Defending with Errors: Approximate Computing for Robustness of Deep Neural Networks

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Abstract—Machine-learning architectures, such as Convolutional Neural Networks (CNNs) are vulnerable to adversarial attacks: inputs crafted carefully to force the system output to a wrong label. Since machine-learning is being deployed in safety-critical and security-sensitive domains, such attacks may have catastrophic security and safety consequences. In this paper, we propose for the first time to use hardware-supported approximate computing to improve the robustness of machine-learning classifiers. We show that successful adversarial attacks against the exact classifier have poor transferability to the approximate implementation. Surprisingly, the robustness advantages also apply to white-box attacks where the attacker has unrestricted access to the approximate classifier implementation: in this case, we show that substantially higher levels of adversarial noise are needed to produce adversarial examples. Furthermore, our approximate computing model maintains the same level in terms of classification accuracy, does not require retraining, and reduces resource utilization and energy consumption of the CNN. We conducted extensive experiments on a set of strong adversarial attacks; We empirically show that the proposed implementation increases the robustness of a LeNet-5, Alexnet and VGG-11 CNNs considerably with up to 50% by-product saving in energy consumption due to the simpler nature of the approximate logic.

Index Terms—Deep neural network, adversarial example, security, adversarial attacks, approximate computing.

1 INTRODUCTION

CONVOLUTIONAL neural networks (CNNs) and other deep learning structures provide state-of-the-art performance in many application domains, such as computer vision, natural language processing, robotics, autonomous driving, and healthcare. With the rapid progress in CNN’s development and deployment, they are increasing concerns about their vulnerability to adversarial attacks: maliciously designed imperceptible perturbations injected within the data that cause CNNs to misclassify. Adversarial attacks have been demonstrated in real-world scenarios [12], making this vulnerability a serious threat to safety-critical and other applications that rely on CNNs.

Several software-based defenses have been proposed against Adversarial Machine Learning (AML) attacks [1], [2], but more advanced attack strategies [3], [15] also continue to evolve that demonstrate vulnerability of some of these defenses. Moreover, many of the proposed defenses introduce substantial overheads to either the training or the inference operation of CNNs [2]. These overheads increase the computational requirements of these systems, which is already a significant challenge driving substantial research into algorithmic and hardware techniques to improve CNN performance and energy-efficiency [4]. Thus, finding new approaches to harden systems against AML without heavy overheads in both design-time and run-time is an area of substantial need.

In this paper, we propose a new hardware based approach to improve the robustness of machine learning (ML) classifiers. Specifically, we show that Approximate Computing (AC), designed to improve the performance and power consumption of algorithms and processing elements, can substantially improve CNN robustness to AML. Our technique, which we call defensive approximation (DA), substantially enhances the robustness of CNNs to adversarial attacks. We show that for a variety of attack scenarios, and utilizing a range of algorithms for generating adversarial attacks, DA provides substantial robustness even under the assumptions of a powerful attacker with full access to the internal classifier structure. Importantly, DA does not require retraining or fine-tuning, allowing pre-trained models to benefit from its robustness and performance advantages by simply replacing the exact multiplier implementations with approximate ones. The approximate classifier achieves similar accuracy to the exact classifier for Lenet-5 and Alexnet.

DA also benefits from the conventional advantages of AC, resulting in a less complex design that is both faster and more energy efficient. Other defenses such as Defensive Quantization (DQ) [5] also provide energy efficiency benefits in addition to robustness. However, we show that because it is input-dependent DA achieves twice higher robustness to attacks than DQ.

We carry out several experiments to better understand the robustness advantages of DA. We show that the unpredictable and input-dependent variations introduced by AC improve the CNN resilience to adversarial perturbations. Experimental results show that DA has a confidence enhancement impact on non-adversarial examples; we believe
that this is due to our AC multiplier which adds input dependent approximation with generally higher magnitude at large multiplication values. In fact, the AC-induced noise in the convolution layer is shown to be higher in absolute value when the input matrix is highly correlated to the convolution filter, and by consequence highlights further the features. This observation at the feature map propagates through the model and results in enhanced classification confidence, i.e., the difference between the 1st class and the "runner-up". Intuitively and as shown by prior work [6], enhancing the confidence furthers the classifier’s robustness. At the same time, we observe negligible accuracy loss compared to a conventional CNN implementation on non-adversarial inputs while providing considerable power savings.

In summary, the contributions of the paper are:

- We build an aggressively approximate floating point multiplier that injects data-dependent noise within the convolution calculation. Subsequently, we used this approximate multiplier to implement an approximate CNN hardware accelerator (Section 4.3).
- To the best of our knowledge, we are the first to leverage AC to enhance CNN robustness to adversarial attacks without the need for re-training, fine-tuning, or input pre-processing. We investigate the capacity of AC to help defending against adversarial attacks in Section 5.3.
- We empirically show that the proposed approximate implementation reduces the success rate of adversarial attacks under grey-box setting by an average of 87% and 71.5% in Lenet-5 and Alexnet CNNs respectively. For a white-box setting, DA is found to help increase model resilience to reach 90% for images from CIFAR-10 and ImageNet under the PGD attack for a noise budget of 0.06.
- The proposed technique has minor impact on model performance on clean images.
- We propose an approximate BFloat16 multiplier that stills perform well in spite of the aggressive approximation.
- We study the impact of introducing approximation to convolution and fully-connected (FC) layers on model accuracy.
- We build an approximate BFloat16 multiplier which resulted in further gain in energy by up to 81% and 88% saving in delay compared to a conventional FP multiplier.
- Open source: for reproducible research, we release the complete source code of our method. [7]

We believe that DA is highly practical; it can be deployed without retraining or fine-tuning, achieving comparable classification performance to exact classifiers. In addition to security advantages, DA improves performance by reducing latency and energy making it an attractive choice even in Edge device settings.

An earlier version of this paper appeared in the International Conference on Architectural Support for Program-

1. https://github.com/AG-X09/Defensive-Approximation

2. The description of the the contributions of the journal extension vs. the conference article is included in the cover letter.
This observation has motivated the development of approximate computing (AC), a computing paradigm that trades power consumption with accuracy. The idea is to implement inexact/AC elements that consume less energy, as far as the overall application tolerates the imprecision level in computation. This paradigm has been shown promising for inherently fault-tolerant applications such as deep/ML, big data analytics, and signal processing. Several AC techniques have been proposed in the literature and can be classified into three main categories based on the computing stack layer they target: software, architecture, and circuit level [16].

In this paper, we consider AC for a totally new objective; enhancing CNNs robustness to adversarial attacks, without losing the initial advantages of AC.

3 THREAT MODEL

We assume an attacker attempting to conduct adversarial attacks to fool a classifier in a variety of attack scenarios.

3.1 Adversary Knowledge (Attacks Scenarios)

In this work, we consider three attack scenarios:

Transferability Attack. We assume the adversary is aware of the exact classifier internal model; its architecture and parameters. The adversary uses the exact classifier to create adversarial examples. Thus, we explore whether these examples transfer effectively to the approximate classifier (DA classifier).

Black-box Attack. We assume the attacker has access only to the input/output of the victim classifier (which is our approximate classifier) and has no information about its internal architecture. The adversary first uses the results of querying the victim to reverse engineer the classifier and create a substitute CNN model. With the substitute model, the attacker can attempt to generate different adversarial examples to attack the victim classifier.

White-box Attack. We assume a powerful attacker who has full knowledge of the victim classifier’s architecture and parameters (including the fact that it uses AC). The attacker uses this knowledge to create adversarial examples.

3.2 Adversarial Example Generation

We consider several adversarial attack generation algorithms for our attack scenarios, including some of the most recent and potent evasion attacks. Generally, in each algorithm, the attacker tries to evade the system by adjusting malicious samples during the inference phase, assuming no influence over the training data. However, as different defenses have started to be deployed that specifically target individual adversarial attack generation strategies, new algorithms have started to be deployed that bypass these defenses. For example, methods such as defensive distillation [1] were introduced and demonstrate robustness against the FGSM attack [10]. However, the new C & W attack was able to bypass these defenses [3]. Thus, demonstrating robustness against a range of these attacks provides confidence that a defense is effective in general, against all known attack strategies, rather than against a specific strategy.

These attacks can be divided into three categories: Gradient-based attacks relying on detailed model information, including the gradient of the loss w.r.t. the input. Score-based attacks rely on the predicted scores, such as class probabilities or logits of the model. On a conceptual level, these attacks use the predictions to estimate the gradient numerically. Finally, decision-based attacks rely only on the final output of the model and minimizing the adversarial examples’ norm.

4 DEFENSIVE APPROXIMATION: IMPLEMENTING APPROXIMATE CNNS

We propose to leverage approximate computing to improve the robustness of ML classifiers, such as CNNs, against adversarial attacks. We call this general approach Defensive Approximation (DA). The closest approach to DA is the perturbation-based defense [6], [19] that either adds noise or otherwise filter the input data to try to interfere with any adversarial modifications to the input of a classifier. However, our approach advances the state-of-the-art by injecting perturbations throughout the classifier and directly by the approximate hardware, thereby enhancing both robustness and power efficiency.

Technically, the approximate design process is driven by two main considerations:

1) Injecting significant noise that can influence the CNN behavior, and allows by-product power gains.
2) Keeping the cumulative noise magnitude under control to avoid impacting the baseline accuracy of the CNN.

For consideration (b), we purpose to an implementation that replaces the conventional mantissa multiplier in floating point multipliers, with a simpler approximate design. This choice is backed by the study in [20], which show that errors in the exponent part might have a drastic impact on CNNs accuracy. Consideration (a) means that the approximate design needs to be aggressive to induce significant noise. Therefore, as detailed in the next subsection, we chose the corner case, i.e., the most aggressive approximate design [21], [22], and used it to replace the mantissa computation logic in a basic floating point multiplier.

In this section, we present our approximate multiplier design and analyze its properties.

4.1 Approximate Floating Point Multiplier

ML structures, such as CNNs, often rely on computationally expensive operations, e.g., convolutions that are composed of multiplications and additions. Floating-point multiplications consume most of the processing energy in both inference and training of CNNs [22]. Although approximate computation can be introduced in different ways (with likely different robustness benefits), DA leverages a new approximate 32-bit floating-point multiplier, which we call approximate floating-point multiplier (Ax-FPM). The IEEE 754-2008 compliant floating-point format binary numbers are composed of three parts: a sign, an exponent, and a mantissa (also called fraction) [23]. The sign is the most significant bit, indicating whether the number is positive or negative.
In a single-precision format, the following 8 bits represent the exponent of the binary number ranging from \(-126\) to 127. The remaining 23 bits represent the fractional part (mantissa). For most of the floating number range, the normalized format is:

\[
val = (-1)^{\text{sign}} \times 2^{\text{exp} - \text{bias}} \times (1.f\text{raction})
\]

A floating-point multiplier (FPM) consists mainly of three units: mantissa multiplier, exponent adder, and a rounding unit. The mantissa multiplication consumes 81% of the overall power of the multiplier [22].

Ax-FPM is designed based on a mantissa multiplication unit that is constructed using approximate full adders (FA). The FAs are aggressively approximated to inject computational noise within the circuit. We describe Ax-FPM by first presenting the approximate FA design, and then the approximate mantissa multiplier used to build the Ax-FPM.

Fig. 1: An illustration of a 4×4 array multiplier architecture.

To build a power-efficient and a higher performance FPM, we propose to replace the mantissa multiplier by an approximate mantissa multiplier; an array multiplier based on an approximate full adder (FA). The FAs are aggressively approximated to inject computational noise within the circuit. We describe Ax-FPM by first presenting the approximate FA design, and then the approximate mantissa multiplier used to build the Ax-FPM.

Fig. 2: Logic diagram of (a) exact Full Adder, (b) AMA5 (used in this work).

Specifically, we build an array multiplier based on an approximate mirror adder (AMA5) [21] in place of exact FAs. The approximation of a conventional FA is performed by removing some internal circuitry, thereby resulting in power and resource reduction at the cost of introducing errors. Consider a FA with (A, B, Cin) as inputs and (Sum, Cout) as outputs (Cin here refers to carry). For any input combination, the logical approximate expressions for Sum and Cout are: \(\text{Sum} = \overline{B}\) and \(\text{Cout} = A\). The AMA5 design is constituted by only two buffers (see Figure 2).

leading to the latency and energy savings relative to the exact design, but more importantly, introduce errors into the computation. It is worth noting that these errors are data dependent, appearing for specific combinations of the inputs, and ignoring the carry in value, making the injected noise difficult to predict or model.

When trying to evaluate the proposed Ax-FPM, we were interested in studying its behavior under small input numbers ranging between \(-1\) and \(+1\) since most of the internal operations within CNNs are in this range. We measure the introduced error as the difference of the output of the approximate multiplier and the exact multiplier. The results are shown in Figure 3 using 100 million randomly generated multiplications across the input range from \(-1\) to 1.

Fig. 3: Noise introduced by the approximate multiplier while the operands in [0, 1].

Three trends can be observed that will be used later to help understanding the impact of the approximation using Ax-FPM on CNN security: (i) The first is the data-dependent discontinuity of the approximation-induced errors, (ii) We noticed that in 96% of the cases, the approximate multiplication results in higher absolute values than the exact multiplication: For positive products, the approximate result is higher than the exact result, and for negative product results the approximate result is lower than the exact result, and (iii) In general, we notice that the larger the multiplied numbers, the larger the error magnitude added to the approximate result. As shown later, these observations will help understand the mechanism that we think is behind robustness enhancement.

4.2 Approximate BFloat16 multiplier

BFloat16 (Brain Floating Point) [31] is a data representation used in machine learning applications and intended to reduce the storage requirements and increase computing speed without losing precision. In this section, we use the same previously described approach to build an approximate BFloat16 multiplier.

The BFloat16 is a truncated version of the 32-bit IEEE 754 single-precision floating-point format (float32). The BFloat16 format is shown in Figure 3; it consists of 1 sign bit, an 8-bit exponent, and a 7-bit mantissa giving the range of a full 32-bit number but in the data size of a 16-bit number.

The proposed approximate BFloat16 multiplier architecture is used an \(8 \times 8\) approximate array mantissa multiplier based on AMA5 full adders. The error distribution induced by the proposed approximate BFloat16 multiplier is shown
4.3 Extending approximation to fully connected layers

In order to investigate the impact of AC at larger scales than the individual multiplication, we track the impact on convolution operations and approximate fully connected layers as building blocks. The activation functions and the pooling layers which do not use multiplication are similar to the conventional CNN.

In Figure 6, we run an experiment where we choose a filter and six different images with different degrees of similarity to the chosen filter (1 to 6 from the least to the most similar), and we perform the convolution operation. We notice that the approximate convolution using Ax-FPM delivers higher results for similar inputs and lower results for dissimilar inputs. We can also notice that the higher the similarity, the higher the gap between the exact and Ax-FPM approximation results.

Therefore, by using the approximate convolution, the main features of the image that are important in the image recognition are retained and further highlighted with higher scores as illustrated in Figure 4.

Same with approximate fully connected (FC) layers, when using our approximate multiplier, we further increase the score of most relevant information and lower that of the less relevant ones. Thus, further increasing the confidence (the output of the pre-softmax layer) of the classification result as shown in Figure 8, where we select 5 random samples \{S_1, ..., S_5\} belonging to the same class and perform inferences using the fully approximate, only approximate convolution bloc, and the conventional models. The score of each class is defined as the average of the 5 samples corresponding score.

Therefore, by using the approximate convolution, the main features of the image that are important in the image recognition are retained and further highlighted with higher scores as illustrated in Figure 4.
Our reference exact CNNs are conventional CNNs based on exact convolution layers with the format Conv2d provided by PyTorch. In contrast, the approximate CNNs emulate the 32-bit Ax-FPM functionality and replace the multiplication in the convolution layers with Ax-FPM in order to assess the behavior of the approximate classifier.

Since we are simulating a cross-layer (approximate) implementation from gate-level up to system-level, the experiments (forward and backward gradient) are highly time consuming, which limited our experiments to the two datasets MNIST and CIFAR-10.

Except for the black-box setting where the attacker trains his own reverse-engineered proxy/substitute model, the approximate and exact classifiers share the same pre-trained parameters and the same architecture: they differ only in the hardware implementation of the multiplier.

5.1.2 Approximate BFloat16
For the proposed approximate BFloat16 multiplier based experiments. Tests were carried out on an 8th Generation Intel core i7-8750H CPU with 12 cores. In order to overcome the issue of extremely slow inference, we used parallel computing, in particular we take advantage of the Joblib [43] Python set of tools; using 8 workers to compute the matrix multiplication per channel in parallel in the convolution layer.

We choose three pre-trained models over the MNIST, CIFAR-10, and ImageNet datasets as target models of attacks and defenses. LeNet5 and AlexNet achieve 98.89% and 81% classification accuracy, respectively. VGG-11 model reaches 90.5% and 76.3% top-5 and top-1 accuracy, respectively. For adversarial example generation, we choose images from the MNIST, CIFAR-10, and ImageNet Validation dataset that are correctly classified by the baseline models: LeNet-5, AlexNet, and VGG-11. For the evaluation of the defenses, we use FGSM, a commonly used baseline attack. We also used PGD, currently the state-of-the-art attack for \( l_{\infty} \) metric. To ensure a stronger adversary, we try achieving maximum confidence rather than minimum distance. This includes making sure that the PGD attack runs through all optimization steps, even if the attack appears to have succeeded on a previous iteration. By default, all experiments will perform PGD with 40 attack iterations.

5.2 Do Adversarial Attacks on Exact CNNs Transfer to an Approximate CNN?
Attack Scenario. In this setting, the attacker has full knowledge of the classifier architecture and hyper-parameters, but without knowing that the model uses approximate hardware. An example of such scenario could be in case an attacker correctly guesses the used architecture based on its widespread use for a given application (e.g., LeNet-5 in digit recognition), but is unaware of the use of DA as illustrated in Figure 4.

Transferability Analysis. The classifier generates adversarial examples using the set of algorithms in Table 1 and assume that the exact classifier from Lenet-5 trained on the MNIST dataset. Notice that the hyperparameters, as well as the structure of the network, are the same between the exact and the approximate classifiers. The attacker then tests...
the adversarial examples against the approximate classifier. Table 1 presents the attacks respective success rates. We notice that the DA considerably reduces the transferability of the malicious samples and, by consequence, increases the robustness of the classifier to this attack setting. We observed that the robustness against transferability is very high, and reaches 99% for C&W attack.

**TABLE 1: Attacks transferability success rates for MNIST.**

| Attack method | Exact LeNet-5 | Approximate LeNet-5 |
|---------------|--------------|---------------------|
| FGSM          | 100%         | 12%                 |
| PGD           | 100%         | 28%                 |
| JSMA          | 100%         | 9%                  |
| C&W           | 100%         | 1%                  |
| DF            | 100%         | 17%                 |
| LSA           | 100%         | 18%                 |
| BA            | 100%         | 17%                 |
| HSJ           | 100%         | 2%                  |

We repeat the experiment for AlexNet with CIFAR-10 dataset. For the same setting, the success of different adversarial attacks is shown in Table 2. While more examples succeed against the approximate classifier, we see that the majority of the attacks do not transfer. Thus, DA offers built-in robustness against transferability attacks.

**TABLE 2: Attacks transferability success rates for CIFAR-10.**

| Attack method | Exact AlexNet | Approximate AlexNet |
|---------------|--------------|---------------------|
| FGSM          | 100%         | 38%                 |
| PGD           | 100%         | 31%                 |
| JSMA          | 100%         | 32%                 |
| C&W           | 100%         | 17%                 |
| DF            | 100%         | 35%                 |
| LSA           | 100%         | 36%                 |
| BA            | 100%         | 37%                 |
| HSJ           | 100%         | 12%                 |

Notice that, unlike other state-of-the-art defenses, our defense mechanism protects the network without relying on the attack details or the model specification and without any training beyond that of the original classifier. Unlike most of the perturbation-based defenses that degrade the classifier’s accuracy on non-adversarial inputs, our defense strategy significantly improves the classification robustness with no baseline accuracy degradation, as we will show in Section 8.1.

### 5.3 Can We Attack an Approximate CNN?

In the remaining attack models, we assume that the attacker has direct access to the approximate CNN. We consider both black-box and white-box settings.

**Black-box Attack.** In a black-box setting, the attacker has no access to the classifier architecture, parameters, and the hardware platform but can query the classifier with any input and obtain its output label. In a typical black-box attack, the adversary uses the results of many queries to the target model to reverse engineer it. Specifically, the adversary trains a substitute (or proxy) using the labeled inputs obtained from querying the original model (see Figure 10). We also conduct a black-box attack on the exact classifier and evaluate how successful the black box attack is in fooling it. Essentially, we are comparing the black-box transferability of the reverse-engineered models to the original models for both the exact and the approximate CNNs.

**TABLE 3: Black-box attacks success rates for MNIST.**

| Attack method | Exact LeNet-5 | Approximate LeNet-5 |
|---------------|--------------|---------------------|
| FGSM          | 100%         | 22%                 |
| PGD           | 100%         | 0%                  |
| JSMA          | 100%         | 13%                 |
| C&W           | 100%         | 0%                  |
| DF            | 100%         | 25%                 |
| LSA           | 100%         | 26%                 |
| BA            | 100%         | 27%                 |
| HSJ           | 100%         | 0%                  |

**White-box Attack (FP32).** In this setting, the attacker has access to the approximate hardware along with the victim model architecture and parameters, as shown in Figure 11. In particular, the adversary has full knowledge of the defender model, its architecture, the defense mechanism, along with full access to approximate gradients used to build the gradient-based attacks. In essence, the attacker is aware of our defense, and can adapt around it with full knowledge of the model and the hardware, which is a recommended methodology for evaluating new defenses [28].
In this scenario, we assume a powerful attacker with full access to the approximate classifier’s internal model and can query it indefinitely to directly create adversarial attacks. Although DA in production would normally reduce execution time, in our experiments, we emulate the 32-bit Ax-FPM functionality within the approximate classifier. As a result, this makes inference extremely slow: on average, it takes 5 to 6 days to craft one adversarial example on an 8th Gen Intel core i7-8750H processor with NVIDIA GeForce GTX 1050. This led us to limit the white-box experiments; we use only two of the most efficient attacks in our benchmark: C & W and DeepFool attacks, and for a limited number of examples selected randomly from our test set for different classes.

In a white box attack, with an unconstrained noise budget, an adversary can always eventually succeed in causing an image to misclassify. Thus, robustness against this type of attack occurs through the magnitude of the adversarial noise to be added: if this magnitude is high, this may exceed the ability of the attacker to interfere, or cause the attack to be easily detectable.

Figures 12a and 12b, respectively, present different measures of $L_2$ for adversarial examples crafted using DF and C & W attacking both a conventional CNN and an approximate CNN. We notice that the distance between a clean image and the adversarial example generated under DA is much larger than the distance between a clean sample and the adversarial example generated for the exact classifier. On average, a difference of 5.12 for $L_2$-DeepFool attacks and 1.23 for $L_2$-C&W attack. This observation confirms that DA is more robust to adversarial perturbations since the magnitude of the adversarial noise has to be significantly higher for DF to fool DA successfully.

White-box Attack (BF16). In this setting, we test models built using the proposed approximate BFloat16 multiplier. MNIST. In this setting, we assume a powerful adversary with full access to the defense mechanism and the victim model architecture and parameters. To evaluate the effectiveness of our proposed method, we measure the model’s classification accuracy of adversarial images constructed using different attacks. In Figure 13, we report the classification accuracy under $L_\infty$ FGSM and PGD attacks for different perturbation magnitudes when testing images from MNIST dataset. We notice that even for high amounts of noise, our defended model maintained high resilience. For instance, using our defense, the model’s accuracy remains up to 80% and 85% under FGSM and PGD, respectively, with a noise budget of $\varepsilon = 0.5$. The images that are consistently correctly classified regardless of the noise budget correspond to the cases where we have a vanishing gradient, i.e., an input gradient almost equal to zero. This vanishing gradient prevents the iterative noise update from evolving in the direction of maximizing the loss function. Further details can be found in Section 6.2.

CIFAR-10. Figure 14a reports the classification accuracy of images from CIFAR-10 dataset when attacking using FGSM and PGD. We notice similar trends to previous results. For example, DA enhances the robustness of the model to reach 80% and 90% under FGSM and PGD attack for a noise budget of 0.06.

ImageNet. Figure 14b summarizes the effectiveness of our defense against FGSM and PGD attacks. Similar to previous experiments, the approximate hardware prevent the attacker from generating efficient AE for deeper networks and more complex data. Even with a high amount of injected noise ($\varepsilon = 0.06$), our model accuracy still reaches 90% under PGD attack.

Higher classification accuracy can be noticed for small noise magnitude. As illustrated in Figure 15, the cases that we have named the strong cases correspond to image samples classified with high confidence and are robust to a high noise magnitude, whereas what we have named weak cases correspond to image samples classified with much lower confidence and are robust to very low noise amplitude but can be eventually transformed into adversarial examples. We believe that these cases are the reason behind the higher classification accuracy for small noise magnitude.

We can conclude that DA provides substantial built-in robustness for all three attack models we considered. Attacks generated against an exact model do not transfer successfully to DA. Black-box attacks also achieve a low success rate against DA. Finally, even white-box attacks require substantial increases in the injected noise to fool DA for $L_2$-based attacks and are inefficient even under high noise magnitude for $L_\infty$-based attacks. Next, we probe deeper into DA’s internal behavior to provide some intuition and explanation for these observed robustness advantages.

6 HOW DOES DA HELP CNN ROBUSTNESS?

In this section, we probe into the DA classifier’s operation to attempt to explain the robustness advantages we observed empirically in the previous section. While the explainability of deep neural networks models is a known hard problem, especially under adversarial settings [20], we attempt to provide an overview of the mechanisms that we think are behind the DA impact on security.

6.1 Impact of approximation on model confidence

We study the impact of the approximation on CNNs’ confidence and generalization property. We follow this analysis in the Appendix with a mathematical argument explaining the observed robustness based on recent formulations by Lecuyer et al. [19].

The output of the CNN is computed using the softmax function, which normalizes the outputs from the fully connected layer into a likelihood value for each output class. Specifically, this function takes an input vector and returns a non-negative probability distribution vector of the same dimension corresponding to the output classes. In this section, we examine the impact of approximation on
the observed classifier confidence. We compare the output scores of an exact and an approximate classifier for a set of 1000 representative samples selected from the MNIST dataset: 100 randomly selected from each class. We define the classification confidence, $C$, as the difference between the true class $l$'s score and the “runner-up” class score, i.e., the class with the second-highest score. $C$ is expressed by $C = \text{output}[l] - \max_{j \neq l} \{ \text{output}[j] \}$. The confidence ranges from 0 when the classifier gives equal likelihood to the top two or more classes, to 1 when the top class has a likelihood of 1, and all other classes 0.

We plot the cumulative distribution of confidence for both classifiers in Figure 16. DA images have higher confidence; for example, in images classified by the exact classifier, less than 20% had higher than 0.8 confidence. On the other hand, for the approximate classifier, 74.5% of the images reached that threshold.

Compared to the baseline feature maps generated from an exact convolution operation, for the same pre-trained weights, our approximate convolution highlights further the features. Recall that the multiplier injected noise is higher when input numbers are higher (i.e., there is a high similarity between the kernel and the input data) and lower when the inputs are lower (when the similarity is small), as shown in Figure 4. We believe that these enhanced features continue to propagate through the model resulting in a higher probability for the predicted class. This higher confidence requires thereby higher noise to decrease the true label’s likelihood, and increase another label’s.

6.2 Impact of approximation on model gradient

In this subsection, we analyze the approximate computing impact on the gradient, which is a key element in adversarial attacks generation process.

In this experiment, we perform the PGD attack and visualize the input gradient used to update the adversarial noise as it represents the direction, in the input space, that results in the largest change in loss for different models with different combinations of approximate convolution and FC layers.

We notice that stacking approximate layers results in vanishing input gradient as shown in Figure 17c or makes almost equal to zero a significant number of input gradient elements as in Figure 17a. In order to generate an adversarial example, the sign of the input gradient, will be multiplied by the noise $\varepsilon$, as in Figures 17b and 17d. A nullified gradient means no $\varepsilon$ step is performed in that case the adversary is unable to create an efficient AE when using an approximate model.

7 HOW DOES DA COMPARE TO OTHER REDUCED PRECISION TECHNIQUES?

In this section, we investigate the impact of other reduced precision techniques on robustness. We first compare DA to DQ, and then study the impact of using BFloat16 data representation on the system performance and robustness.

7.1 Defensive Quantization

Defensive quantization [5] was proposed to jointly optimize the efficiency and robustness of deep learning models. A 4-bit quantized model was trained on CIFAR-10 using the Dorefa-Net method [30]. We consider two ways of quantization: (i) Weight quantization, where only the weights are quantized, and (ii) Full quantization where the weights of each convolutional and dense block and the output of each activation function are quantized. In Table 4, we report transferability between exact (32-bit floating point), approximate model (using DA), fully quantized and weight-only
Table 4: Comparing attacks transferability success rates for CIFAR-10 when using DA and DQ.

| Attack method | Exact | DA: | DQ: | DQ: |
|---------------|-------|-----|-----|-----|
| FGSM          | 100%  | 38% | 60% | 61% |
| PGD           | 100%  | 31% | 74% | 73% |
| C&W           | 100%  | 17% | 68% | 68% |

Table 5: Comparing attacks transferability success rates for CIFAR-10 when using DA and BFloat16.

| Attack method | Exact | DA | BFloat16 |
|---------------|-------|----|----------|
| FGSM          | 100%  | 38%| 100%     |
| PGD           | 100%  | 31%| 100%     |
| C&W           | 100%  | 17%| 100%     |

Figure 18 shows the multiplication noise distribution for $10^8$ randomly generated BFloat16 numbers compared to their corresponding 32-bit floating point. We notice that, in contrast with our approximate multiplier (Figure 3), BFloat16 multiplication results in mostly negative noise with orders of magnitude lower than DA-induced noise. Moreover, the BFloat16 noise has no specific impact on the model confidence. Accordingly, no improvement in BFloat16 models robustness was noticed under FGSM, PGD and $C \& W$.

8 Baseline Performance Implications

8.1 Impact on Model Accuracy

When fully approximating (both convolution and FC layers) deeper models, we recorded a drop in models' classification accuracy. In fact, we notice 14% and 26% drop in accuracy for the AlexNet and VGG-11, respectively. In Table 6, we perform an ablation study to track the impact of each approximate layer on deep networks accuracy. We found that the first convolution layer has the highest impact on models accuracy. Specifically, when using an exact first convolution layer, models recover 12% and 23% of their classification accuracy. Based on this observation, we used an exact first convolution layer when running the security experiments.
Fig. 17: a. & c. Input gradient and b. & d. Sign of Input gradient for different models (top) for CIFAR-10 dataset (bottom) for ImageNet dataset.

Fig. 18: Noise introduced by multiplying Bfloat16 while the operands $\in [0, 1]$.

TABLE 6: Impact of approximation on model classification accuracy for a set of clean Inputs from Cifar-10 and ImageNet.

| Model                      | CIFAR-10 accuracy | ImageNet accuracy |
|----------------------------|-------------------|-------------------|
| Full exact model           | 100%              | 100%              |
| Full approximate model     | 85.7%             | 73.23%            |
| Exact: 1st conv layer      | 98.34%            | 97.18%            |
| Exact: 2nd conv layer      | 93.4%             | 83.60%            |
| Exact: 3rd conv layer      | 93.4%             | 83.60%            |
| Exact: 1st FC layer        | 88.04%            | 75.4%             |
| Exact: 2nd FC layer        | 88.04%            | 75.4%             |
| Exact: all FC layers       | 95%               | 78.87%            |

A defense mechanism that aims to improve robustness against adversarial attacks must maintain at least a reasonable performance for clean inputs. For our defense, even with the approximate noise injected in the calculations, approximate models achieve comparable recognition rates to the exact models. A drop of less than 1% in the recognition rate for MNIST, less than 2% for CIFAR-10, and 3% for Imagenet is recorded as mentioned in Table 7.

TABLE 7: Top-1 Accuracy results of exact Float32, approximate Float32, exact BFloat16 and approximate Bfloat16 models.

| Used Multiplier            | MNIST  | CIFAR-10 | ImageNet |
|----------------------------|--------|----------|----------|
| Exact Float32              | 98.89% | 81%      | 76.3%    |
| Approximate Float32        | 98.76% | 79.34%   | 73%      |
| Exact BFloat16             | 98.89% | 81%      | 76.3%    |
| Approximate BFloat16       | 98.76% | 79.34%   | 73%      |

8.2 Impact on Performance and Energy Consumption

Here we show the additional benefit of using AC, especially in the context of power-limited devices, such as mobile, embedded, and Edge devices. The experiments evaluate normalized energy and delay achieved by the proposed approximate multiplier compared to a conventional baseline multiplier. Multipliers are implemented using 45 nm technology via the Predictive Technology Model (PTM) using the Keysight Advanced Design System (ADS) simulation platform [32].

TABLE 8: Energy and delay Comparison.

| Multiplier        | Average energy | Average delay |
|-------------------|----------------|--------------|
| Exact Float32     | 1              | 1            |
| Approximate Float32| 0.487         | 0.29         |
| Exact BFloat16    | 0.4            | 0.4          |
| Approximate BFloat16| 0.19          | 0.12         |

Table 8 compares the energy and delay for the approximate Float32 multiplier, the BFloat16 multiplier, and the approximate BFloat16 normalized to a conventional Float32 multiplier. Ax-FPM achieves up to 51% and 71% savings in energy and delay, respectively, compared to the baseline multiplier. An exact BFloat16 implementation results in around 60% lower power and delay. This comes with no robustness advantages, as mentioned earlier. However, the proposed approximate BFloat16 multiplier ensures a gain in energy of up to 81% and 88% saving in delay along with robustness advantages. Unlike most of the state-of-the-art defense strategies that lead to power, resource, or timing overhead, DA results in saving energy and area.
We report in Table 9 the obtained speedup when using parallel computing in the inference of different approximate BFloat16-based models. In fact, for samples from ImageNet, we were able to make the model inference almost $10 \times$ faster.

TABLE 9: Inference time with and without parallel computing of approximate BFloat16 models.

| Run-time (s) | LeNet-5 | AlexNet | VGG-11 |
|--------------|---------|---------|---------|
| without parallelism | 57      | 1 290   | 69 110  |
| with parallelism   | 9       | 450     | 7 200   |

9 Discussion

This work tackles the problem of robustness to adversarial attacks from a new perspective: approximation in the underlying hardware. DA exploits the inherent fault tolerance of deep learning systems to provide resilience while also obtaining the by-product gains of AC in terms of energy and resources. Our empirical study shows promising results in terms of robustness across a wide range of attack scenarios. We notice that AC-induced perturbations tend to help the classifier generalize and enhances its confidence. We believe that this observation is possibly due to the specific AC multiplier we used where the introduced noise is input-dependent and non-uniform. When we observe the effect on the convolution layer, we see higher absolute values when the inputs are similar to the convolution filter. This observation at the feature map propagates through the model and results in enhanced classification confidence, i.e., the difference between the 1st and runner-up classes. This aspect of confidence enhancement resembles the smoothing effect observed by some recently proposed randomization techniques [19].

We believe that our study makes important contributions in demonstrating the general potential of approximate computing in this new dimension. However, we believe that substantial further research remains which we hope to tackle in our future work: (1) More work is needed to carefully understand the relationship between the patterns of induced noise and the observed robustness to adversarial attacks to guide the selection of approximation approaches; (2) We would also like to explore whether there is additional protection that results from adapting the approximation function over time; (3) We believe that DA is orthogonal to some of the other AML defenses and, deployed together, they may result in even higher protection against AML; (4) Some AML defenses unintentionally make the model more susceptible to privacy related attacks [33]; we believe that DA does not have a similar effect and would like to study its implication on privacy-preserving in the future; and (5) We would like to explore DA in the context of other learning structures beyond CNNs.

DA has two important advantages compared to DQ: (1) DA results in input-dependent noise, while DQ results in a deterministic network that can be efficiently reverse engineered and undermined by adaptive white-box attacks; (2) DQ requires retraining/fine-tuning the model to avoid drastic accuracy drop, while DA does not require retraining.

Compared to DA, when proceeding to BFloat16 quantization, we did not notice any improvement in the model robustness, which could be explained by the fact that BFloat16 results in uniform low-amplitude noise distribution that is not sufficient to impact CNNs behavior.

While we considered full precision floating point CNNs, we believe that DA can also apply to quantized and sparse networks [34], [35], [36] with similar impact on security. Prior work [20] shows that quantized networks tolerate errors, implying that DA can potentially be deployed without degrading accuracy.

Adaptive attacks: The main challenge for designing adaptive attacks to DA is to theoretically model the impact of AC on the gradient, knowing that the approximate multiplication is locally non differentiable (as shown by the noise distribution in Figure 3). However, while AC injects random noise within the model, this noise is not time-variant for the same input. Therefore, we believe that adaptive attacks are possible by defining a surrogate function that models the noisy DNN’s gradient. A potential extension of DA to cope with adaptive attacks is to introducing stochastic approximate noise. The stochastic aspect could be either built-in in the circuit, or injected numerically at higher abstraction levels.

10 Related Work

Several defense mechanisms were proposed to combat adversarial attacks and can be categorized as follows:

Adversarial Training (AT). AT is one of the most explored defenses against adversarial attacks. The main idea can be traced back to [10], in which models were hardened by including adversarial examples in the training data set of the model. As a result, the trained model classifies evasive samples with higher accuracy. Various attempts to combine AT with other methods have resulted in better defense approaches such as cascade adversarial training [2]. Nonetheless, AT is not effective when the attacker uses a different attack strategy than the one used to train the model [37]. Moreover, adversarial training is much more computationally intensive than training a model on the training data set only because generating evasive samples needs more computation and model fitting is more challenging (takes more epochs) [38].

Input Preprocessing (IP). Input preprocessing depends on applying transformations to the input to remove the adversarial perturbations [40], [44]. Examples of transformation are the median, averaging, and Gaussian low-pass filters [40], and JPEG compression [39]. However, it was shown that these defenses are insecure under strong white-box attacks [41]; if the attacker knows the specific used transformation, it can be taken into account when creating the attack. Furthermore, preprocessing requires additional computation on every input.

Gradient Masking (GM). GM relies on applying regulariza
tion to the model to make its output less sensitive to input perturbations. Papernot et al. proposed defensive distillation [1], which is based on increasing the generalization of the model by distilling knowledge out of a large model to train a compact model. Nonetheless, distillation was found weak against $C & W$ attack [6]. Moreover, GM approaches
found to make white-box attacks harder and vulnerable against black-box attacks [38]. Furthermore, they require re-training of pre-trained networks.

**Randomization-based Defenses.** These techniques are the closest to our work [6], [19], [42]. Lecuyer et al. [19] also suggest to add random noise to the first layer of the DNN and estimate the output by a Monte Carlo simulation. These techniques offer a bounded theoretical guarantee of robustness. From a practical perspective, none of these works has been evaluated at scale or with realistic implementations. For example, Raghunathan et al. [42] evaluate only a tiny neural network. Other works [6], [19] consider scalability but require high overhead to implement the defense (specifically, to estimate the model output which requires running a heavy Monte Carlo simulation involving a number of different runs of the CNN). Our approach is different since not only our noise does not require overhead but comes naturally from the simpler and faster AC implementation. Moreover, while these techniques require additional training, DA is a drop-in replacement of the hardware without specific training requirements, and with no changes to the architecture nor the parameters of the CNN.

**11 Conclusion**

To the best of our knowledge, this is the first work that proposes the use of hardware-supported approximation as a defense strategy against adversarial attacks for CNNs. We propose a CNN implementation based on an energy-efficient approximate floating-point multiplier. While AC is used in the literature to reduce the energy and delay of CNNs, we show that AC also enhances their robustness to adversarial attacks. The proposed defense is, on average, 87% more robust against strong grey-box attacks and 87.5% against strong black-box attacks than a conventional CNN for the case of MNIST dataset, with negligible loss in accuracy. The approximate CNN achieves a significant reduction in power and delay of 50% to 88% and 67% to 81%, respectively.

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