obtaining four genotypes: $P_{a,1}$, $P_{a,2}$, $P_{b,1}$ and $P_{b,2}$. Two offsprings are then obtained concatenating the four genotypes as follows:

$$Q_a = P_{a,1} \& P_{b,2} \quad Q_b = P_{b,1} \& P_{a,2} \quad (8)$$

To perform a mutation, a random parameter of a random layer descriptor is selected and modified. In particular, the kernel size, the stride, the skip connections, and the number of output capsules can be affected. When the generation of the offsprings is complete, it is necessary to check the validity of the solutions and in case remove the invalid candidates.

After the crossover and mutation processes, the set of candidates is the union of the parents and the offsprings sets. To select the best candidates, that will then be the parents in the next generation, the solutions are divided into a series

F_1, F_2, \dots, F_N of Pareto-fronts, where F_1 is the best Pareto-front. The next-generation parents' set P_{i+1} is filled with the solutions from the best Pareto-front. To obtain the chosen number of candidates, it may be necessary to select only a certain number of solutions from a Pareto-front (e.g., F_3 in Figure 7). In this case, the Pareto-front's solutions are sorted by *crowding distance*, and the best ones are picked.

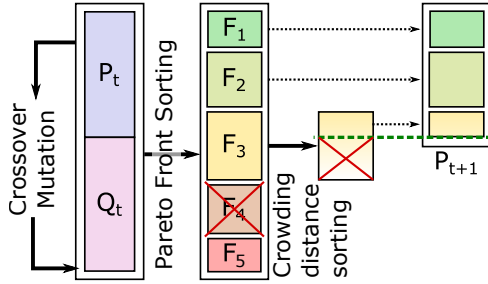


FIGURE 7: One iteration of the NSGA-II algorithm.

IV. EVALUATION OF THE ROHNAS FRAMEWORK

A. EXPERIMENTAL SETUP

The flow of our experiments and the tools used to implement the *RoHNAS* framework are summarized in Fig. 8. The PGD adversarial attack algorithm [10] has been implemented with the *CleverHans* library [53]. The hardware model has been implemented using the open-source *NASCaps* library [49], which is based on the *CapsAcc* architecture [33] synthesized using the *Synopsys Design Compiler* tool, with a 45nm technology node and a clock period of 3ns. The training and testing of the DNNs, implemented in *TensorFlow* [18] have been running on the GPU-HPC computing nodes equipped with four *NVIDIA Tesla V100-SXM2* GPUs. Note that, our experiments were running for 2,000 GPU hours with our fast evaluation method and 8,000 GPU hours for the final training and PGD attack evaluation. Without such exploration time reductions, or by considering more complex optimization problems (e.g., larger datasets or deeper DNN models), the exploration time would have lasted several GPU months.

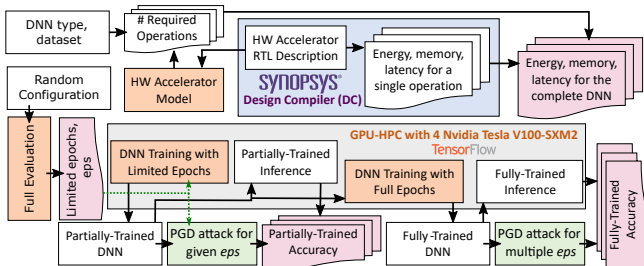


FIGURE 8: Tool-flow and setup for conducting the experiments.

The search algorithm is initialized with a random population of 10 elements, running for a maximum of 20 iterations of the genetic loop. The offspring population size is 10, and the mutation probability is 10%. Each convolutional layer can be composed of a 3×3 , 5×5 , or 9×9 kernel, with

a stride of either 1 or 2. The channels and capsule dimensions can both span between 1 and 64.

B. SELECTION OF ADVERSARIAL PERTURBATION FOR THE NAS

The amount of adversarial perturbation is a key parameter to be selected for performing the NAS. Following the procedure described in Section III-B, the Pareto-optimal DNNs of the *NASCaps* library [49] have been tested under the PGD attack [10], with different values of the adversarial perturbation ϵ . The results reported in Fig. 9 show that, as expected, the higher ϵ is, the lower the DNNs' accuracy drops. The selected values for the NAS are reported in Table 1. The selection process follows the procedure described in Algorithm 1. The *One EPS* column refers to the search using a single value of ϵ , while the *Two EPS* column refer to a search conducted with two different values of ϵ , which are called ϵ_{low} and ϵ_{high} . Note, a simple dataset like the MNIST requires a relatively high adversarial perturbation to impact the DNN robustness. On the other hand, on a more complex dataset like the CIFAR-10, a smaller perturbation is already sufficient to misclassify a certain set of inputs.

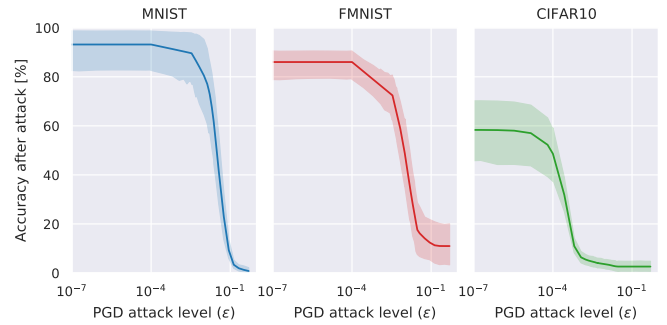


FIGURE 9: Analysis of the DNN robustness under the PGD attack, with different adversarial perturbation values, for MNIST, Fashion-MNIST, and CIFAR-10.

TABLE 1: Selected values of the adversarial perturbation ϵ for the NAS, for MNIST, Fashion-MNIST and CIFAR-10 datasets. There are also reported the values of ϵ_{low} and ϵ_{high} for the *Two EPS* search, which will be used for comparison in Section IV-D.

	Two EPS ϵ_{low}	One EPS ϵ	Two EPS ϵ_{high}
MNIST	3e-3	3e-2	1e-1
F-MNIST	1e-3	1e-2	3e-2
CIFAR-10	3e-5	3e-4	1e-3

C. ROHNAS RESULTS WITH FAST DNN ROBUSTNESS EVALUATION

As discussed in Section III, to reduce the exploration time, our algorithm trains the DNNs only for a limited number of epochs, which results in a fast robustness evaluation. The similarity w.r.t. the full-training robustness has been measured through the Pearson Correlation Coefficient [50], using the procedure described in [49]. The choice of 10 training epochs for the CIFAR-10 dataset and 5 epochs for the

Fashion-MNIST and MNIST datasets leverages the tradeoff between a high correlation and low training time.

The results of the *RoHNAS - One EPS* with fast robustness evaluation are reported in Fig. 10. The earliest generation of the algorithm produces sub-optimal DNN solutions, while most Pareto-optimal solutions are found in the latest generation. Note that, for the *RoHNAS* evaluated on the CIFAR-10 dataset, the latest generations find DNNs that are less robust to the PGD attack, but still belong to the Pareto-frontier due to the low energy consumption (see pointer ①). Note that, as highlighted by pointer ②, several candidate DNNs found in the earliest generations are highly vulnerable to the PGD attack and are automatically discarded by the Pareto-frontier selection.

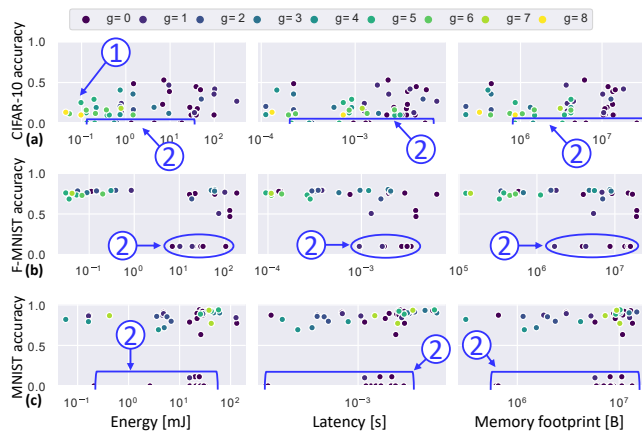


FIGURE 10: *RoHNAS'* fast evaluation of DNN robustness under PGD attack, showing tradeoffs w.r.t. energy, latency and memory footprint. (a) Results for CIFAR-10. (b) Results for Fashion-MNIST. (c) Results for MNIST.

D. ROHNAS EXACT RESULTS FOR PARETO-OPTIMAL DNNs

The Pareto-optimal DNNs that are selected at the previous stage have been *fully-trained* to obtain an exact robustness evaluation. The DNNs for the MNIST and Fashion-MNIST datasets have been trained for 100 epochs, while 300 epochs of training has been used for the DNNs targeting the CIFAR-10 dataset. The results reported in Fig. 11 show tradeoffs between the design objectives. As highlighted by pointer ① in Fig. 11, a Pareto-optimal solution found by the *RoHNAS* framework for the CIFAR-10 dataset achieves 86.07% accuracy while having an energy consumption of 38.63 mJ, a memory footprint of 11.85 MiB, and a latency of 4.47 ms. Similarly, the solution for the Fashion-MNIST dataset pointed in ② reaches an accuracy of 93.40% while having 6.40 ms latency, 61.19 mJ energy, and 16.82 MiB memory. Note that, while the *Two EPS* search finds Pareto-optimal solutions in the middle range of energy (see pointer ③), other interesting low-energy solutions are found by the *One EPS* search, as indicated in pointer ④. The Pareto-optimal DNNs's search for MNIST covers a more

heterogeneous range of values, leveraging tradeoffs between different objectives (see pointer ⑤).

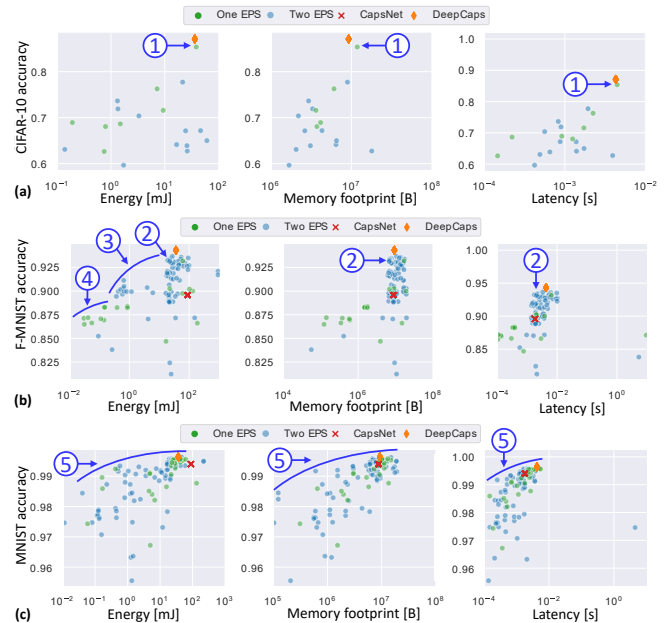


FIGURE 11: *RoHNAS'* exact robustness evaluation of Pareto-optimal DNN solutions under the PGD attack, showing tradeoffs w.r.t. hardware-efficiency. (a) Results for CIFAR-10. (b) Results for Fashion-MNIST. (c) Results for MNIST.

The *RoHNAS* framework has been compared with other state-of-the-art DNN and CapsNet architectures, and NAS methodologies that include capsule layers in the search space. Fig. 12 shows the comparison between our *RoHNAS* framework (*One EPS* setting), NASCaps [49], CapsNet [4] and DeepCaps [13]. For the MNIST dataset, the Pareto-optimal solutions generated with the *RoHNAS* framework are particularly robust for a high range of perturbation ε (see pointer ①). Indeed, the accuracy starts dropping at around one order of magnitude higher ε than NASCaps (see pointer ②). For the Fashion-MNIST, the robustness behavior of the Pareto-optimal DNNs selected with the *RoHNAS* framework is closely related to the CapsNet. Instead, for the CIFAR-10 dataset, the *RoHNAS* DNNs' behavior is similar to the DeepCaps for low values of ε (see pointer ③), while a Pareto-optimal *RoHNAS* solution offer a respectable robustness also with higher adversarial perturbation (see pointer ④).

The evaluation of the *RoHNAS* framework with the *Two EPS* setting is shown in Fig. 13. Compared to the *One EPS* setting, the NAS produces different levels of robustness w.r.t. ε for the MNIST and Fashion-MNIST datasets (see pointer ① in Fig. 13). However, for the CIFAR-10 dataset, the *Two EPS* search leads to worse results than the *One EPS* counterpart (see pointer ②).

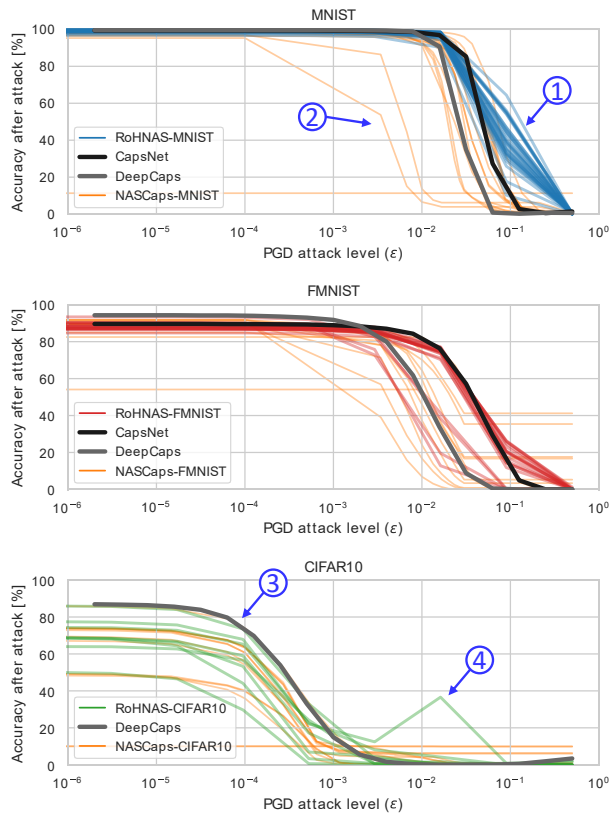


FIGURE 12: Evaluation of the *RoHNAS* framework with the *One EPS* setting, compared to other state-of-the-art architectures and NAS algorithms.

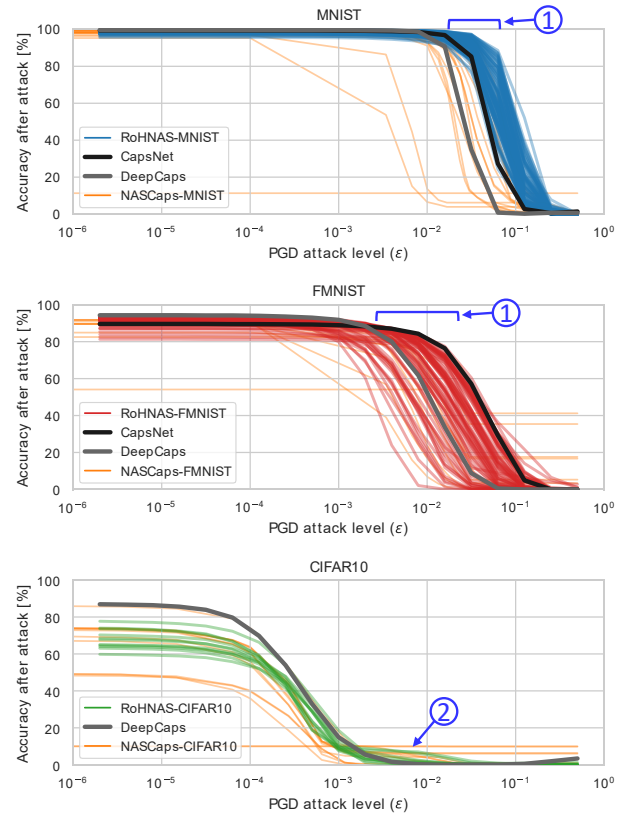


FIGURE 13: Evaluation of the *RoHNAS* framework with the *Two EPS* setting, compared to other state-of-the-art architectures and NAS algorithms.

E. ROHNAS RESULTS VS. RANDOM SEARCH

The *RoHNAS* framework based on the evolutionary search algorithm has been compared to a modified version using random search. The results of the fast DNN robustness evaluation for the *Two EPS* configuration are shown in Figures 14 and 15, where Fig. 14 shows the accuracy measured when the adversarial perturbation value for the PGD attack is ϵ_{high} , while Fig. 15 uses ϵ_{low} . Pointer ① in Fig. 14 indicates the Pareto frontier for the CIFAR-10 dataset obtained by random search, which is outperformed by several candidate DNN models found using the NSGA-II algorithm of our *RoHNAS* framework (see pointer ② in Fig. 14). For the Fashion-MNIST dataset, some candidate DNNs found using the random search show high hardware efficiency, but the solution generated through the NSGA-II algorithm indicated by pointer ③ shows higher robustness. Also for the MNIST dataset, the NSGA-II generates solutions that have better tradeoffs between the objectives, compared to using random search (see pointer ④).

Similar observations can be made when the adversarial perturbation value for the PGD attack is ϵ_{low} . As indicated by pointer ① in Fig. 15, several candidate DNN models for the CIFAR-10 dataset found using the NSGA-II algorithm have better tradeoffs than the Pareto-frontier obtained with



FIGURE 14: *RoHNAS*' fast evaluation of DNN robustness under PGD attack in the *Two EPS* setting using the ϵ_{high} value, compared to the solutions found with random search, showing tradeoffs w.r.t. energy, latency, and memory footprint.

random search. However, for the Fashion-MNIST dataset, the solutions with high hardware efficiency (especially low energy and low latency) are found by random search (see

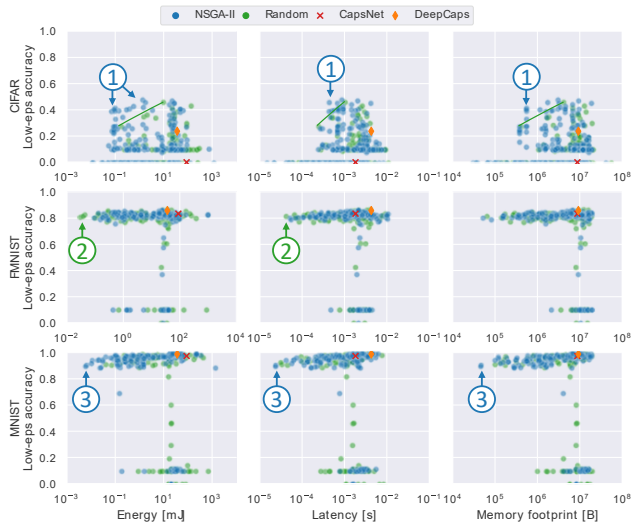


FIGURE 15: *RoHNAS*’ fast evaluation of DNN robustness under PGD attack in the *Two EPS* setting using the ε_{low} value, compared to the solutions found with random search, showing tradeoffs w.r.t. energy, latency, and memory footprint.

pointer ②). On the other hand, the NSGA-II algorithm generates solutions with higher hardware efficiency for the MNIST dataset (see pointer ③).

The Pareto-optimal DNNs selected using random search for the *Two EPS* setting are *fully-trained* and compared to the results of the *RoHNAS* framework in Fig. 16. As highlighted by pointer ①, the Pareto-optimal solutions generated by both algorithms are robust for a high range of perturbation values ε . However, the key differences can be observed in some curves belonging to the *RoHNAS* search, which exhibit higher robustness than the curves obtained with the random search (see pointer ② in Fig. 16).

Our framework supports the integration of different search techniques. Therefore, depending upon the requirements of a system, different search techniques can be run and the best possible solutions can be picked. However, this will lead to a higher experimentation time. Therefore, we recommend using the NSGA-II search algorithm that outperforms the random search in most of the cases.

V. CONCLUSION

In this paper, we proposed *RoHNAS*, a novel framework for the Neural Architecture Search, jointly optimizing for the hardware efficiency (latency, energy, and memory footprint) and robustness against adversarial attacks. Our optimizations for reducing the search space and the exploration time allow finding a set of CNNs and CapsNets, which are Pareto-optimal w.r.t. the above-discussed objectives, in a fast fashion. In our experiments, 900 different DNN models have been evaluated, using 2,000 GPU hours with our fast training settings. Thanks to our *RoHNAS* framework, the deployment of robust DNNs in resource-constrained IoT/neuromorphic edge devices is made possible. We will open-source our framework upon acceptance.

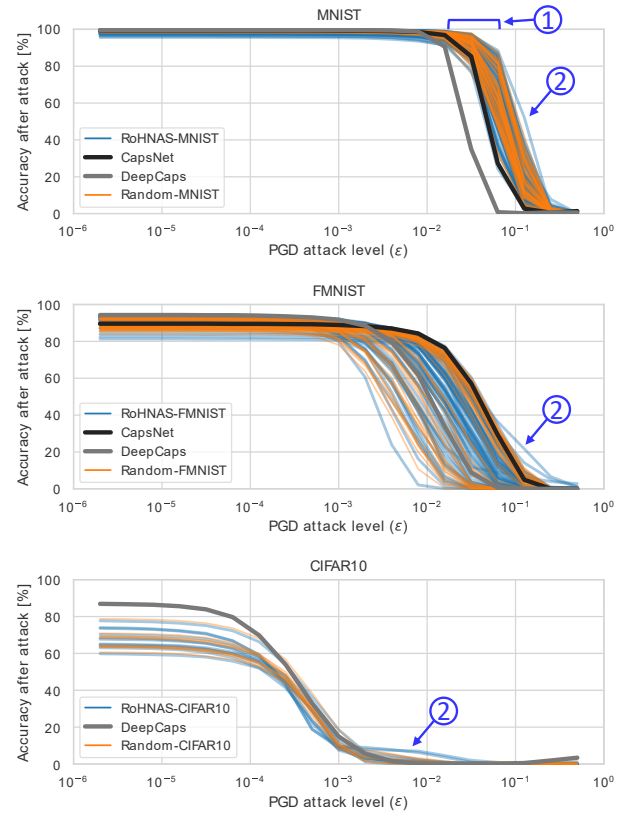


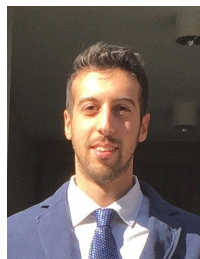
FIGURE 16: Evaluation of the *RoHNAS* framework with the *Two EPS* setting, compared to the random search.

REFERENCES

- [1] M. Capra, B. Bussolino, A. Marchisio, G. Masera, M. Martina, and M. Shafique, “Hardware and software optimizations for accelerating deep neural networks: Survey of current trends, challenges, and the road ahead,” *IEEE Access*, vol. 8, pp. 225 134–225 180, 2020. [Online]. Available: <https://doi.org/10.1109/ACCESS.2020.3039858>
- [2] S. Grigorescu, B. Trasnea, T. Cocias, and G. Macesanu, “A survey of deep learning techniques for autonomous driving,” *Journal of Field Robotics*, 2019. [Online]. Available: <http://dx.doi.org/10.1002/rob.21918>
- [3] H. Pham, M. Y. Guan, B. Zoph, Q. V. Le, and J. Dean, “Efficient neural architecture search via parameter sharing,” in *Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholm, Sweden, July 10–15, 2018*, ser. *Proceedings of Machine Learning Research*, J. G. Dy and A. Krause, Eds., vol. 80. PMLR, 2018, pp. 4092–4101. [Online]. Available: <http://proceedings.mlr.press/v80/pham18a.html>
- [4] S. Sabour, N. Frosst, and G. E. Hinton, “Dynamic routing between capsules,” in *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4–9, 2017, Long Beach, CA, USA*, I. Guyon, U. von Luxburg, S. Bengio, H. M. Wallach, R. Fergus, S. V. N. Vishwanathan, and R. Garnett, Eds., 2017, pp. 3856–3866. [Online]. Available: <https://proceedings.neurips.cc/paper/2017/hash/2cad8fa47bbef282badbb8de5374b894-Abstract.html>
- [5] A. Marchisio, M. A. Hanif, F. Khalid, G. Plastiras, C. Kyrkou, T. Theodoridis, and M. Shafique, “Deep learning for edge computing: Current trends, cross-layer optimizations, and open research challenges,” in *2019 IEEE Computer Society Annual Symposium on VLSI, ISVLSI 2019, Miami, FL, USA, July 15–17, 2019*. IEEE, 2019, pp. 553–559. [Online]. Available: <https://doi.org/10.1109/ISVLSI.2019.00105>
- [6] M. Shafique, M. Naseer, T. Theodoridis, C. Kyrkou, O. Mutlu, L. Orosa, and J. Choi, “Robust machine learning systems: Challenges, current trends, perspectives, and the road ahead,” *IEEE Des. Test*, vol. 37,

- no. 2, pp. 30–57, 2020. [Online]. Available: <https://doi.org/10.1109/MDAT.2020.2971217>
- [7] C. Cheng, F. Diehl, G. Hinz, Y. Hamza, G. Nührenberg, M. Rickert, H. Ruess, and M. Truong-Le, “Neural networks for safety-critical applications - challenges, experiments and perspectives,” in 2018 Design, Automation & Test in Europe Conference & Exhibition, DATE 2018, Dresden, Germany, March 19–23, 2018, J. Madsen and A. K. Coskun, Eds. IEEE, 2018, pp. 1005–1006. [Online]. Available: <https://doi.org/10.23919/DATE.2018.8342158>
- [8] S. Dave, A. Marchisio, M. A. Hanif, A. Guesmi, A. Shrivastava, I. Alouani, and M. Shafique, “Special session: Towards an agile design methodology for efficient, reliable, and secure ML systems,” CoRR, vol. abs/2204.09514, 2022. [Online]. Available: <https://doi.org/10.48550/arXiv.2204.09514>
- [9] M. Shafique, A. Marchisio, R. V. W. Putra, and M. A. Hanif, “Towards energy-efficient and secure edge AI: A cross-layer framework ICCAD special session paper,” in IEEE/ACM International Conference On Computer Aided Design, ICCAD 2021, Munich, Germany, November 1–4, 2021. IEEE, 2021, pp. 1–9. [Online]. Available: <https://doi.org/10.1109/ICCAD51958.2021.9643539>
- [10] A. Madry, A. Makelov, L. Schmidt, D. Tsipras, and A. Vladu, “Towards deep learning models resistant to adversarial attacks,” in 6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 – May 3, 2018, Conference Track Proceedings. OpenReview.net, 2018. [Online]. Available: <https://openreview.net/forum?id=JzIBFZAb>
- [11] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, “Gradient-based learning applied to document recognition,” Proc. IEEE, vol. 86, no. 11, pp. 2278–2324, 1998. [Online]. Available: <https://doi.org/10.1109/5.726791>
- [12] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in 2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27–30, 2016. IEEE Computer Society, 2016, pp. 770–778. [Online]. Available: <https://doi.org/10.1109/CVPR.2016.90>
- [13] J. Rajasegaran, V. Jayasundara, S. Jayasekara, H. Jayasekara, S. Seneviratne, and R. Rodrigo, “Deepcaps: Going deeper with capsule networks,” in IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16–20, 2019. Computer Vision Foundation / IEEE, 2019, pp. 10725–10733. [Online]. Available: http://openaccess.thecvf.com/content_CVPR_2019/html/Rajasegaran_DeepCaps_Going_Deeper_With_Capsule_Networks_CVPR_2019_paper.html
- [14] A. Krizhevsky, “Learning multiple layers of features from tiny images,” Department of Computer Science, University of Toronto, Tech. Rep., 2009.
- [15] X. Yuan, P. He, Q. Zhu, and X. Li, “Adversarial examples: Attacks and defenses for deep learning,” IEEE Trans. Neural Networks Learn. Syst., vol. 30, no. 9, pp. 2805–2824, 2019. [Online]. Available: <https://doi.org/10.1109/TNNLS.2018.2886017>
- [16] M. Guo, Y. Yang, R. Xu, Z. Liu, and D. Lin, “When NAS meets robustness: In search of robust architectures against adversarial attacks,” in 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13–19, 2020. Computer Vision Foundation / IEEE, 2020, pp. 628–637. [Online]. Available: https://openaccess.thecvf.com/content_CVPR_2020/html/Guo_When_NAS_Meets_Robustness_In_Search_of_Robust_Architectures_Against_CVPR_2020_paper.html
- [17] K. Deb, S. Agrawal, A. Pratap, and T. Meyarivan, “A fast and elitist multiobjective genetic algorithm: NSGA-II,” IEEE Trans. Evol. Comput., vol. 6, no. 2, pp. 182–197, 2002. [Online]. Available: <https://doi.org/10.1109/4235.996017>
- [18] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard, M. Kudlur, J. Levenberg, R. Monga, S. Moore, D. G. Murray, B. Steiner, P. A. Tucker, V. Vasudevan, P. Warden, M. Wicke, Y. Yu, and X. Zheng, “Tensorflow: A system for large-scale machine learning,” in 12th USENIX Symposium on Operating Systems Design and Implementation, OSDI 2016, Savannah, GA, USA, November 2–4, 2016, K. Keeton and T. Roscoe, Eds. USENIX Association, 2016, pp. 265–283. [Online]. Available: <https://www.usenix.org/conference/osdi16/technical-sessions/presentation/abadi>
- [19] C. Barata and J. S. Marques, “Deep learning for skin cancer diagnosis with hierarchical architectures,” in 16th IEEE International Symposium on Biomedical Imaging, ISBI 2019, Venice, Italy, April 8–11, 2019. IEEE, 2019, pp. 841–845. [Online]. Available: <https://doi.org/10.1109/ISBI.2019.8759561>
- [20] R. Zanc, T. Cioara, and I. Anghel, “Forecasting financial markets using deep learning,” in 15th IEEE International Conference on Intelligent Computer Communication and Processing, ICCP 2019, Cluj-Napoca, Romania, September 5–7, 2019, S. Nedeveschi, R. Potolea, and R. R. Slavescu, Eds. IEEE, 2019, pp. 459–466. [Online]. Available: <https://doi.org/10.1109/ICCP48234.2019.8959715>
- [21] C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. J. Goodfellow, and R. Fergus, “Intriguing properties of neural networks,” in 2nd International Conference on Learning Representations, ICLR 2014, Banff, AB, Canada, April 14–16, 2014, Conference Track Proceedings, Y. Bengio and Y. LeCun, Eds., 2014. [Online]. Available: <http://arxiv.org/abs/1312.6199>
- [22] J. J. Zhang, K. Liu, F. Khalid, M. A. Hanif, S. Rehman, T. Theodoridis, A. Artusi, M. Shafique, and S. Garg, “Building robust machine learning systems: Current progress, research challenges, and opportunities,” in Proceedings of the 56th Annual Design Automation Conference 2019, DAC 2019, Las Vegas, NV, USA, June 02–06, 2019. ACM, 2019, p. 175. [Online]. Available: <https://doi.org/10.1145/3316781.3323472>
- [23] I. J. Goodfellow, J. Shlens, and C. Szegedy, “Explaining and harnessing adversarial examples,” in 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7–9, 2015, Conference Track Proceedings, Y. Bengio and Y. LeCun, Eds., 2015. [Online]. Available: <http://arxiv.org/abs/1412.6572>
- [24] A. Kurakin, I. J. Goodfellow, and S. Bengio, “Adversarial examples in the physical world,” in 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24–26, 2017, Workshop Track Proceedings. OpenReview.net, 2017. [Online]. Available: <https://openreview.net/forum?id=HJGU3Rodl>
- [25] Q. Liu, T. Liu, Z. Liu, Y. Wang, Y. Jin, and W. Wen, “Security analysis and enhancement of model compressed deep learning systems under adversarial attacks,” in 23rd Asia and South Pacific Design Automation Conference, ASP-DAC 2018, Jeju, Korea (South), January 22–25, 2018, Y. Shin, Ed. IEEE, 2018, pp. 721–726. [Online]. Available: <https://doi.org/10.1109/ASPDAC.2018.8297407>
- [26] A. Guesmi, I. Alouani, K. N. Khasawneh, M. Baklouti, T. Frikha, M. Abid, and N. B. Abu-Ghazaleh, “Defensive approximation: securing cnns using approximate computing,” in ASPLOS ’21: 26th ACM International Conference on Architectural Support for Programming Languages and Operating Systems, Virtual Event, USA, April 19–23, 2021, T. Sherwood, E. D. Berger, and C. Kozyrakis, Eds. ACM, 2021, pp. 990–1003. [Online]. Available: <https://doi.org/10.1145/3445814.3446747>
- [27] V. Sze, Y. Chen, T. Yang, and J. S. Emer, “Efficient processing of deep neural networks: A tutorial and survey,” Proc. IEEE, vol. 105, no. 12, pp. 2295–2329, 2017. [Online]. Available: <https://doi.org/10.1109/JPROC.2017.2761740>
- [28] M. Capra, B. Bussolino, A. Marchisio, M. Shafique, G. Masera, and M. Martina, “An updated survey of efficient hardware architectures for accelerating deep convolutional neural networks,” Future Internet, vol. 12, no. 7, 2020. [Online]. Available: <https://www.mdpi.com/1999-5903/12/7/113>
- [29] A. Marchisio, V. Mrazek, M. A. Hanif, and M. Shafique, “FEECA: design space exploration for low-latency and energy-efficient capsule network accelerators,” IEEE Trans. Very Large Scale Integr. Syst., vol. 29, no. 4, pp. 716–729, 2021. [Online]. Available: <https://doi.org/10.1109/TVLSI.2021.3059518>
- [30] S. R. Venkatraman, A. Anand, S. Balasubramanian, and R. R. Sarma, “Learning compositional structures for deep learning: Why routing-by-agreement is necessary,” CoRR, vol. abs/2010.01488, 2020. [Online]. Available: <https://arxiv.org/abs/2010.01488>
- [31] G. E. Hinton, A. Krizhevsky, and S. D. Wang, “Transforming auto-encoders,” in Artificial Neural Networks and Machine Learning - ICANN 2011 - 21st International Conference on Artificial Neural Networks, Espoo, Finland, June 14–17, 2011, Proceedings, Part I, ser. Lecture Notes in Computer Science, T. Honkela, W. Duch, M. A. Girolami, and S. Kaski, Eds., vol. 6791. Springer, 2011, pp. 44–51. [Online]. Available: https://doi.org/10.1007/978-3-642-21735-7_6
- [32] K. Sun, L. Yuan, H. Xu, and X. Wen, “Deep tensor capsule network,” IEEE Access, vol. 8, pp. 96920–96933, 2020. [Online]. Available: <https://doi.org/10.1109/ACCESS.2020.2996282>
- [33] A. Marchisio, M. A. Hanif, and M. Shafique, “Capsacc: An efficient hardware accelerator for capsule networks with data reuse,” in Design, Automation & Test in Europe Conference & Exhibition, DATE 2019,

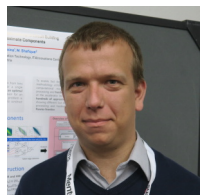
- Florence, Italy, March 25–29, 2019, J. Teich and F. Fummi, Eds. IEEE, 2019, pp. 964–967. [Online]. Available: <https://doi.org/10.23919/DATE.2019.8714922>
- [34] A. Marchisio, V. Mrazek, M. A. Hanif, and M. Shafique, “Descnet: Developing efficient scratchpad memories for capsule network hardware,” *IEEE Trans. Comput. Aided Des. Integr. Circuits Syst.*, vol. 40, no. 9, pp. 1768–1781, 2021. [Online]. Available: <https://doi.org/10.1109/TCAD.2020.3030610>
- [35] B. Zoph and Q. V. Le, “Neural architecture search with reinforcement learning,” in 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24–26, 2017, Conference Track Proceedings. OpenReview.net, 2017. [Online]. Available: <https://openreview.net/forum?id=r1Ue8Hcxg>
- [36] D. Stamoulis, R. Ding, D. Wang, D. Lymberopoulos, B. Priyantha, J. Liu, and D. Marculescu, “Single-path NAS: designing hardware-efficient convnets in less than 4 hours,” in Machine Learning and Knowledge Discovery in Databases - European Conference, ECML PKDD 2019, Würzburg, Germany, September 16–20, 2019, Proceedings, Part II, ser. Lecture Notes in Computer Science, vol. 11907. Springer, 2019, pp. 481–497. [Online]. Available: https://doi.org/10.1007/978-3-030-46147-8_29
- [37] M. P. Marcus, B. Santorini, and M. A. Marcinkiewicz, “Building a large annotated corpus of English: The Penn Treebank,” *Computational Linguistics*, vol. 19, no. 2, pp. 313–330, 1993. [Online]. Available: <https://www.aclweb.org/anthology/J93-2004>
- [38] L. Sekanina, “Neural architecture search and hardware accelerator co-search: A survey,” *IEEE Access*, vol. 9, pp. 151 337–151 362, 2021. [Online]. Available: <https://doi.org/10.1109/ACCESS.2021.3126685>
- [39] P. Achararit, M. A. Hanif, R. V. W. Putra, M. Shafique, and Y. Hara-Azumi, “APNAS: accuracy-and-performance-aware neural architecture search for neural hardware accelerators,” *IEEE Access*, vol. 8, pp. 165 319–165 334, 2020. [Online]. Available: <https://doi.org/10.1109/ACCESS.2020.3022327>
- [40] D. Wang, M. Li, C. Gong, and V. Chandra, “Attentivenas: Improving neural architecture search via attentive sampling,” in IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2021, virtual, June 19–25, 2021. Computer Vision Foundation / IEEE, 2021, pp. 6418–6427. [Online]. Available: https://openaccess.thecvf.com/content/CVPR2021/html/Wang_AttentiveNAS_Improving_Neural_Architecture_Search_via_Attentive_Sampling_CVPR_2021_paper.html
- [41] M. Tan, B. Chen, R. Pang, V. Vasudevan, M. Sandler, A. Howard, and Q. V. Le, “Mnasnet: Platform-aware neural architecture search for mobile,” in IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16–20, 2019. Computer Vision Foundation / IEEE, 2019, pp. 2820–2828. [Online]. Available: http://openaccess.thecvf.com/content_CVPR_2019/html/Tan_MnasNet_Platform-Aware_Neural_Architecture_Search_for_Mobile_CVPR_2019_paper.html
- [42] Q. Lu, W. Jiang, X. Xu, Y. Shi, and J. Hu, “On neural architecture search for resource-constrained hardware platforms,” *CoRR*, vol. abs/1911.00105, 2019. [Online]. Available: <http://arxiv.org/abs/1911.00105>
- [43] W. Jiang, X. Zhang, E. H. Sha, L. Yang, Q. Zhuge, Y. Shi, and J. Hu, “Accuracy vs. efficiency: Achieving both through fpga-implementation aware neural architecture search,” in Proceedings of the 56th Annual Design Automation Conference 2019, DAC 2019, Las Vegas, NV, USA, June 02–06, 2019. ACM, 2019, p. 5. [Online]. Available: <https://doi.org/10.1145/3316781.3317757>
- [44] W. Jiang, L. Yang, S. Dasgupta, J. Hu, and Y. Shi, “Standing on the shoulders of giants: Hardware and neural architecture co-search with hot start,” *IEEE Trans. Comput. Aided Des. Integr. Circuits Syst.*, vol. 39, no. 11, pp. 4154–4165, 2020. [Online]. Available: <https://doi.org/10.1109/TCAD.2020.3012863>
- [45] Z. Guo, X. Zhang, H. Mu, W. Heng, Z. Liu, Y. Wei, and J. Sun, “Single path one-shot neural architecture search with uniform sampling,” in Computer Vision - ECCV 2020 - 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XVI, ser. Lecture Notes in Computer Science, vol. 12361. Springer, 2020, pp. 544–560. [Online]. Available: https://doi.org/10.1007/978-3-030-58517-4_32
- [46] L. L. Zhang, Y. Yang, Y. Jiang, W. Zhu, and Y. Liu, “Hardware-aware one-shot neural architecture search in coordinate ascent framework,” *CoRR*, vol. abs/1910.11609, 2019. [Online]. Available: <http://arxiv.org/abs/1910.11609>
- [47] B. Wu, X. Dai, P. Zhang, Y. Wang, F. Sun, Y. Wu, Y. Tian, P. Vajda, Y. Jia, and K. Keutzer, “Fbnet: Hardware-aware efficient convnet design via differentiable neural architecture search,” in IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16–20, 2019. Computer Vision Foundation / IEEE, 2019, pp. 10 734–10 742. [Online]. Available: http://openaccess.thecvf.com/content_CVPR_2019/html/Wu_FBNet_Hardware-Aware_Efficient_ConvNet_Design_via_Differentiable_Neural_Architecture_Search_CVPR_2019_paper.html
- [48] S. Kotyan and D. V. Vargas, “Evolving robust neural architectures to defend from adversarial attacks,” in Proceedings of the Workshop on Artificial Intelligence Safety 2020 co-located with the 29th International Joint Conference on Artificial Intelligence and the 17th Pacific Rim International Conference on Artificial Intelligence (IJCAI-PRICAI 2020), Yokohama, Japan, January, 2021, ser. CEUR Workshop Proceedings, H. Espinoza, J. McDermid, X. Huang, M. Castillo-Effen, X. C. Chen, J. Hernández-Orallo, S. Ó. hEigeartaigh, and R. Mallah, Eds., vol. 2640. CEUR-WS.org, 2020. [Online]. Available: http://ceur-ws.org/Vol-2640/paper_1.pdf
- [49] A. Marchisio, A. Massa, V. Mrazek, B. Bussolino, M. Martina, and M. Shafique, “Nascaps: A framework for neural architecture search to optimize the accuracy and hardware efficiency of convolutional capsule networks,” in IEEE/ACM International Conference On Computer Aided Design, ICCAD 2020, San Diego, CA, USA, November 2–5, 2020. IEEE, 2020, pp. 114:1–114:9. [Online]. Available: <https://doi.org/10.1145/3400302.3415731>
- [50] K. Pearson, “Note on regression and inheritance in the case of two parents,” *Proceedings of the Royal Society of London*, vol. 58, pp. 240–242, 1895. [Online]. Available: <http://www.jstor.org/stable/115794>
- [51] N. P. Jouppi, C. Young, N. Patil, D. Patterson, G. Agrawal, R. Bajwa, S. Bates, S. Bhatia, N. Boden, A. Borchers et al., “In-datacenter performance analysis of a tensor processing unit,” in Proceedings of the 44th Annual International Symposium on Computer Architecture, ISCA 2017, Toronto, ON, Canada, June 24–28, 2017. ACM, 2017, pp. 1–12. [Online]. Available: <https://doi.org/10.1145/3079856.3080246>
- [52] S. Li, K. Chen, J. H. Ahn, J. B. Brockman, and N. P. Jouppi, “Cacti-p: Architecture-level modeling for sram-based structures with advanced leakage reduction techniques,” in 2011 IEEE/ACM International Conference on Computer-Aided Design, ICCAD 2011, San Jose, California, USA, November 7–10, 2011. IEEE Computer Society, 2011, pp. 694–701. [Online]. Available: <https://doi.org/10.1109/ICCAD.2011.6105405>
- [53] I. J. Goodfellow, N. Papernot, and P. D. McDaniel, “cleverhans v0.1: an adversarial machine learning library,” *CoRR*, vol. abs/1610.00768, 2016. [Online]. Available: <http://arxiv.org/abs/1610.00768>



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