

Chapter 1

Machine Learning Robustness: A Primer

Housseem Ben Braiek and Foutse Khomh

{housseem.ben-braiek, foutse.khomh}@polymtl.ca

ABSTRACT

This chapter explores the foundational concept of robustness in Machine Learning (ML) and its integral role in establishing trustworthiness in Artificial Intelligence (AI) systems. The discussion begins with a detailed definition of robustness, portraying it as the ability of ML models to maintain stable performance across varied and unexpected environmental conditions. ML robustness is dissected through several lenses: its complementarity with generalizability; its status as a requirement for trustworthy AI; its adversarial vs non-adversarial aspects; its quantitative metrics; and its indicators such as reproducibility and explainability. The chapter delves into the factors that impede robustness, such as data bias, model complexity, and the pitfalls of underspecified ML pipelines. It surveys key techniques for robustness assessment from a broad perspective, including adversarial attacks, encompassing both digital and physical realms. It covers non-adversarial data shifts and nuances of Deep Learning (DL) software testing methodologies. The discussion progresses to explore amelioration strategies for bolstering robustness, starting with data-centric approaches like debiasing and augmentation. Further examination includes a variety of model-centric methods such as transfer learning, adversarial training, and randomized smoothing. Lastly, post-training methods are discussed, including ensemble techniques, pruning, and model repairs, emerging as cost-effective strategies to make models more resilient against the unpredictable. This chapter underscores the ongoing challenges and limitations in estimating and achieving ML robustness by existing approaches. It offers insights and directions for future research on this crucial concept, as a prerequisite for trustworthy AI systems.

KEYWORDS

Machine Learning, Deep Learning, Robust AI, Trustworthy AI, Adversarial Robustness, Non-Adversarial Robustness, Model Verification, DL Software Testing, Robust Training, Robustness Assurance

1.1 DEFINITION

In general, robustness is a predicate that applies to a single entity. For instance, we might consider a sensor robust if it is resilient to disturbances from the environment. In more detail, robustness refers to the ability of a system, model,

or entity to maintain stable and reliable performance across a broad spectrum of conditions, variations, or challenges, demonstrating resilience and adaptability in the face of uncertainties or unexpected changes. Hence, we use the following general definition for Machine Learning (ML) Model robustness.

*ML Model robustness denotes the capacity of a model to **sustain stable predictive performance** in the face of **variations and changes in the input data**.* To better understand this definition, we add concrete illustrations of how performance degradation and data changes manifest in real-world scenarios.

Examples of variations and changes in the input data:

- Variations in input features or object recognition patterns that challenge the inductive bias learned by the model from the training data.
- Production data distribution shifts due to naturally occurring distortions, such as lighting conditions or other environmental factors.
- Malicious input alterations that are deliberately introduced by an attacker to fool the model or even steer its prediction in a desired direction.
- Gradual data drift resulting from external factors, such as evolution in social behavior and economic conditions.

Examples of model flaws and threats to stable predictive performance :

- Exploitation of irrelevant patterns and spurious correlations that will not hold up in production settings.
- Difficulty in adapting to edge-case scenarios that are often underrepresented by training samples.
- Susceptibility to adversarial attacks and data poisonings that target the vulnerabilities of overparametrized modern ML models.
- Inability of the model to generalize well to gradually-drifted data, leading to concept drift as its learned concepts become obsolete or less representative of the current data distribution.

Nevertheless, leaving the range of input data changes unspecified makes it hard to assess the robustness of ML model in practice. We should define the data changes against which the model would be tested. Even if the naturally occurring data distribution shifts are often unanticipated, we usually come up with data distortions that can serve as a proxy for unforeseen data shifts and help us compare the robustness of different ML models. Furthermore, the objective of sustaining stable predictive performance is vague. It is often sufficient for the model to maintain its performance to a certain degree (i.e., the tolerance level) against unexpected changes in input data. This level of tolerance depends on the application context and the assurances needed. For example, the target tolerance for an ML model designed to support clinical decision-making is considerably lower than for an ML model that has been designed to detect spam emails.

Based on these considerations, we can refine further the ML model robustness as follows:

When deployed in a production environment, an ML model is considered robust if variations of input data, as specified by a domain of potential changes,

do not degrade the model's predictive performance below the permitted tolerance level.

Robustness is a standalone epistemic concept, presupposing the generalizability of the model's inductive bias on the in-distribution data, and extending further to evaluate the stability and resilience of its inductive bias in real-world deployment scenarios.

1.1.1 Robustness complements (iid) generalizability

In supervised learning, models are commonly estimated via empirical risk minimization (ERM) [1], a principle that considers minimizing the average loss on observed samples of data, as an empirical estimate of the true risk, i.e., the expected true loss for the entire input distribution. ERM assumes that training and test data are identically and independently distributed (a.k.a. i.i.d. assumption), known as closed-world assumption. The i.i.d. generalization refers to the ability of a trained model to deal with novel data inputs, but drawn from the same or close distribution as the training set, called in-distribution data (ID). The i.i.d. generalization ensures stable predictive performance under static environmental conditions, but it provides no guidance on how to handle out-of-distribution data (OOD) [2]. In contrast, robustness focuses on capturing the level of predictive performance maintained by the trained model in dynamic environment settings, where input data constantly changes. Robustness could be of little concern if the model fails to i.i.d. generalize well. In order to achieve robustness, we consider i.i.d. generalization to be a necessary but not sufficient condition. For instance, ML models might fail to i.i.d. generalize due to unreliable inductive bias (short-cut learning) or under-fitting (trained with too little/biased data). These models will most likely also perform poorly when input data distributions change.

The ascent of deep learning has initiated a new era in artificial intelligence (AI), empowering models to tackle open-world learning challenges in domains like face recognition [3] and autonomous driving [4]. The term "generalization" has expanded beyond denoting the model's performance strictly in an i.i.d. setting, encompassing its ability to cope with out-of-distribution situations, hereafter referred to as o.o.d. generalization. Although o.o.d. generalization seems to fit our definition of robustness, it actually refers to the overall predictive performance of an ML model beyond its in-data distribution. It lacks a proper definition of its scope and success criteria since there is no indication of which data distributions the model should generalize, or how strict the original predictive performance should be maintained. In contrast, ML model robustness is an inherently causal concept since it concerns two causally related entities: the level of predictive performance and the input data change domain, so its assessment, as a model property, requires detailed specification of both.

1.1.2 Robustness is a requirement of Trustworthy AI

The adoption of machine learning, especially deep neural networks, has been largely promoted as a result of its impressive performance in terms of accuracy. Meanwhile, a variety of challenges outside of accuracy expectations have emerged, such as malicious attacks against ML-powered systems and misuses of ML that could be harmful. As a result, the Artificial Intelligence (AI) trustworthiness standards [5,6] have been established to outline representative requirements for current AI systems. These encompass six critical facets: (i) Safety & Robustness, (ii) Nondiscrimination & Fairness, (iii) Transparency & Explainability, (iv) Privacy, (v) Accountability & Auditability, and (vi) Environmental Well-being. The complex interplay between these aspects is vital in fostering trustworthy real-world AI systems. For instance, maintaining data privacy might interfere with the desire to explain the system output in detail.

In this sense, robustness is an integral part of AI trustworthiness, while interacting and combining with the other aspects. In fact, model robustness is a cornerstone of safety because robust AI systems are able to deal with unexpected inputs and perturbations without compromising their functionality. It is especially crucial to ensure the appropriate level of model robustness in safety-critical applications, where erroneous behaviors and failures can have catastrophic consequences.

Furthermore, the safety of AI systems relies on the integration of two pivotal elements along with robustness assurance: reliable quantification of uncertainty and effective out-of-distribution detection capabilities.

The uncertainty quantification [7] refers to methodologies for evaluating uncertainties associated with predictions made by a ML model. It involves assessing the confidence levels or lack thereof in the model's predictions, taking into account factors such as data variance and model error. The quantified uncertainties combined with predictions enable more informed decision-making with AI. More specifically, uncertainty in predictions can manifest as either aleatoric (non-reducible), stemming from inherent randomness in the data, such as noise, or as epistemic (reducible), arising from limitations within the model's bias and the training data used. In simpler terms, the uncertainty component provides the AI system with a way to "know what they do not know". Its main contribution to safety is that uncertain predictions can be ignored from the decision-making flow, avoiding risks in real-world applications. Estimating uncertainties significantly benefits the model robustness analysis by providing an essential means to gauge how individual predictions respond to changes in their data points. This aids in delimiting the domain of input changes on which an ML model is expected to be robust.

Out-of-distribution detection [2] involves identifying OOD instances at test time that differ significantly from the in-data distribution and might result in mispredictions. It also serves the same purpose of recognizing the boundaries within which the model's patterns are applicable, avoiding the use of its pre-

dictions when such restrictions are violated. OOD detection strengthens the reliability of uncertainty quantification by filtering out unusual inputs, on which the uncertainties, as any statistically-inferred estimates, are unlikely to be dependable. Therefore, out-of-distribution detection also contributes to further refinement of the data changes domain during the model robustness analysis, and its deployment in safety-critical systems ensures effective operation of robust ML models.

1.1.3 Adversarial vs Non-adversarial robustness

Adversarial robustness is concerned with changes in data distribution that are induced by adversaries to deceive or mislead the ML model. Adversarial distribution shifts can be described as deliberate alterations to original data distribution. The alterations initially focused on introducing well-crafted but imperceptible noises in the data. As an example, a human-imperceptible noise can be applied to medical images to falsify the diagnostic by misleading an ML model into labeling moles as malignant skin tumors [8]. Then, the input alterations include intelligently-designed changes that are perceptible and can be applied in physical real-world environments. For example, adding sunglasses to a face image is different from slightly distorting the image pixels when evaluating the adversarial robustness of a face detection model. Therefore, adversarial robustness consists of enhancing the model's resilience against these subtle, non-random data distribution shifts without compromising its predictive performance on genuine data.

Non-adversarial robustness studies the model's ability to maintain its performance across data distribution shifts arising from naturally-occurring distortions or synthetic data variations that represent conditions more likely to occur in the real world. For instance, a natural shift in images of traffic signs, collected in an area where it rarely snows, can be images of the same sign under severe snowing conditions [9]. Alternatively, a partial discoloration of the traffic sign image, i.e., a region replaced by white pixels, may mimic the effect of snow or other neutral obstructions. Natural data shifts often result from changing environmental conditions that lead to mismatch between the deployment and the training distribution [10]. The changes can be both temporal (i.e., social norms, evolution of subjects' behavior) or non-temporal (i.e., changes across locations, sensor settings). The non-adversarial robustness of the ML model ensures reliability across various real-world scenarios, including natural noise, or changes in inputs that might happen organically without malicious intent.

1.1.4 Robustness Measurement

In the following, we introduce several robustness scoring metrics developed by researchers to evaluate the stability of models' performance when data changes [11]. These metrics are designed with the assumption of having two

datasets: one clean, sampled from in-distribution data, and another perturbed, sampled from shifted or even out of distribution data.

The first metric is called robustness score [12], and it measures the accuracy loss due to the ϕ perturbation. For a given model, m , we denote A_{clean} as the accuracy of the model, m , on the original (clean) test dataset, whereas A_ϕ is the accuracy of the model, m , on the test set modified with a ϕ perturbation. Data modifications may stem from natural perturbations collected from deployment environments, or they may result from applying an adversarial perturbation to the samples of the original test set. In the same form as [12], we formulate the robustness score of m to a perturbation in the data inputs, noted ϕ , with the expression:

$$R_m^\phi = \frac{A_\phi}{A_{\text{clean}}}$$

The more the robustness score of a model is close to one, the more it is robust to the considered perturbation. To measure the robustness score of a neural network, m , to a set of perturbations S , we can use:

$$R_m^S = \sum_{\phi \in S} R_m^\phi$$

Furthermore, Hendrycks and Dietterich [13] define robustness as average-case performance over a set of corruptions that gives rise to the definition of mean Corruption Error (mCE) and relative Corruption Error (rCE). The metrics mCE and rCE can be defined as:

$$mCE = \sum_{c \in C} \sum_{s=1}^5 \frac{E_s^c}{E_{\text{AlexNet},s}^c}$$

$$rCE = \sum_{c \in C} \sum_{s=1}^5 \frac{E_s^c - E_{\text{clean}}}{E_{\text{AlexNet},s}^c - E_{\text{AlexNet},\text{clean}}}$$

where E is the classifier’s error rate, C is a set of corruptions, and s is the severity of the corruption. The AlexNet model [14] served as a common reference point among models.

Recently, Taori et al. [15] present two metrics for effective and relative robustness which considers how performance on natural distribution shifts relates to performance on an original test set. The metrics are defined as follows:

$$\rho(f) = acc_2(f) - \beta \cdot acc_1(f)$$

$$\tau(f') = acc_2(f') - acc_2(f)$$

where f is the model under test, acc_1 , acc_2 are the accuracy on the original and shifted datasets respectively, β is a log-linear fit to the baseline accuracy of a large set of independent models on the original (clean) test set, and f' represents

the model resulting from a robustness improvement. The effective robustness measure captures how well a specific model does beyond what is expected given a group of models in general. The relative robustness measure quantifies the effect of a robustness amelioration strategy on the accuracy under distribution shift. Overall, a robust model should obtain both positive effective and relative robustness scores.

1.1.5 Robustness Indicators: Reproducibility and Explainability

We introduced robustness as a quality predicate for an ML model that should be carefully specified, evaluated, and sometimes certified before the deployment of the model in production. Nevertheless, the ML model is the result of a ML engineering process, thus some desirable properties in regards to this process should be satisfied in order to prepare the grounds to reach the level of robustness.

A reproducible ML workflow controls its randomness and is resilient to slight variations in data samples, i.e., there are high chances to converge to the same conclusions when run on two samples from the same underlying distribution [16]. For researchers in all scientific fields, including machine learning, reproducibility is essential in order to achieve the same results with the same data and algorithms. The absence of reproducibility may lead scientists to claim gains from changing one parameter while the real source of improvement is a hidden source of randomness. Furthermore, reproducibility is also a strong stability property since it ensures a high probability of replicating results when the datasets are drawn from the same distribution. Consequently, achieving such property on a given learning problem ensures less bias in model estimation (M) since achieving such property confirms that the difference between the empirical risk of M obtained on the training samples and the (true) risk of M is marginal, which implies that M is more likely independent of the training set. For instance, ?? constructs an ensemble of predictors from a given model by perturbing components of the ML pipeline like random seeds for initialization, and retraining the model several times. As a result, they demonstrate that output differences between predictors against stress tests can be used as a conservative indicator of the ML pipeline credibility, i.e., its ability to produce a robust model.

Explainability is crucial in the ML workflow, which addresses how an AI model makes decisions [17]. Being aware of the reasoning behind predictions can be a fundamental factor that determines the trust in the ML model. Deep learning models are complex and known to share “blackbox” nature, which raises a lot of concerns about their deployment in real-world applications despite their better performance compared to interestically-intereparable models such as decision trees and linear models. As a result, researchers have developed post-hoc explainers that identify a complex model’s behavior by analyzing its input, intermediate result, and output. A representative category in this vein approximates the non-linear decision surface either globally or locally by using an explainable ML model, i.e., an explainer, such as a linear model [17] and rules [18]. For

deep convolutional neural networks or transformers, the inspection of intermediate features is a widely used means of explaining model behavior [19,20]. In terms of robustness, our aim is sustainable predictive performance under data changes, especially, unexpected distribution shifts. However, predictive performance can include more fine-grained measures on the model's behaviors than the accuracy of predictions. For instance, the post-hoc explanations obtained for novel inputs should also be stable, otherwise, the model is likely to become brittle due to changes in the data distribution. In the following, we will describe model testing coverage criteria that rely on intermediate states of a neural network to characterize its "behavior" when given a particular input. They can be seen as ways to capture the distribution shifts from the lens of the model itself by estimating how its intermediary states differ from the "normal" levels observed on the training samples.

1.2 CHALLENGES

1.2.1 Data Bias: Train-Serving Skew

The goal of classical ML research and statistical learning theory is to achieve stable performance in an i.i.d. environment, the training data and the unseen data come from the same distribution [21]. However, the iid assumption is not satisfied in most cases because the construction of training datasets with high probability to represent the true data distribution (the inputs in production) is extremely difficult [22]. Real-world data is multi-faceted and virtually infinite, whereas training datasets are finite and constrained by the resources available during the dataset preparation. There are many ways that data bias can occur and misrepresent training datasets for real-world applications. This leads to a common failure mode known as the train-serving skew: models that perform well in development but poorly in deployment.

There are two main categories of data bias in ML applications: erroneous bias and discriminatory. Erroneous bias can be viewed as a systematic error caused by faulty assumptions. For instance, due to selection bias [23] or sampling bias [24], the chosen training samples may not be able to represent the real data distribution. Measurement bias happens when the device used to measure the signal has systematic value distortion that tends to skew the data in a particular direction that prevents the generalization of other data collected by other devices. Discriminatory bias is one of the concerns in AI nondiscrimination and fairness. As opposed to fairness, discriminatory bias reflects an algorithm's unfair behaviors toward a certain group or individual, such as producing discriminatory content or performing less well for some people [25]. The model is likely to inherit this discrimination bias and leads to undesirable performance on the minority groups in real-world settings.

A robust ML workflow requires dealing with data bias, especially addressing the long-tailed distribution modeling and the edge cases. Indeed, the long-tailed

distributions of data are extremely common in machine learning, reflecting the state of the real world and typical data collection practices. These distributions are influenced by natural events, and not necessarily introduced by skewed data collection. Nonetheless, ML algorithms fail to handle them properly as they are statistically optimized to perform well on common inputs (i.e. the head of the distribution) but struggle where examples are sparse (the tail). The tail often comprises the largest proportion of possible inputs, which makes their inclusion a laborious iterative procedure, i.e., collecting new data and retraining to account for edge cases. In safety-critical applications, an ML model that performs well on most cases but fails on infrequent edge cases might not be usable because these failures could cause catastrophic consequences. For this reason, major self-driving car companies strive to gather edge cases [26], this is also applicable to safety-critical applications such as medical diagnosis, and traffic control.

1.2.2 Model Complexity: A Double-Edge Sword

Conventionally, it has been assumed that the use of models with increasing capacity will systematically result in overfitting the training data. Hence, the capacity of the models is usually controlled either by limiting the size of the model (number of parameters) or via various explicit or implicit regularizations, such as early stopping [27], batch normalization [28], dropout [29], and weight decay [30]. This aims to push learning to a subspace of a hypothesis with manageable complexity and reduce overfitting [31]. Nonetheless, researchers have found that increasing model complexity not only allows for perfect interpolation but also results in low generalization error. Various studies have been conducted to analyze such overparameterized models, i.e., trainable parameters are much higher in number than the training data points. From the statistical viewpoint, the majority of overparameterized models exhibit a double-descent effect [32,33]. In fact, the generalization error follows the traditional U-shaped curve until a specific point, after which the error decreases, and reaches a global minimum in the overparameterized regime. According to the double-descent phenomenon, the minimum generalization error tends to appear at infinite complexity, i.e., the more overparameterized the model, the smaller the error. From the optimization viewpoint, the good generalization behavior of highly overparameterized models is also commonly attributed to the inductive bias of gradient-based algorithms which helps with selecting models that generalize well despite the non-convexity, e.g., [34]. Intuitively, the large number of hidden units here represent all possible features, and hence the optimization problem involves just picking the right features that will minimize the training loss. This suggests that as we overparameterize the networks, the optimization algorithms need to do less work in tuning the weights of the hidden units to find the right solution.

A disadvantage of overparameterized deep learning architectures is that they are highly susceptible to perturbations in adversarial or non-adversarial settings, compared to conventional, less sophisticated models. To illustrate the inher-

ent brittleness of overparameterized neural networks, we refer to the notion of “neuron coverage” that is inspired by the code coverage in traditional software testing [35]. It involves generating synthetic test input data to trigger the neurons that have not been activated by the original test data. The success of this coverage criterion suggests that only a subset of the parameters is responsible for capturing the patterns needed for the task. The rest of the parameters might be unoptimized (almost stalled at initial random weights) or have received fewer updates over the training. The presence of these suboptimal subnetworks might not harm the model’s performance under iid conditions. However, it does affect the model’s robustness negatively. Any unusual changes in inputs that accidentally activate these neurons could lead to unpredictable model behaviors. In addition, any attacker can exploit the larger space of these suboptimal neurons by designing a malicious input that yields a particular model’s output.

1.2.3 Underspecified ML Pipeline: One Pipeline, Many Models

In order to solve an ML problem, we expect the model to encode some essential structure of the underlying distribution, which is inferred from the data using a designed ML pipeline, and is often what makes a model credible. Nevertheless, many explorations of the failures of ML pipelines that optimize for iid generalization, reveal a conflict between iid generalization and encoding credible inductive biases. It is called structural failure mode, as it is often diagnosed as a misalignment between the predictor learned by empirical risk minimization and the causal structure of the desired predictor [36]. In medical applications of ML, training inputs often include markers representing a doctor’s diagnostic judgments [37]. An analysis of a CNN model for diagnosing skin lesions showed that it relied heavily on surgical ink markings around skin lesions that doctors had deemed cancerous [38]. In these situations, a predictor with credible inductive biases cannot achieve optimal iid generalization in the training distribution, because there are so-called “spurious” features that are strongly associated with the label in the training data, but are not associated with the label in practically important settings. In fact, an iid-optimal predictor would incorporate the ink markings as they are highly correlated with positive cases, but these markings would not be expected to be present in deployment, where the predictor would itself be part of the workflow for making a diagnostic judgment. There is clearly an underspecification problem as there is not enough information (a lack of positivity) in the training distribution to distinguish between credible inductive biases and spurious relationships. Geirhos et al. [39] connect this underspecification issue to the notion of “shortcut learning”. They point out that there may be many predictors that generalize well in iid settings, but only a few of them align with the intended solution to the learning problem. Shortcut learning resembles surface learning of students in classrooms, relying on simple decision rules to pass an exam [39]. The problem with shortcuts is that they might go unnoticed during the iid testing and only occur in deployment scenarios. In the

absence of large, diverse datasets, their risk is higher. For example, diagnostic data for rare or novel diseases is usually limited to small datasets, and unbiased validation data could be difficult to acquire.

Modern ML pipelines are poorly set up for satisfying the system requirements [40]. Their iid evaluation procedure often results in multiple models with equivalent (similar) predictive risk (performance) while they encode substantially different inductive biases. This implies that the ML pipeline could not distinguish between these iid-optimal models despite their potential differences in terms of robustness. The ML pipelines must be specified and designed in a way that promotes the selection of the model, encoding credible inductive biases, to bridge the gap between testing behavior and deployment behavior.

1.3 ROBUSTNESS ASSESSMENT

1.3.1 Adversarial Attacks: Categories and Aims

The first proposed evaluation methods for ML model robustness are the adversarial attacks, where the community invents many ways to carefully craft perturbations that can deceive a given ML model. The purpose of such attacks is to produce an adversarial example (AX), i.e., an input x' close to a valid input x according to some distance metric (i.e., similarity) or admissibility criteria (i.e., semantically-preserving modification ranges), whose model's predictions, denoted as $f(x')$ and $f(x)$, respectively, are different ($f(x') \neq f(x)$). First, they can be categorized into white-box attacks and black-box attacks according to how much knowledge an attacker has about the subject model. White-box attacks are implemented with direct access to the model or its training data, whereas black-box attacks can only access the target model through queries: pairs of inputs and outputs. The growth of black-box attacks started with the discovery of the transferability of adversarial examples [41]. Cross-model transferable, where attackers can construct adversarial examples in known deep learning models and subsequently attack a related unknown model. Cross training-set transferable refers to the attacks that exploit shared vulnerabilities across different datasets or domains. Second, adversarial attacks can be targeted or non-targeted. If we consider the example of image classification, targeted attacks aim to force the classifier to output a particular (chosen) class, whereas untargeted attacks attempt to make it return any class other than the original label. This categorization of adversarial attacks is based on the attacker's goal and information access, which determines the relevance of an attack for an application. For instance, targeted white-box attacks are more suitable for security concerns, while untargeted black-box attacks can be appropriate for assessing robustness to noise.

1.3.1.1 White-box Adversarial Attacks

The most notorious adversarial attack is the Fast Gradient Sign Method (FGSM) [42]. It operates as a one-step method by computing the gradient of the model's cost

function (J) with respect to the input data (x) and then perturbing the input along this gradient direction. Specifically, it alters the input (x) by adding noise (η) in the direction that maximizes the loss, using a magnitude defined by an epsilon value (ϵ) to limit the perturbation within a certain range. The attack aims to maximize the loss by perturbing the input data without exceeding the epsilon-boundary, calculated using a distance metric (e.g., L_∞ or L_2 norm). The formulation can be represented as:

$$x_{\text{adv}} = x + \epsilon \cdot \text{sign}(\nabla_x J(\theta, x, y))$$

Here, x_{adv} denotes the adversarial example, x is the original input, ϵ represents the magnitude of perturbation, $\nabla_x J(\theta, x, y)$ signifies the gradient of the cost function with respect to the input data, and θ represents the model's parameters. Despite its effectiveness in rapidly generating AXs, FGSM's limitation lies in its single-step approach to input perturbation.

Iterative-FGSM or IFGSM [43] is a straightforward enhancement to FGSM. It involves iteratively applying the same step as FGSM with a small step size and clipping the pixel values of intermediate results after each step to ensure proximity to an ϵ -neighbourhood of the original input. The attacking scheme can be represented mathematically as follows:

$$x_{t+1}^{\text{adv}} = \text{clip}\left(x_t^{\text{adv}} + \alpha \cdot \text{sign}(\nabla_x J(f(x_t^{\text{adv}}), y)), x - \epsilon, x + \epsilon\right)$$

Where x_{t+1}^{adv} denotes the adversarial sample at the $(t+1)$ -th step, x_t^{adv} represents the adversarial sample at step t , J signifies the objective (cost) function, f is the model, y is the true label, α is the step size, ϵ is the maximum perturbation limit, and $\text{clip}(\cdot)$ confines the values within the specified range.

Projected Gradient Descent (PGD) [43] attack represents one of the most established and efficient methods. It is a variant of Iterative FGSM, differing in their initialization strategy. More specifically, PGD initializes the example randomly within the sphere of interest determined by the L_∞ norm and does random restarts, whereas IFGSM starts from the original point.

Carlini and Wagner (C&W) [44] attack focuses on minimizing the input perturbations with respect to different vector norms along with the maximization of the cost in order to find subtle adversarial examples: 1) the L_2 attack uses a smoothing of clipped gradient descent approach, displaying low distortion; 2) the L_0 attack uses an iterative algorithm that, at each iteration, fixes the pixels that do not have much effect on the classifier and finds the minimum amount of pixels that need to be altered; and 3) the L_∞ attack also uses an iterative algorithm with an associated penalty, penalizing every perturbation that exceeds a predefined value.

Jacobian-based Saliency Maps [45] explore the forward derivatives to calculate the model gradients and discover which input regions/pixels that contribute the most to the predicted output. In fact, it uses saliency maps that highlight the most relevant or influential features within the input data concerning the

model's decision-making process. Hence, the adversary consists of targeting the perturbations of these critical input regions to create effective adversarial examples.

DeepFool [46] is an iterative attack that aims to find the minimal perturbation required to misclassify an input by exploiting the model's decision boundaries. It works by iteratively adjusting the input in the direction orthogonal to the decision boundary hyperplane, and it stops when it reaches an adversarial perturbation that causes a change in the model's output classification. This approach often results in the smallest perturbations that are imperceptible but effective in causing misclassification.

AdvGAN [47] uses Generative Adversarial Networks (GAN) [48] to create adversarial examples that not only have high attack success rate, but they are statistically distinguishable from the original ones. Indeed, AdvGAN operates iteratively, with a generator and a discriminator, engaged in a GAN-style training process. The generator aims to create perturbations that deceive the target model, while the discriminator learns to differentiate between original and perturbed instances. Through this adversarial training, AdvGAN seeks to produce adversarial examples that are both effective in fooling the target model and visually realistic, making them challenging for the target model to detect while maintaining a high attack success rate.

1.3.1.2 Black-box Adversarial Attacks

Black-box adversarial attacks are less effective than white-box approaches because they often require a higher number of queries, but they can expose different adversarial examples and are better representative of external attack system simulations. Narodytska et al. [49] performed a local-search-based attack. Chen et al. [50] and Bhagoji et al. [51] proposed black-box attacks based on gradient estimation [52]. Moon et al. [53] leveraged algorithms in combinatorial optimization. As opposed to white box gradient-based attacks, certain black-box adversarial attacks [54] leverage Evolutionary Strategies to estimate the gradients used to perform a PGD-like attack. Alzantot et al. [55] recently reported about GenAttack, a gradient-free optimizer that uses Genetic Algorithms (GA) to produce subtle perturbations, which successfully fool state-of-the-art image recognition models with significantly fewer queries. Feature-Guided Black-Box (FGBB)s [54] uses Scale Invariant Feature Transform to extract image features, emphasizing pixels that impact human visual perception. Then, crafting adversarial examples is framed as a strategic two-player game: one player manipulates features to minimize the distance to an adversarial example, while the other player adopts diverse strategies, i.e., cooperative, adversarial, or random. Using Monte Carlo tree search, FGBB systematically explores game states to uncover adversarial examples.

Many improvements have been proposed to upgrade white-box adversarial attacks for better transferability. SmoothFool (SF)s [54] is an improved version

of DeepFool that aims to produce smoother perturbations compared to the initial ones obtained through DeepFool. These smoother perturbations are intended to enhance the transferability of adversarial examples, making them more effective across different models or datasets. Dong et al. [56] developed an improved IFGSM with momentum to accumulate a velocity vector along the gradient direction. This accumulation of previous gradients stabilizes the updates and aids in navigating narrow valleys, small fluctuations, and suboptimal local extrema. Hence, the momentum-based IFGSM improves the transferability of the produced AXs across models. The momentum-based update is given by:

$$v_{t+1} = \mu \cdot v_t + \frac{\nabla_x J(f(x_t), y)}{\|\nabla_x J(f(x_t), y)\|_p}$$

The adversarial sample at the $(t + 1)$ -th step is computed as:

$$x_{t+1} = x_t + \alpha \cdot \text{clip}(v_{t+1}, -\epsilon, \epsilon)$$

Here, v_{t+1} is the updated velocity vector, x_{t+1} is the adversarial sample at the $(t+1)$ -th step, x_t is the input at step t , J represents the objective (cost) function, f is the model, y is the true label, α is the step size, ϵ is the maximum perturbation limit, μ is the momentum parameter, and $\|\cdot\|_p$ denotes the L_p norm.

In a broader sense, Meta Gradient Adversarial Attack [57] is an innovative architecture designed to enhance cross-model transferability within gradient-based attack methods. This method operates through multiple iterations, where models are sampled from a model zoo in each iteration to create adversarial perturbations using the chosen model. These perturbations are then incorporated with previously generated ones. By leveraging multiple models, this approach simulates both white- and black-box settings, enhancing the effectiveness of the attacks.

The revelation of numerous inputs causing incorrect predictions by ML models, despite being anticipated as accurate, has garnered significant attention [58]. This discovery sparked a race to create finely-tuned adversarial attacks, aiming to generate imperceptible noise capable of manipulating deep neural networks (DNNs) to produce erroneous outputs. However, criticism has surfaced regarding the practicality of these digital adversarial inputs in real-world scenarios. For example, even if an attacker possesses access to the autonomous driving car’s model, applying optimized imperceptible noise to a traffic sign on the road for misleading passing cars remains impractical. Although digital adversarial attacks may be successful in lab experiments or with models accessed through APIs, they are limited in the physical world. Consequently, physical adversarial attacks have emerged to execute unrestricted input alterations, which assemble all the synthetically-generated inputs without any l_p norm bounding, but preserve the semantic identity of the source input. As a result, physical AXs are effective in complex real-world scenarios.

1.3.1.3 Physical Adversarial Attacks

The first physical adversarial attack [59] was released in 2016 and it fools facial recognition systems by creating adversarial eyeglass frames designed with patterns that, when worn by individuals, cause mis-recognition of the individual. These patterns were strategically crafted to be imperceptible to humans while leading the facial recognition system to misidentify the wearer. This study marked an important milestone in the exploration of adversarial attacks in the physical domain, highlighting the susceptibility of facial recognition systems to imperceptible modifications applied to physical objects, such as glasses or eyeglass frames. Next, Engstrom et al. [60] showed the vulnerability of visual object recognition models against affine transformations (such as translations and rotations) of the images, which can be applied physically to the objects. More broader study [61] showed that visual object recognition models are prone to failing against simple guess-and-check of naturally-occurring situations related to the application domain, like taking pictures from another perspective angle.

Afterwards, more subtle physical attacks are proposed including patch-based and texture-based attacks. Patch-based attacks engender a universal adversarial image patch, which is stuck on the target object's surface to mislead the DNNs. In performing patch-based physical attacks, the adversary prints the patch image and then sticks/hangs it on the surface of the target, covering its original appearance. For instance, a patch-based attack [62] was proposed to deceive a traffic sign recognition model by generating strategically designed patches with specific patterns, colors, leading to erroneous predictions when placed on or near traffic signs. A more sophisticated patch-based attack [63] inserts natural stickers that appear benign to humans but deceive facial recognition systems when placed on faces. Texture-based attacks manipulate the appearance of objects by generating adversarial textures applied to 3D models. The attacker first makes the adversarial texture physically, then wraps them over the target object's surface, and the original texture is covered. For instance, the most representative form is the adversarial camouflage for vehicles [64], which subtly changes the visual appearance of vehicles, confusing detection models.

The environment-driven optical attacks exploit devices like projectors [65], laser emitters [66], flashlights [67], as well as natural occurrences like shadows [68] and reflected light [67]. These methods are used to conduct physical adversarial attacks against visual models, taking advantage of environmental factors like lighting alterations, reflections, or other optical distortions that can negatively affect the model performance.

The emergence of generative models has expanded adversarial attacks to create meaningful perturbations aiming to generate semantic adversarial examples. For instance, SemanticAdv [69] leverages attribute-conditioned image editing via a generator to alter specific semantic attributes like hair color, facial expressions, or a car's position on the road. These modifications retain a realistic visual appearance and resemblance to the original image while changing specific

semantic details.

Research into the causes of brittleness against adversarial attacks leads to the association-based statistical learning nature of supervised ML [70,71] (Buckner, 2020; Ilyas et al., 2019). Nevertheless, their prevalence in modern ML models like deep neural networks is due to overparameterization that make them tend to exploit all patterns inherent in the data that contain predictive information, including such patterns that are inscrutable to human cognition or only associative but not causal for the prediction target [72]. This inherent tendency might clarify why various models trained on the same dataset can be deceived by identical adversarial examples.

1.3.2 Non-adversarial Shifts: From Synthetic to Real-World

Non-adversarial shifts, including natural data corruptions and perturbations, are rarely characterized. Only a few works in Computer Vision focus on such a type of model robustness assessment. They have introduced various benchmarking datasets [17] to investigate the impact of naturally-shifted inputs on modern machine learning models. These benchmarks involve the introduction of corruptions and/or perturbations to standard (clean) datasets, allowing the assessment of different models' resilience against corrupted images. For instance, ImageNet-C [13] and ImageNet- [13] serve as synthetic benchmarks, each focusing on distinct aspects of robustness: corruption and perturbation. These benchmarks decouple robustness benchmarking by applying image transformations to the original images from the ImageNet dataset. Corruptions involve significant changes in image statistics, offering a testing ground for out-of-distribution scenarios. The benchmark includes 15 types of corruption transformations selected from noise, blur, weather, and digital categories, with five severity levels controlling the degree of distribution shift. Perturbations, on the other hand, entail subtle transformations of original images, drawn from the same categories as corruptions but are designed to be more challenging to perceive visually. The perturbation benchmark aims to assess models' performance in the face of subtle data distribution shifts.

Creating a comprehensive real-world robustness benchmark that incorporates systematic distribution shifts poses challenges compared to synthetic benchmarks. The complexity arises from the multifaceted variations that can simultaneously occur in real-world data. For instance, images featuring the same object may be captured with different cameras, from diverse viewpoints, in various locations, and under different weather conditions. However, the issue raised in [15] underscores the necessity of real-world benchmarking datasets. ImageNetV2 [73], generated by replicating the original ImageNet data collection process, serves as an example. While explicit definitions of distribution shifts may be elusive, classifiers trained on ImageNet and assessed on ImageNetV2 demonstrate reduced performance, indicating inherent natural distribution shifts in the ImageNetV2 dataset. A parallel observation holds for ImageNet-Renditions

(ImageNet-R) [74], encompassing renditions such as paintings, sculptures, and embroidery for ImageNet classes. This dataset introduces images with distinctly different textures and local image statistics, inducing a distribution shift relative to ImageNet. The StreetView StoreFronts (SVSF) [74] dataset contains business storefront images. In the dataset, there is a wide variation in location, date of creation, and camera properties which cause sensor-induced distribution shifts. The real-world benchmark DeepFashion Remixed (DFR) [74] leverages descriptive information to make systematic changes in object occlusion, zoom, orientation, and scale. Temporal Perturbations [75] are natural perturbations that are deduced from small changes occurring in assembled sets of contiguous video frames that appear perceptually similar to humans, but might produce inconsistent predictions for ML models. All these perturbations result in a condition where the distribution of the test set differs from the one of the training set.

Unlike adversarial attacks that aim to exploit model vulnerabilities, non-adversarial or natural perturbations serve as synthetic or newly created testing datasets for evaluating models in an out-of-distribution manner, simulating shifts from their original training distribution. These perturbations effectively highlight the models' fragility to naturally occurring data distortions. However, the absence of performance degradation on these datasets does not necessarily imply robustness, as they may suffer from selection and sample bias. For instance, when creating datasets with data augmentation techniques like changing image brightness, the use of brightness-based corruptions might not be indicative of model robustness, as the training data distribution already encompasses various brightness levels. In this case, non-adversarial robustness represents how well the model maintains its predictive performance under foreseeable input shifts (i.e., variation of brightness level).

1.3.3 DL Software Testing: Test-Driven Model Verification

Deep Learning (DL) software testing has emerged as a class of model verification techniques which bridges the gap between adversarial attacks and non-adversarial data shifts. As such, it differs from adversarial attacks in the sense that the methods are not used to improve a model resilience, but rather to evaluate a certain number of properties (associated with robustness) after the model was refined and/or trained. Hence, it does not act on the model but rather aims at verifying it. DL software testing renovates the conventional software testing methods, including test oracle identification, test adequacy evaluation, and test input generation, to be specialized for finding unrestricted adversarial examples that expose the target DNN brittleness. The goal is to construct systematic approaches that produce synthetic inputs, representing both major and minor naturally-occurring conditions to reveal potential incorrect behaviors. This involves optimizing the search over the space of transformed data as opposed to randomly sampling non-adversarially distorted inputs (i.e., non-adversarial shifts). Therefore, the designed test cases should cover effectively a broader set

of input-output mappings than iid evaluations to complement the conventional statistical testing.

1.3.3.1 *Pseudo Oracle*

Classical testing methods for DNN classifiers require testing the prediction of an input against a ground truth value. Even if this is possible for labeled datasets, labeling data can be labor-intensive and costly. In particular, the absence of ground truth, or “oracle”, is known in software engineering as the oracle problem. One way to circumvent this problem is to introduce a “pseudo” oracle to test correctness of an input..

The most common pseudo-oracle adopted by DL software testing is metamorphic testing, which allows finding incorrect behaviors by detecting violations of identified metamorphic relations (MRs). The MRs define data transformations to derive new synthetic inputs from the original ones while preserving the relationship between their expected outputs. The most prevalent type of MRs for metamorphic DL testing is called, semantically-preserving metamorphic relations. The latter include data transformations that retain the task-related semantics; as a result, both labels of the original input and its transformed counterpart must be equal. To meet this requirement for visual recognition models, researchers [76–78] have adapted numerous image transformations that include changing lighting conditions such as brightness and contrast, applying geometric distortions such as translation and scaling, and simulating weather conditions such as fog and rain. DeepRoad [79] relies on a Generative Adversarial Network (GAN [48])-based method to provide realistic snowy and rainy scenes, which can hardly be distinguished from original scenes and cannot be generated by DeepTest [76] using simple affine transformations. DeepRoad leveraged a recent unsupervised DNN-based method (i.e., UNIT [80]) which is based on GANs and VAEs [81], to perform image-to-image transformations. UNIT [80] can project images from two different domains (e.g., a dry driving scene and a snowy driving scene) into a shared latent space, allowing the generative model to derive the artificial image (e.g., the snowy driving scene) from the original image (e.g., the dry driving scene).

Differential testing [82] is also a well-established pseudo-oracle that takes the shape of N-versioning, which consists in N semantically equivalent models that will be used to test an input. N-versioning is strongly related to the notion of ensemble learning, which uses the knowledge of multiple models. DeepXplore [35] applies the DT approach on DL models by comparing the behaviour of multiple implementations or models for the same task. The goal of the systematic test input generation is to increase the divergence between the models’ predictions on these test inputs. However, differential testing is not limited to semantically similar models, any semantic comparison allowing building the pseudo-oracle proxy is valid. Ma et al. [83] leverages the DT approach based on subspecialized models, i.e., models that are trained on sliced training data only.

1.3.3.2 Test Adequacy Criteria

The input space of ML problems is often large, high-dimensional, which necessitates prioritizing and selecting test cases in order to reduce the model testing workload. To increase the likelihood of fault exposure, there are several proposed adequacy criteria that estimate if the generated test cases are ‘adequate’ enough to terminate the testing process with confidence that the DNN under test will behave properly in real-world settings.

Neuron Coverage (NC) [35] was inspired by the code coverage used for traditional software systems. NC computes the rate of activated neurons to estimate the amount of neural network’s logic explored by a set of inputs. Formally, given a set of neurons N , the neuron coverage of a test set T of inputs was originally defined as follows.

$$\text{NC}(T) := \frac{\#\{n \in N \mid \text{act}(n, x) \geq \tau \forall x \in T\}}{\#N}$$

where the symbol $\#$ refers to the cardinality of T and $\text{act}(n, x)$ is the activation of the neuron n when the test input x is fed to the network. Then, Ma et al. [84] generalized the concept of NC by proposing DeepGauge, a set of multi-granularity testing criteria for DNNs, including multi-level neuron coverage criteria that capture both major function regions as well as the boundary regions of activations. Additionally, DeepGauge provides layer-level coverage metrics such as Top-k Neuron Coverage (TKNC) and Bottom-k Neuron Coverage (BKNC), measuring the activation rates of k neurons in, respectively, hyperactive state and hypoactive state on each layer. In our previous work [78], we defined two levels of distance-based neuron coverage as follows: (i) local-neuron coverage measures the neurons covered by a generated test input that were not covered by its corresponding original input; and (ii) global-neuron coverage counts the neurons covered by a generated test input that were not covered by all previous test inputs. Furthermore, Odena and Goodfellow [85] propose a structural coverage for DNN that considers the positions of activated neurons in the network layers via an encoding of the neurons’ activations into a trace (i.e., a concatenated vector), then, only the entries that trigger novel activation traces would be preserved along with their traces to improve the diversity of the forthcoming test generations. Li et al. [86] show that obtained failures are pervasively distributed in the finely divided space defined by such coverage criteria; so the correlation between high structural coverage and fault-revealing capabilities (i.e., failure counts) is more likely due to the adversary-oriented search rather than the resulting enhancement of the structural coverage criteria. The global neuron coverage in DeepEvolution [78] quickly reaches a state of little or no change, while the local neuron coverage remains more effective in helping the optimization process around the original test input.

The following criteria were more focused on the behavioral deviations caused by the synthetic inputs compared to their original sources and aid in the model confidence reduction while promoting for diverse inputs.

Kim et al. [87] proposed Surprise Adequacy (SA) that computes the distance between the activation trace spawned by a given test input and its nearest neighbor obtained by a training data input with the same actual label. Increased SA values should lead to irregular network behaviors with a high chance of uncovering hidden errors. Deepfault [88] was developed to identify the pattern of neurons that are more present in error inducing inputs, which leads to pinpoint the suspicious neurons, i.e., neurons likely to be more responsible for incorrect DNN behaviour. Then, it enables the generation of failure inducing tests through the use of suspicious neurons' activation gradients on correctly classified examples. DeepGini [89] was designed based on a statistical perspective of DNN, which allows reducing the problem of measuring misclassification probability to the problem of measuring set impurity, which allows us to quickly identify possibly-misclassified tests. Intuitively, a test is likely to be misclassified by a DNN if the DNN outputs similar probabilities for each class. Thus, the set impurity metric yields the maximum value when DNN outputs the same probability for each class.

1.3.3.3 Systematic Test Input Generation

The above-mentioned test adequacy criteria are not used as a plain testing metric like with traditional software, but rather as a way to incrementally generate test cases that maximize/minimize those given criteria. To achieve this, techniques such as the fuzzing process to randomly mutate samples from a dataset or greedy search, and evolutionary algorithms to evolve test inputs into more fault-revealing ones.

DeepXplore [35], leverages first-order gradient ascent algorithms to produce the inputs, maximizing simultaneously neuron coverage and multiple DNNs' outputs divergence ratios. DeepTest and DeepRoad [76] uses a coverage-guided greedy search technique to systematically explore further within the inputs that trigger uncovered neurons, in order to efficiently produce synthetic tests that can increase neuron coverage. TensorFuzz [85], DLFuzz [85], and DeepHunter [77] relies on a coverage-guided fuzzing process that keeps transforming the test inputs triggering uncovered DNN activations. Both aim to evaluate the DNN robustness and the performance degradation caused by quantization. Last, we find the search-based approaches specialized for DL testing, which employ gradient-free optimizers (i.e, metaheuristics) to increase the fitness of the generated test inputs (i.e., faulty-revealing ability). DiffChaser [90] implements GA to expose divergences amongst different DNNs with different arithmetic precisions. DeepEvolution [78] implements different swarm-based metaheuristic algorithms to optimize the search of prominent data transformations that are likely to derive either adversarial examples or difference-inducing inputs aiming at revising, respectively, the DNN robustness assessment.

1.3.4 Empirical Methods and Their Limitations

The common limitation of these assessment approaches is their empirical nature, as they all depend on the process of data generation or the collection of shifted data to test the model's robustness against altered inputs. They compute robustness scores on this data to infer a statistical estimation of the confidence we place in the model facing unexpected changes in its input. If these methods do not uncover failed tests, it does not guarantee the model's robustness. This prompts consideration of formal verification methods that conduct a complete exploration of a system's space given a set of properties to check, as opposed to empirically-guided verification methods. Researchers [91] have proposed the implementation of formal verification methods like ReluPlex [92] and FAN-NETT [93], to provide guarantees on a model based on specified mathematical verification criteria. However, these methods face challenges such as combinatorial explosion due to the model's size and complexity, as well as the high dimensionality of input data, making it computationally intensive to cover all possible input variations. Hence, their utilization is often restricted to certain types of models, lagging behind the state of the art and less prevalent in modern ML applications. Another significant limitation is the formalization of the property to be verified; if a property cannot be properly formulated, it cannot be verified. This explains why most verification methods [94] focus on model robustness against l_p norm-bounded, as defining and expressing properties for rigorous robustness verification against natural shifts or application-specific invariances is challenging.

Empirical robustness assessment provides a practical, but valuable approach to complement the iid performance by statistical scoring of the model robustness in the face of unexpected data changes. On one extreme, adversarial examples provide worst-case perturbations with a defined expectation that models should remain performant under small, bounded perturbations. On the other extreme, naturally-occurring distortions that can produce corrupted entries under various sources of noise require a controlled severity procedure to avoid generating unrecognizable inputs, even to humans. Robustness assessment needs to better account for expected model behavior between these extremes, emphasizing the necessity to identify data changes' preconditions under which a model's performance is not expected to deteriorate. Especially for robustness to natural and non-adversarial perturbations, characterizing the type of data the model might encounter is crucial. This cannot be done algorithmically based on the analysis of the model's behaviors or in-data distribution features. It is vital to find better interfaces for domain knowledge in modern ML pipelines. Domain-aware testing methods are needed to thoroughly test models on application-specific tasks and check that performance on these tasks remains stable beyond the collected data samples used as in-distribution data. Designing stress tests [40] well-matched to applied requirements and providing good "coverage" of potential failure modes is a significant challenge that requires incorporating domain knowledge. For

instance, [95] proposed to leverage physics first principles and system-related design properties in the form of input-output sensitivities to generate invariance or directional expectations tests, i.e., the prediction should remain the same or should change direction under the introduction of input changes, respectively. Thus, the failed tests expose the inconsistencies of trained aircraft performance models with the domain-specific knowledge.

Regarding data generation methods and guidance for fault-revealing test cases, we have observed modest use of generative models, and researchers should further investigate the generative modeling approach for crafting and simulating edge cases to challenge supervised ML models. Indeed, deep generative models can discover hidden patterns within in-distribution data, and then, leverage them to perform nonlinear data transformations and semantically-sounded feature-based alterations. In fact, GANs [47,69,79] have shown their effectiveness for image-to-image transformation, semantically-attribute change, and style transfer between images, that offer more diversity and naturalness than simple pixel-value and affine transformations. There is a need to explore more recent generative models not yet applied to model robustness verification. For instance, Generative Pre-trained Transformers (GPTs) [96] can be employed to create test case generators producing application-specific stress tests for supervised NLP models that go beyond rule-based transformations [97] like word replacement and typos injection.

1.4 ROBUSTNESS AMELIORATION

1.4.1 Data-Centric Amelioration Strategies

1.4.1.1 Data Debiasing

Data debiasing refers to the process of countering biases present in datasets used for training machine learning models to avoid unfair or skewed predictions. Sampling bias is one of the most frequent data biases in ML applications that can be handled algorithmically. The training data samples are debiased with different techniques to mitigate the proneness of ERM to learning patterns associated with the majority, which makes it vulnerable to minority inputs, such as edge cases.

Conventional practice is to employ either upsampling and/or downsampling to mitigate sample bias in the data. Upsampling (oversampling) increases the number of instances in the minority group by generating synthetic samples or replicating existing ones. Popular algorithms for upsampling include SMOTE (Synthetic Minority Over-sampling Technique) [98] and ADASYN (Adaptive Synthetic Sampling) [99]. Downsampling (undersampling) decreases instead the number of instances in the majority group by removing them to match the minority group's size. Using mini-batch gradient optimization, we could virtually balance the group ratio of training samples by updating gradients on batches with equal input sizes for every data group in the data distribution [100]. This balanced batching method has shown to be more effective than traditional over-

sampling or under-sampling methods on unbalanced classification problems.

Resampling approaches have primarily targeted on rectifying class imbalances [101], as opposed to biases within individual classes. To apply them to debiasing variabilities within a class, subgroups must be manually identified through annotations, which necessitates a priori knowledge of the latent structure to the data. To minimize human effort, clustering algorithms have been used to identify clusters in the input data prior to training and to inform resampling the training data into a smaller set of representative examples [102]. However, this method cannot scale to high dimensional data like images or cases, where a semantic-based distance between instances is difficult to implement because it often relies on significant pre-processing to extract features. Regarding this challenge, Amini et al. [103] proposed an innovative debiasing technique to adjust the respective sampling probabilities of individual data points while training. This was accomplished by designing a variational autoencoder (VAE), specifically made for debiasing, called DB-VAE. The latter learns the underlying latent variables within the data distribution in an entirely unsupervised manner. It then allows for adaptive resampling of batches of data according to their inherent attributes during training. The adaptive resampling aims to feed the learning model batches with equally-distributed latent features. Assessed for algorithmic fairness, DB-VAE has successfully trained debiased models on facial recognition data containing racial and gender biases, and significantly improves classification accuracy and decreases categorical bias.

1.4.1.2 Data Augmentation

Data augmentation aims to enhance the diversity among the training samples and enlarge the size of distinctive instances through the ERM. It involves data transformations that derive new synthetic inputs supporting the model generalization by promoting the learning of feature representations insensitive to irrelevant noises or naturally-occurring distortions. For instance, basic image augmentations can be pixel-value transformations like brightness and contrast modifiers, or geometric transformations such as random rotation, translation, and mirroring. The severity of such distortions should be tuned to prevent significantly altering the data distribution but ensures a beneficial regularization effect on the model. Other augmentation techniques [104,105] systematically eliminate information from the training inputs to increase the robustness of the model against occlusions and information loss in general. The cutout augmentation [104] works similarly to dropout, by nullifying activations of input neurons associated with arbitrary input image patches. As a result, the network learns not to heavily rely on any specific feature of the data. In order to step beyond the null patches, Cutmix [106] propose to instead inject patches that have been cut out from other images in the training dataset. In a higher level of sophistication, we can find the mixup augmentation [107] that relies on linear mixing of training images and labels to encourage more stable predictions on data outside the training distribu-

tion. Mixup-derived [104] methods have contributed to continued enhancements in corruption robustness. PuzzleMix [108] improves upon Mixup by optimizing the amount of information retained in the original pairs of images while preserving saliency information during the mixing procedure. To alleviate sharp edge effects, Smoothmix [105] creates a smooth blending mask by randomly sampling mask shape and associated shape parameters (e.g., a square mask with sampled dimensions), then, the pairs of images are combined using the relative proportions of each image derived from the mask.

In order to create a complex augmentation, multiple simple augmentations can be chained together [109]. In a more recent method, AugMix [110] further improved corruption robustness of models by using a weighted combination of augmentations while enforcing consistent embeddings of the augmented images. Even though studies [104,105,111] emphasize the importance of combining multiple augmentations to achieve good generalization, it is a non-trivial task to find the optimal combination. In some cases, inappropriate combinations can cause a degradation in model generalization such as in [111] for DeepFashion Remixed benchmark dataset. Most software model testing approaches [35,76,89] implement test input prioritization and systematic test generation that uses data transformations similar to augmentation techniques, but searches for more diverse transformed data with fault-revealing abilities. The generated synthetic datasets, especially those resulting in false predictions, can be added to augment the training data. Indeed, their associated labels can be deduced based on the predefined metamorphic relationship of the input-output transformation [76,89], or based on the majority voting [35] to automatically generate labels for the generated test inputs. Thus, no manual labeling is required to perform a conventional supervised learning of the model using the original dataset plus a selection of synthetically-produced inputs. This retraining often results in fixing the majority of the revealed erroneous behaviors while preserving or hopefully improving its performance.

However, data augmentation has been criticized because it heavily relies on rule-based data transformations, which can lead to semantically non-meaningful combinations that are not compatible with real-world data [15], e.g., a horse with a patch covering the head of a frog]. Therefore, generative-based augmentations are an important initiative to produce uniquely synthetic images using generative models trained on the in-data distribution, but they can override the inherent characteristics of samples in order to cover underrepresented input regions. For instance, a style transfer variant of generative adversarial networks (GAN) [48] proposed in [15] has been shown to facilitate robustness against out-of-distribution when used as an augmentation technique [74]. GAN-based solutions are also proven useful in enhancing the model's immunity to adversarial attacks [112–114]. In particular, they are employed to generate adversarial samples [112], perturbations [113], and boundary samples [114] to defend the networks against adversarial attacks.

1.4.2 Model-Centric Optimization Methods

1.4.2.1 Transfer Learning

Transfer learning is a machine learning technique that involves transferring knowledge learned by the model in one task to improve another, related task. Transfer learning is based on the notion that DNN learns feature representations gradually from simple, task-agnostic features (e.g., lines) to complex, task-specific features (e.g., nose or ears for face recognition task) that can be fully or partially transferred to another problem. A common way to implement transfer learning is to pretrain a DNN on a large and diverse dataset and then use the first n pretrained layers (i.e., known as feature extractor) as an initialization for a new DNN that is then trained on a new dataset. Transfer learning methods are many, and the selected method determines the efficiency of the knowledge transfer from the pretrained model to the new one. In regards to robustness, it has been demonstrated that in certain settings it can increase the models OOD robustness, both in adversarial and non-adversarial settings [115]. Intuitively, the use of a small supervised dataset with an overparameterized neural network may provide high IID performance, but there is no guarantee regarding its behavior against out of distribution inputs due to shortcut learning and under-fitted neurons. This risk of shortcut learning and under-fitted neurons can be diminished by using pretrained models. Furthermore, the advances in self-supervised learning (SSL) for representation learning enables the exploitation of massive unlabeled target datasets to train models that solve an auxiliary, pretext task to learn rich feature representations, e.g., learning to distinguish between images [116,117]. Transfer learning with SSL [118,119] involves using these self-learned models as pretrained feature extractors.

1.4.2.2 Adversarial Training

Adversarial training [42] has emerged as a class of techniques which bridges the gap between pure data augmentation and the model optimization process. In adversarial training (AT), the model parameters are iteratively adjusted to minimize the worst-case adversarial loss by incorporating adversarial examples into the training process. At its core, AT consists of alternating between two steps:

1. *Finding worst-case adversarial perturbations:* For each original training input, AT computes the perturbation that maximizes the adversarial loss within a certain constraint (such as a bounded perturbation). This can be formulated as follows.

$$\delta^* = \underset{\delta \in \Delta}{\operatorname{argmax}} \ell(h_{\theta}(x + \delta), y)$$

where, δ is the adversarial perturbation added to input x , Δ is the set of possible perturbations, h_{θ} is the neural network with parameters θ , x is the input data, ℓ is the loss function, and y is the true label of x .

2. *Training on these adversarial examples:* It takes a gradient step at these worst-case adversarial examples to update the model’s parameters. Essentially, this can be stated as follows.

$$\theta := \theta - \nabla_{\theta} \ell (h_{\theta} (x + \delta^*), y)$$

where, θ is the parameter vector, ∇_{θ} is the gradient with respect to θ , ℓ is the loss function, h_{θ} is the neural network with parameters θ , x is the input data, δ^* is the optimal adversarial perturbation, and y is the true label of x .

Thus, AT solves a min-max problem where the inner maximization aims to find effective perturbations δ from some distribution Δ (e.g., adversarial or noise) while the outer minimization aims to update the model parameters θ to reduce expected error.

Kurakin et al. [43] demonstrates that adversarial training can be applied in massive datasets like ImageNet, showing an increase in robustness for one-step adversarial methods. As a result, several adversarial training approaches have been proposed to maximize the robustness of a model during deployment by adjusting the decision boundaries in response to adversarial perturbations computed based on training data.

Ensemble Adversarial Training [120] is proposed to mitigate the overfitting problem observed with fast single-step adversarial methods on large datasets. Indeed, this overfitting leads to a poor convergence of the global minimum, i.e., the obtained models often remain vulnerable to black-box attacks. Therefore, Ensemble Adversarial Training leverages existing static pre-trained models to craft adversarial examples required by AT, preventing the adversarially-trained model from weakening the credibility of adversarial examples.

Shared Adversarial Training [121] is an extended version of AT that aims to model robustness against universal perturbations. It computes the loss gradients w.r.t a mini-batch of training inputs as a stack, then, a shared perturbation that is applied to the entire stack is derived. Afterward, these perturbations are iteratively added and clipped to meet predefined magnitude constraints that are required for adversarial training.

Due to its reliance on gradients, AT can be costly when creating adversarial examples, particularly for large datasets such as ImageNet. For this reason, Free Adversarial Training [122] exploits the gradient information used in updating model parameters to craft the adversarial examples, thereby reducing computational costs.

In most cases, AT often leads to unfounded increases in the margin along decision boundaries, which negatively affects the original accuracy. The following strategies propose mitigations for better trade-offs between original and robust accuracy. Misclassification Aware Adversarial Training [123] suggests the differentiation between the misclassified and correctly classified original inputs during adversarial training because the minimization step is more important for misclassified examples than the maximization one that is negligible. Friendly Adversarial Training [124] targets the least adversarial examples (referred to as “friendly”)

among the adversarial data that is confidently misclassified. When executing the adversarial training, the friendly adversarial examples can be identified by PGD attacks with an early stopping condition. Geometry-aware Instance-reweighted Adversarial Training [125] proposes to leverage standard adversarial training with instance-level weights based on how difficult it is to attack an original data point. Indeed, the original data points that are close to the class boundary are less robust, which is why larger weights are assigned to them. Helper-based Adversarial Training [126] introduces an additional set of wrongly-labeled examples during adversarial training, achieving a balanced trade-off between accuracy and robustness.

1.4.2.3 Randomized Smoothing

Randomized smoothing [127] is a probabilistic adversarial defense technique that involves the systematic injection of controlled random noise to original data points, which adjusts the model to become noise-invariant. Unlike adversarial training that responds to individual adversarial examples, randomized smoothing aims for a more globally resilient model through smoothing its decision boundaries. Mathematically, randomized smoothing can be represented as follows:

Given a classification model f and an input x , the smoothed prediction $S_f(x)$ is obtained by aggregating predictions over multiple noisy perturbations of the input:

$$S_f(x) = \operatorname{argmax}_c \sum_{i=1}^N \mathbb{I}[f(x + \epsilon_i) = c]$$

Where:

- $S_f(x)$ represents the smoothed prediction for input x under model f .
- N is the number of noisy samples or perturbations applied to x .
- $f(x + \epsilon_i)$ denotes the model's prediction on the perturbed input $x + \epsilon_i$ (where ϵ_i is a random noise vector).
- argmax_c finds the class with the maximum aggregated prediction.

The advantages of randomized smoothing [128] are: (i) It provides theoretical guarantees for robustness of models within certain probabilistic bounds, which is defined as certified robustness that guarantees a stable prediction for any input within a certain range. Thus, it offers a more principled approach to ensuring model robustness compared to empirical adversarial training strategies. (ii) It allows leveraging sophisticated pre-trained models as foundation to build robust ones through smoothing their decision boundaries using relevant datasets.

Fast Adversarial Training (FAT) [129] combines the strengths of randomized smoothing and single-step robust training methods, extracting the beneficial aspects from both approaches. On one hand, FAT performs randomized smoothing to optimize the inner maximization problem efficiently. On the other hand, it proposes a new initialization strategy, named backward smoothing, to improve

the stability and robustness of a model using single-step robust training methods. This combination shows its effectiveness in improving model resilience against adversarial attacks while minimizing the risk of overfitting on adversary noises.

1.4.2.4 *Adapted Loss and Regularizers*

Concerning robustness, a variety of loss functions have been used to incorporate specific objectives: triplet loss [130], minimising distance between true and false classes because adversarial attacks shift the internal representation towards the “false” class, consistency across data augmentation strategies [131], and adding maximal class separation constraints [132]. In a similar manner, adapted regularisation can be designed to make models more robust. Li and Zhang [133] propose a PAC-Bayesian approach to tackle the memorization of training labels in fine-tuning. Chan et al. [134] develop an approach to optimize the saliency of classifiers’ Jacobian by adversarially regularizing the model’s Jacobian in line with natural training inputs. Curvature Regularization [135] minimizes the curvature of the loss surface, which induces a more “natural” behavior of the network because robustness requires quasi-linear behavior in the proximity of data points. Adversarial Weight Perturbation [136] performs a double-perturbation mechanism that disturbs both inputs and weights to regularize the flatness of weight loss landscape and robustness gap.

1.4.2.5 *Defensive Distillation*

Another defense class of techniques against adversarial examples is Defensive Distillation [137], which trains a Distilled Network on the predictions from a previously trained neural network (the Initial Network). By replacing dataset labels with continuous prediction values, the Distilled Network is likely to be more resilient to adversarial attacks. In light of the promising results achieved by defensive distillation, Papernot and McDaniel [138] suggest combining the original label with the Initial model uncertainty when training the distilled network. Furthermore, Robust Soft Label Adversarial Distillation method is proposed to train robust small student DNNs using robust soft labels produced by an adversarially-trained larger teacher DNN to supervise the student training on natural and adversarial examples. In this method, the student DNN does not access the original complex labels through the training process. Low Temperature Distillation (LTD) [139] uses a relatively low temperature in the teacher model and different, but fixed, temperatures for the teacher and student models. Indeed, the temperature is a scaling parameter used to adjust the sharpness of the probability distribution over classes. Lower temperatures make the distribution sharper, emphasizing the most probable class, while higher temperatures result in a softer, more uniform distribution over classes. LTD lowers the temperature of the teacher model used for crafting soft labels to boost the student model’s robustness by only lowering the temperature of the teacher model for crafting soft labels without encountering the gradient masking problem (occurs when

the loss gradients w.r.t inputs significantly diminish during the training of the distilled model).

1.4.3 Post-training Model Enhancements

1.4.3.1 *Ensembling*

Ensembling is a powerful technique in ML that combines multiple individual models, independently optimized on the same datasets, to achieve more accurate predictions and enhanced predictive performance compared to using a single model. The impact of ensemble learning on robustness has also been studied, and ensemble models have been shown to be more robust than a single model [140], since redundancy can provide extra resilience. Mani et al. [141] take another step, by training each model of an ensemble to be resilient to a different adversarial attack by injecting a small subset of adversarial examples, which profit to the ensemble globally, even though it comes at the cost of training more models.

1.4.3.2 *Pruning*

Pruning is the act of removing weights connections from pre-trained NNs, which has mainly been used for model compression to reduce their footprints for on-edge deployment. Tong et al. [142] showed that pruning can result in models that are more resilient to adversarial attacks. The pruning is motivated by the “Lottery Ticket Hypothesis”, which basically assumes that any randomly initialized DNN contains a subnetwork that can match the same level of its accuracy when trained separately. This “winner” subnetwork will be more robust if redundant or suboptimal neurons are deleted, since erroneous behaviors will be less frequent. Studies [143,144] tested this hypothesis and confirms that the pruned model tends to be more robust to adversarial attacks. Chen et al. [145] show that replacing unstable and insignificant neurons (i.e., operating in the flat area of ReLU activation) by linear function significantly raises the robustness at minimal predictive performance cost.

Several mechanisms have been suggested for dealing with unnecessary and/or unstable computation units by systematically identifying and trimming them. DeepCloak [146] enables the detection and elimination of unnecessary features in deep neural networks, thereby reducing the ability of attackers to craft adversarial examples. HYDRA [147] implements a DNN pruning technique that explicitly includes a robust training objective to guide the search for connections to prune. The outcome of such robustness-aware pruning is compressed models that are state-of-the-art in standard and robust accuracy. Dynamic Network Rewiring (DNR) [148] is another pruning technique that defines a unified, constrained optimization formulation that combines model compression targets with robust adversarial training. In addition, DNR relies on a one-shot training strategy that achieves an overall target pruning ratio with only a single training iteration.

1.4.3.3 Model Repairs

The strategies, which involve changing training data or updating the model, require retraining or fine-tuning, which is costly since modern neural networks are complex. Moreover, pretrained models can sometimes be obtained from a third party or training data may be confidential, making access to the whole in-data distribution challenging. Importantly, there is a disconnection between the assessment techniques and the improvement processes for model robustness. There is no guarantee that the new optimized or upgraded model will respond correctly to the counterexamples discovered during the assessment using most amelioration techniques. Robust models are often evaluated on adversarial examples or shifted inputs generated by assessment methods. It is important to show that the amelioration strategy does not overfit on counterexamples, but it is often overlooked how successful it is at fixing the revealed erroneous behaviors. Therefore, researchers have proposed post-training, model-level repair of DNNs, i.e., repair through the modification of the weights of an already trained model. In conventional software systems, these narrowly-defined modifications are called patches. When it comes to deep learning, the patch aims to fix the model's erroneous behaviors against a specific subset of counterexamples. Although the high complexity of modern ML models makes it difficult to perform provable model repairs (i.e., the counterexample provided will always be corrected), heuristic repair strategies that do not guarantee to repair all observed counterexamples still have benefits when compared to retraining or fine-tuning the model. Indeed, the original neural network likely went through training and functions properly on most inputs, so applying small, less impactful but precise changes to fix brittleness makes sense. CAusality-based REpair (CARE) [149] identifies the “guilty” neurons (i.e., the ones that caused the false prediction) using causality-based fault localization, then, modifies the weights of these identified neurons to reduce the misbehaviors. Arachne [150] is similar to CARE, but ensures no disturbance of the model's correct behaviors. Indeed, it uses differential evolution to generate effective patches for the localised weights that can fix specific mispredictions of a DNN without drastically reducing its clean accuracy. GenMuNN [151] ranks the weights based on their influences on the model's predictions. It then generates mutants using the computed ranks and evolves them using genetic algorithms to increase the chances of finding mutants that satisfy the stopping criteria. By tracking the training history, NeuRecover [152] finds weights that have changed significantly over time. A weight becomes a subject for repair when it is no longer contributing to correct predictions in the earlier stage of training but is leading to incorrectly-predicted inputs. Similarly to NeuRecover, I-Repair [153] modifies localised weights to influence predictions for a specific set of fault-revealing inputs while minimising the impact on correct predictions. NNrepair [68] uses fault localisation to identify suspicious weights, and then uses constraint solving to modify them marginally. There are provable model repairs like PRDNN [154], REASSURE [155], and Minimal Modifications of

DNNs (MMDNN) [156]. However, these approaches are not scalable to large DNNs, only support ReLU activation, and often do not support polytope repair or multilayer repairs.

1.4.4 Bridging the Theoretical-Practical Divide

Regarding adversarial robustness [157], while methods like randomized smoothing aim to provide guarantees within specific scenarios or against certain types of attacks, achieving a universally certified model that is completely immune to all possible adversarial perturbations remains an ongoing research challenge. In terms of non-adversarial robustness [11], no method has demonstrated constant or near-constant performance across all corruptions, alterations, and severities. Few or no guarantees on performance were provided for non-adversarial distortions.

Improvements in model robustness under narrow sets of data changes, mostly synthetically generated, tend to result in narrow robustness for similar or close conditions. This indicates that while modern high-capacity models benefit from controlling covariates during training to learn robust inductive bias, the set of covariates is still small compared to the combinatorial explosion of covering all possibilities. In the field of computer vision, recent work [158] suggests that increasing dataset size is a successful strategy for improving deep neural network (DNN) robustness. However, even with datasets of hundreds of millions of images, a measurable gap remains, raising sustainability concerns for this strategy.

Generative models show promise in natural, application-specific test case generation [79], leveraging semantic latent features for model debiasing [103]. These models can capture how important features vary across different segments or instances of the data. They learn to transform instances from segment to segment through style transfer or generate unique examples with semantic attributes [69]. Incorporating domain knowledge and subject-matter expertise to explain latent features discovered by generative models can lead to insights into the structural weaknesses of a model's inductive bias.

Human-in-the-Loop ML Pipelines (HIL ML) [159] traditionally address learning frameworks that accommodate noisy crowd labels, known as “learning from crowds”. Recent developments in HIL ML focus on building improved model pipelines by engaging the crowd, identifying weak components of a system [160], recognizing noise and biases in training data [161], and proposing data-based explanations for incorrect predictions [162]. Research studies [163–165] demonstrate that training more robust models involves leveraging human uncertainty on sample labels, integrating human rationales for instance labeling into the training process, or actively querying relevant perturbations from an expert during training. While these are promising research directions, further enhancements can be achieved by exploiting deep active learning [166], lifelong or curriculum learning [167], offering alternative tactics for increasing train-

ing data efficiency. Indeed, continual learning strategies [168] are capable of enhancing the model adaptability to long-tail events and changing conditions.

The widespread use of ML in real-world applications requires an urgent transition from theoretical concepts to practical implementations of ML robustness. Nowadays, ML systems are crafted by practitioners, so their robustness enhancements depend on the practitioners' participation, as exemplified by Jin et al. [169], where potential adversarial examples are collected through a sequence of engineering steps. [95] leverage a physics-guided adversarial testing method to craft inputs on which the model violates physics-grounded sensitivity rules that are derived beforehand by aircraft engineers. Afterward, all revealed counter-examples are exploited to perform a physics-informed regularization, which constrains the model optimization with the desired level of consistency w.r.t the physics domain knowledge.

In practice, model robustness should be evaluated within a predefined input domain. As a result, practitioners should be provided with tools to gauge their robustness with respect to their application-specific conditions, then integrate a reject option [170] when deploying ML systems in production. This option can, for instance, rely on uncertainty or out-of-distribution layers, to effectively discard untrusted predictions. Thus, the decision about entries can then be deferred to an alternative backup treatment, e.g., involving human agents when necessary [170].

1.5 CONCLUSION

The comprehensive exploration of Machine Learning (ML) robustness in this chapter culminates in the recognition of model robustness as a pivotal element in ensuring the trustworthiness and reliability of AI systems. The academic discussion traverses multifaceted dimensions, highlighting the dichotomy between adversarial and non-adversarial aspects. This distinction underscores the diverse array of unforeseen data changes that ML models face after deployment, from intentionally-crafted adversarial attacks that aim to exploit model vulnerabilities, to the subtler but equally impactful non-adversarial shifts in data distributions. These insights emphasize the necessity for robustness in safeguarding against a spectrum of potential threats and uncertainties in real-world applications.

Central to the chapter's analysis are the fundamental challenges to a truly robust ML model. It delves into the ramifications of data bias, model complexity, and the critical issue of underspecification in ML pipelines, illustrating how these factors can significantly impede the robustness of AI systems. The exploration continues through different perspectives in the domain of robustness assessment methods. Adversarial attacks, both digital and physical, serve as powerful tools to expose vulnerabilities in models, especially when confronted with maliciously crafted inputs or specific use cases. Non-adversarial shifts, including natural data corruptions and systematic distribution changes, are scrutinized in the context of real-world data challenges. Subsequently, we delve into how DL software

testing leverages established techniques to enhance the search for data changes that reveal model's faults, ultimately aiming to efficiently verify the model's robustness in the face of naturally occurring distribution shifts.

In addressing the strategies to fortify ML robustness, the chapter does not present a singular solution but rather a constellation of approaches, each with its unique strengths and limitations, offering a nuanced understanding of their potential impact and the trade-offs they entail. Techniques such as data debiasing and data augmentation are applied during data training preparation, while transfer learning, adversarial training, and adapted regularizers form the foundations of robust model optimization. Last but not least are post-training methods such as pruning and model repairs that operate directly on the original model to trim its weak components or adapt them to mitigate identified brittleness.

The conclusion of this chapter is not an end but a beginning – a call to action for continued research and innovation in the field of ML robustness. It recognizes that robustness is not a static goal but a continuous pursuit, one that requires persistent refinement and adaptation in the face of increasingly-complex models and ever-changing real-world conditions. The insights and methodologies discussed herein, not only expands the understanding of robustness in the context of ML but also emphasizes the need for a shift from theoretical concepts to practical implementations of ML robustness. It advocates providing practitioners with tools that assist them in continuously evaluating and enhancing the robustness of their models on a human-in-the-loop basis, enabling them to effectively satisfy the requirements of real-world machine learning applications, especially safety-critical ones.

BIBLIOGRAPHY

- [1] I. Goodfellow, Y. Bengio, A. Courville, *Deep learning*, MIT press, 2016.
- [2] J. Yang, K. Zhou, Y. Li, Z. Liu, Generalized out-of-distribution detection: A survey, arXiv preprint arXiv:2110.11334 (2021).
- [3] Y. Guo, L. Zhang, Y. Hu, X. He, J. Gao, Ms-celeb-1m: A dataset and benchmark for large-scale face recognition, in: *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part III 14*, Springer, 2016, pp. 87–102.
- [4] M. Bojarski, D. Del Testa, D. Dworakowski, B. Firner, B. Flepp, P. Goyal, L. D. Jackel, M. Monfort, U. Muller, J. Zhang, et al., End to end learning for self-driving cars, arXiv preprint arXiv:1604.07316 (2016).
- [5] H. Liu, Y. Wang, W. Fan, X. Liu, Y. Li, S. Jain, Y. Liu, A. Jain, J. Tang, Trustworthy ai: A computational perspective, *ACM Transactions on Intelligent Systems and Technology* 14 (1) (2022) 1–59.
- [6] B. Li, P. Qi, B. Liu, S. Di, J. Liu, J. Pei, J. Yi, B. Zhou, Trustworthy ai: From principles to practices, *ACM Computing Surveys* 55 (9) (2023) 1–46.
- [7] M. Abdar, F. Pourpanah, S. Hussain, D. Rezazadegan, L. Liu, M. Ghavamzadeh, P. Fieguth, X. Cao, A. Khosravi, U. R. Acharya, et al., A review of uncertainty quantification in deep learning: Techniques, applications and challenges, *Information fusion* 76 (2021) 243–297.
- [8] S. G. Finlayson, J. D. Bowers, J. Ito, J. L. Zittrain, A. L. Beam, I. S. Kohane, Adversarial attacks on medical machine learning, *Science* 363 (6433) (2019) 1287–1289.
- [9] G. Gojić, V. Vincan, O. Kundačina, D. Mišković, D. Dragan, Non-adversarial robustness of deep learning methods for computer vision, arXiv preprint arXiv:2305.14986 (2023).
- [10] R. Xie, F. Yu, J. Wang, Y. Wang, L. Zhang, Multi-level domain adaptive learning for cross-domain detection, in: *Proceedings of the IEEE/CVF international conference on computer vision workshops, 2019*, pp. 0–0.
- [11] N. Drenkow, N. Sani, I. Shpitser, M. Unberath, A systematic review of robustness in deep learning for computer vision: Mind the gap?, arXiv preprint arXiv:2112.00639 (2021).
- [12] A. Laugros, A. Caplier, M. Ospici, Are adversarial robustness and common perturbation robustness independent attributes?, in: *Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops, 2019*, pp. 0–0.
- [13] D. Hendrycks, T. Dietterich, Benchmarking neural network robustness to common corruptions and perturbations, arXiv preprint arXiv:1903.12261 (2019).
- [14] A. Krizhevsky, I. Sutskever, G. E. Hinton, Imagenet classification with deep convolutional neural networks, *Advances in neural information processing systems* 25 (2012).
- [15] R. Taori, A. Dave, V. Shankar, N. Carlini, B. Recht, L. Schmidt, Measuring robustness to natural distribution shifts in image classification, *Advances in Neural Information Processing Systems* 33 (2020) 18583–18599.
- [16] R. Albertoni, S. Colantonio, P. Skrzypczyński, J. Stefanowski, Reproducibility of machine learning: Terminology, recommendations and open issues, arXiv preprint arXiv:2302.12691 (2023).
- [17] D. V. Carvalho, E. M. Pereira, J. S. Cardoso, Machine learning interpretability: A survey on methods and metrics, *Electronics* 8 (8) (2019) 832.
- [18] R. Guidotti, A. Monreale, S. Ruggieri, D. Pedreschi, F. Turini, F. Giannotti, Local rule-based explanations of black box decision systems, arXiv preprint arXiv:1805.10820 (2018).
- [19] M. Tu, K. Huang, G. Wang, J. Huang, X. He, B. Zhou, Select, answer and explain: Interpretable multi-hop reading comprehension over multiple documents, in: *Proceedings of the*

- AAAI conference on artificial intelligence, Vol. 34, 2020, pp. 9073–9080.
- [20] Z. Yang, P. Qi, S. Zhang, Y. Bengio, W. W. Cohen, R. Salakhutdinov, C. D. Manning, Hotpotqa: A dataset for diverse, explainable multi-hop question answering, arXiv preprint arXiv:1809.09600 (2018).
- [21] C. M. Bishop, N. M. Nasrabadi, Pattern recognition and machine learning, Vol. 4, Springer, 2006.
- [22] M. Sugiyama, M. Kawanabe, Machine learning in non-stationary environments: Introduction to covariate shift adaptation, MIT press, 2012.
- [23] B. Marlin, R. S. Zemel, S. Roweis, M. Slaney, Collaborative filtering and the missing at random assumption, arXiv preprint arXiv:1206.5267 (2012).
- [24] N. Mehrabi, F. Morstatter, N. Saxena, K. Lerman, A. Galstyan, A survey on bias and fairness in machine learning, ACM computing surveys (CSUR) 54 (6) (2021) 1–35.
- [25] D. Shah, H. A. Schwartz, D. Hovy, Predictive biases in natural language processing models: A conceptual framework and overview, arXiv preprint arXiv:1912.11078 (2019).
- [26] R. Brooks, Edge cases for self driving cars, Post on Rodney Brooks' blog, "Robots, AI, and other stuff." June 17 (2017).
- [27] Y. Yao, L. Rosasco, A. Caponnetto, On early stopping in gradient descent learning, Constructive Approximation 26 (2007) 289–315.
- [28] S. Ioffe, C. Szegedy, Batch normalization: Accelerating deep network training by reducing internal covariate shift, in: International conference on machine learning, pmlr, 2015, pp. 448–456.
- [29] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, R. Salakhutdinov, Dropout: a simple way to prevent neural networks from overfitting, The journal of machine learning research 15 (1) (2014) 1929–1958.
- [30] A. Krogh, J. Hertz, A simple weight decay can improve generalization, Advances in neural information processing systems 4 (1991).
- [31] C. Zhang, S. Bengio, M. Hardt, B. Recht, O. Vinyals, Understanding deep learning (still) requires rethinking generalization, Communications of the ACM 64 (3) (2021) 107–115.
- [32] M. Belkin, S. Ma, S. Mandal, To understand deep learning we need to understand kernel learning, in: International Conference on Machine Learning, PMLR, 2018, pp. 541–549.
- [33] S. Mei, A. Montanari, The generalization error of random features regression: Precise asymptotics and the double descent curve, Communications on Pure and Applied Mathematics 75 (4) (2022) 667–766.
- [34] P. L. Bartlett, A. Montanari, A. Rakhlin, Deep learning: a statistical viewpoint, Acta numerica 30 (2021) 87–201.
- [35] K. Pei, Y. Cao, J. Yang, S. Jana, Deepxplore: Automated whitebox testing of deep learning systems, in: Proceedings of the 26th Symposium on Operating Systems Principles, ACM, 2017, pp. 1–18.
- [36] M. Arjovsky, L. Bottou, I. Gulrajani, D. Lopez-Paz, Invariant risk minimization, arXiv preprint arXiv:1907.02893 (2019).
- [37] L. Oakden-Rayner, J. Dunnmon, G. Carneiro, C. Ré, Hidden stratification causes clinically meaningful failures in machine learning for medical imaging, in: Proceedings of the ACM conference on health, inference, and learning, 2020, pp. 151–159.
- [38] J. K. Winkler, C. Fink, F. Toberer, A. Enk, T. Deinlein, R. Hofmann-Wellenhof, L. Thomas, A. Lallas, A. Blum, W. Stolz, et al., Association between surgical skin markings in dermoscopic images and diagnostic performance of a deep learning convolutional neural network for melanoma recognition, JAMA dermatology 155 (10) (2019) 1135–1141.
- [39] R. Geirhos, J.-H. Jacobsen, C. Michaelis, R. Zemel, W. Brendel, M. Bethge, F. A. Wichmann,

- Shortcut learning in deep neural networks, *Nature Machine Intelligence* 2 (11) (2020) 665–673.
- [40] A. Mitani, A. Karthikesalingam, A. Beutel, A. N. D’Amour, A. Montanari, B. Alipanahi, B. Adlam, C. Chen, C. Nielsen, C. McLean, D. Sculley, D. Moldovan, D. Mincu, F. Hormozdiari, G. Jerfel, H. Suresh, J. Eisenstein, J. Schrouff, J. Deaton, K. Heller, K. Webster, K. Ramasamy, M. Lučić, M. G. Seneviratne, M. D. Hoffman, M. Vladymyrov, N. Houlisby, R. Raman, R. A. Sayres, S. Sequeira, S. Hou, S. Yadlowsky, T. Yun, T. Osborne, V. Veitch, V. Natarajan, X. Zhai, X. Wang, Y. Ma, Z. Nado, [Underspecification presents challenges for credibility in modern machine learning](#), *Journal of Machine Learning Research* (2020). URL <https://arxiv.org/abs/2011.03395>
- [41] N. Papernot, P. McDaniel, I. Goodfellow, Transferability in machine learning: from phenomena to black-box attacks using adversarial samples, *arXiv preprint arXiv:1605.07277* (2016).
- [42] I. Goodfellow, J. Shlens, C. Szegedy, [Explaining and harnessing adversarial examples](#), in: *International Conference on Learning Representations*, 2015. URL <http://arxiv.org/abs/1412.6572>
- [43] A. Kurakin, I. Goodfellow, S. Bengio, Adversarial machine learning at scale, *arXiv preprint arXiv:1611.01236* (2016).
- [44] N. Carlini, D. Wagner, Towards evaluating the robustness of neural networks, in: *2017 IEEE Symposium on Security and Privacy (SP)*, IEEE, 2017, pp. 39–57.
- [45] N. Papernot, P. McDaniel, S. Jha, M. Fredrikson, Z. B. Celik, A. Swami, The limitations of deep learning in adversarial settings, in: *2016 IEEE European symposium on security and privacy (EuroS&P)*, IEEE, 2016, pp. 372–387.
- [46] S.-M. Moosavi-Dezfooli, A. Fawzi, P. Frossard, Deepfool: a simple and accurate method to fool deep neural networks, in: *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 2574–2582.
- [47] C. Xiao, B. Li, J.-Y. Zhu, W. He, M. Liu, D. Song, Generating adversarial examples with adversarial networks, *arXiv preprint arXiv:1801.02610* (2018).
- [48] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative adversarial nets, *Advances in neural information processing systems* 27 (2014).
- [49] N. Narodytska, S. P. Kasiviswanathan, Simple black-box adversarial attacks on deep neural networks., in: *CVPR Workshops*, Vol. 2, 2017.
- [50] P.-Y. Chen, H. Zhang, Y. Sharma, J. Yi, C.-J. Hsieh, Zoo: Zeroth order optimization based black-box attacks to deep neural networks without training substitute models, in: *Proceedings of the 10th ACM workshop on artificial intelligence and security*, 2017, pp. 15–26.
- [51] A. N. Bhagoji, W. He, B. Li, D. Song, Practical black-box attacks on deep neural networks using efficient query mechanisms, in: *Proceedings of the European Conference on Computer Vision (ECCV)*, 2018, pp. 154–169.
- [52] J. C. Spall, *Introduction to stochastic search and optimization: estimation, simulation, and control*, Vol. 65, John Wiley & Sons, 2005.
- [53] S. Moon, G. An, H. O. Song, Parsimonious black-box adversarial attacks via efficient combinatorial optimization, in: *International Conference on Machine Learning*, PMLR, 2019, pp. 4636–4645.
- [54] H. Qiu, L. L. Custode, G. Iacca, Black-box adversarial attacks using evolution strategies, in: *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, 2021, pp. 1827–1833.
- [55] M. Alzantot, Y. Sharma, S. Chakraborty, H. Zhang, C.-J. Hsieh, M. B. Srivastava, Genattack:

- Practical black-box attacks with gradient-free optimization, in: Proceedings of the Genetic and Evolutionary Computation Conference, 2019, pp. 1111–1119.
- [56] Y. Dong, F. Liao, T. Pang, H. Su, J. Zhu, X. Hu, J. Li, Boosting adversarial attacks with momentum, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 9185–9193.
- [57] Z. Yuan, J. Zhang, Y. Jia, C. Tan, T. Xue, S. Shan, Meta gradient adversarial attack, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 7748–7757.
- [58] K. Ren, T. Zheng, Z. Qin, X. Liu, Adversarial attacks and defenses in deep learning, *Engineering* 6 (3) (2020) 346–360.
- [59] M. Sharif, S. Bhagavatula, L. Bauer, M. K. Reiter, Accessorize to a crime: Real and stealthy attacks on state-of-the-art face recognition, in: Proceedings of the 2016 acm sigsac conference on computer and communications security, 2016, pp. 1528–1540.
- [60] L. Engstrom, B. Tran, D. Tsipras, L. Schmidt, A. Madry, [A rotation and a translation suffice: Fooling CNNs with simple transformations](#) (2019).
URL <https://doi.org/10.48550/arXiv.1712.02779>
- [61] J. Gilmer, R. P. Adams, I. Goodfellow, D. Andersen, G. E. Dahl, Motivating the rules of the game for adversarial example research, arXiv preprint arXiv:1807.06732 (2018).
- [62] K. Eykholt, I. Evtimov, E. Fernandes, B. Li, A. Rahmati, C. Xiao, A. Prakash, T. Kohno, D. Song, Robust physical-world attacks on deep learning visual classification, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 1625–1634.
- [63] X. Wei, Y. Guo, J. Yu, Adversarial sticker: A stealthy attack method in the physical world, *IEEE Transactions on Pattern Analysis and Machine Intelligence* 45 (3) (2022) 2711–2725.
- [64] J. Wang, A. Liu, Z. Yin, S. Liu, S. Tang, X. Liu, Dual attention suppression attack: Generate adversarial camouflage in physical world, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021, pp. 8565–8574.
- [65] B. Huang, H. Ling, Spaa: Stealthy projector-based adversarial attacks on deep image classifiers, in: 2022 IEEE Conference on Virtual Reality and 3D User Interfaces (VR), IEEE, 2022, pp. 534–542.
- [66] R. Duan, X. Mao, A. K. Qin, Y. Chen, S. Ye, Y. He, Y. Yang, Adversarial laser beam: Effective physical-world attack to dnns in a blink, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021, pp. 16062–16071.
- [67] D. Wang, W. Yao, T. Jiang, C. Li, X. Chen, Rfla: A stealthy reflected light adversarial attack in the physical world, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023, pp. 4455–4465.
- [68] Y. Zhong, X. Liu, D. Zhai, J. Jiang, X. Ji, Shadows can be dangerous: Stealthy and effective physical-world adversarial attack by natural phenomenon, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, pp. 15345–15354.
- [69] H. Qiu, C. Xiao, L. Yang, X. Yan, H. Lee, B. Li, Semanticadv: Generating adversarial examples via attribute-conditioned image editing, in: Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XIV 16, Springer, 2020, pp. 19–37.
- [70] C. Buckner, Understanding adversarial examples requires a theory of artefacts for deep learning, *Nature Machine Intelligence* 2 (12) (2020) 731–736.
- [71] A. Ilyas, S. Santurkar, D. Tsipras, L. Engstrom, B. Tran, A. Madry, Adversarial examples are not bugs, they are features, *Advances in neural information processing systems* 32 (2019).
- [72] T. Freiesleben, The intriguing relation between counterfactual explanations and adversarial examples, *Minds and Machines* 32 (1) (2022) 77–109.

- [73] B. Recht, R. Roelofs, L. Schmidt, V. Shankar, Do imagenet classifiers generalize to imagenet?, in: International conference on machine learning, PMLR, 2019, pp. 5389–5400.
- [74] D. Hendrycks, S. Basart, N. Mu, S. Kadavath, F. Wang, E. Dorundo, R. Desai, T. Zhu, S. Parajuli, M. Guo, et al., The many faces of robustness: A critical analysis of out-of-distribution generalization, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 8340–8349.
- [75] V. Shankar, A. Dave, R. Roelofs, D. Ramanan, B. Recht, L. Schmidt, Do image classifiers generalize across time?, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 9661–9669.
- [76] Y. Tian, K. Pei, S. Jana, B. Ray, Deeptest: Automated testing of deep-neural-network-driven autonomous cars, in: Proceedings of the 40th International Conference on Software Engineering, ACM, 2018, pp. 303–314.
- [77] X. Xie, L. Ma, F. Juefei-Xu, M. Xue, H. Chen, Y. Liu, J. Zhao, B. Li, J. Yin, S. See, Deephunter: a coverage-guided fuzz testing framework for deep neural networks, in: Proceedings of the 28th ACM SIGSOFT International Symposium on Software Testing and Analysis, 2019, pp. 146–157.
- [78] H. B. Braiek, F. Khomh, Deepevolution: A search-based testing approach for deep neural networks, in: 2019 IEEE International Conference on Software Maintenance and Evolution (ICSME), IEEE, 2019, pp. 454–458.
- [79] M. Zhang, Y. Zhang, L. Zhang, C. Liu, S. Khurshid, Deeproad: Gan-based metamorphic testing and input validation framework for autonomous driving systems, ASE 2018, Association for Computing Machinery, New York, NY, USA, 2018, p. 132–142.
- [80] M.-Y. Liu, T. Breuel, J. Kautz, Unsupervised image-to-image translation networks, *Advances in neural information processing systems* 30 (2017).
- [81] C. Doersch, Tutorial on variational autoencoders, arXiv preprint arXiv:1606.05908 (2016).
- [82] W. M. McKeeman, Differential testing for software, *Digital Technical Journal* 10 (1) (1998) 100–107.
- [83] Y.-S. Ma, S. Yoo, T. Kim, Selecting test inputs for dnns using differential testing with sub-specialized model instances, in: Proceedings of the 29th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering, 2021, pp. 1467–1470.
- [84] L. Ma, F. Juefei-Xu, F. Zhang, J. Sun, M. Xue, B. Li, C. Chen, T. Su, L. Li, Y. Liu, et al., Deepgauge: multi-granularity testing criteria for deep learning systems, in: Proceedings of the 33rd ACM/IEEE International Conference on Automated Software Engineering, ACM, 2018, pp. 120–131.
- [85] A. Odena, C. Olsson, D. Andersen, I. Goodfellow, Tensorfuzz: Debugging neural networks with coverage-guided fuzzing, in: International Conference on Machine Learning, PMLR, 2019, pp. 4901–4911.
- [86] Z. Li, X. Ma, C. Xu, C. Cao, Structural coverage criteria for neural networks could be misleading, in: 2019 IEEE/ACM 41st International Conference on Software Engineering: New Ideas and Emerging Results (ICSE-NIER), IEEE, 2019, pp. 89–92.
- [87] J. Kim, R. Feldt, S. Yoo, Guiding deep learning system testing using surprise adequacy, in: 2019 IEEE/ACM 41st International Conference on Software Engineering (ICSE), IEEE, 2019, pp. 1039–1049.
- [88] H. F. Eniser, S. Gerasimou, A. Sen, Deepfault: Fault localization for deep neural networks, in: International Conference on Fundamental Approaches to Software Engineering, Springer, 2019, pp. 171–191.
- [89] Y. Feng, Q. Shi, X. Gao, J. Wan, C. Fang, Z. Chen, Deepgini: prioritizing massive tests to

- enhance the robustness of deep neural networks, in: Proceedings of the 29th ACM SIGSOFT International Symposium on Software Testing and Analysis, 2020, pp. 177–188.
- [90] X. Xie, L. Ma, H. Wang, Y. Li, Y. Liu, X. Li, Diffchaser: Detecting disagreements for deep neural networks., in: IJCAI, 2019, pp. 5772–5778.
- [91] C. Urban, A. Miné, A review of formal methods applied to machine learning, arXiv preprint arXiv:2104.02466 (2021).
- [92] G. Katz, C. Barrett, D. L. Dill, K. Julian, M. J. Kochenderfer, Reluplex: An efficient smt solver for verifying deep neural networks, in: Computer Aided Verification: 29th International Conference, CAV 2017, Heidelberg, Germany, July 24–28, 2017, Proceedings, Part I 30, Springer, 2017, pp. 97–117.
- [93] M. Naseer, M. F. Minhas, F. Khalid, M. A. Hanif, O. Hasan, M. Shafique, Fannet: formal analysis of noise tolerance, training bias and input sensitivity in neural networks, in: 2020 design, automation & test in Europe conference & exhibition (date), IEEE, 2020, pp. 666–669.
- [94] M. H. Meng, G. Bai, S. G. Teo, Z. Hou, Y. Xiao, Y. Lin, J. S. Dong, Adversarial robustness of deep neural networks: A survey from a formal verification perspective, IEEE Transactions on Dependable and Secure Computing (2022).
- [95] H. B. Braiek, T. Reid, F. Khomh, Physics-guided adversarial machine learning for aircraft systems simulation, IEEE Transactions on Reliability (2022).
- [96] G. Yenduri, G. Srivastava, P. K. R. Maddikunta, R. H. Jhaveri, W. Wang, A. V. Vasilakos, T. R. Gadekallu, et al., Generative pre-trained transformer: A comprehensive review on enabling technologies, potential applications, emerging challenges, and future directions, arXiv preprint arXiv:2305.10435 (2023).
- [97] M. T. Ribeiro, T. Wu, C. Guestrin, S. Singh, Beyond accuracy: Behavioral testing of nlp models with checklist, arXiv preprint arXiv:2005.04118 (2020).
- [98] N. V. Chawla, K. W. Bowyer, L. O. Hall, W. P. Kegelmeyer, Smote: synthetic minority over-sampling technique, Journal of artificial intelligence research 16 (2002) 321–357.
- [99] H. He, Y. Bai, E. A. Garcia, S. Li, Adasyn: Adaptive synthetic sampling approach for imbalanced learning, in: 2008 IEEE international joint conference on neural networks (IEEE world congress on computational intelligence), IEEE, 2008, pp. 1322–1328.
- [100] R. Shimizu, K. Asako, H. Ojima, S. Morinaga, M. Hamada, T. Kuroda, Balanced mini-batch training for imbalanced image data classification with neural network, in: 2018 First International Conference on Artificial Intelligence for Industries (AI4I), IEEE, 2018, pp. 27–30.
- [101] A. More, Survey of resampling techniques for improving classification performance in unbalanced datasets, arXiv preprint arXiv:1608.06048 (2016).
- [102] G. H. Nguyen, A. Bouzerdoum, S. L. Phung, A supervised learning approach for imbalanced data sets, in: 2008 19th international conference on pattern recognition, IEEE, 2008, pp. 1–4.
- [103] A. Amini, A. P. Soleimany, W. Schwarting, S. N. Bhatia, D. Rus, Uncovering and mitigating algorithmic bias through learned latent structure, in: Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society, 2019, pp. 289–295.
- [104] T. DeVries, G. W. Taylor, Improved regularization of convolutional neural networks with cutout, arXiv preprint arXiv:1708.04552 (2017).
- [105] J.-H. Lee, M. Z. Zaheer, M. Astrid, S.-I. Lee, Smoothmix: a simple yet effective data augmentation to train robust classifiers, in: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops, 2020, pp. 756–757.
- [106] S. Yun, D. Han, S. J. Oh, S. Chun, J. Choe, Y. Yoo, Cutmix: Regularization strategy to train strong classifiers with localizable features, in: Proceedings of the IEEE/CVF international conference on computer vision, 2019, pp. 6023–6032.

- [107] H. Zhang, M. Cisse, Y. N. Dauphin, D. Lopez-Paz, mixup: Beyond empirical risk minimization, arXiv preprint arXiv:1710.09412 (2017).
- [108] J.-H. Kim, W. Choo, H. O. Song, Puzzle mix: Exploiting saliency and local statistics for optimal mixup, in: *International Conference on Machine Learning*, PMLR, 2020, pp. 5275–5285.
- [109] G. Costante, M. Mancini, P. Valigi, T. A. Ciarfuglia, Exploring representation learning with cnns for frame-to-frame ego-motion estimation, *IEEE robotics and automation letters* 1 (1) (2015) 18–25.
- [110] D. Hendrycks, N. Mu, E. D. Cubuk, B. Zoph, J. Gilmer, B. Lakshminarayanan, Augmix: A simple data processing method to improve robustness and uncertainty, arXiv preprint arXiv:1912.02781 (2019).
- [111] S. Dodge, L. Karam, Can the early human visual system compete with deep neural networks?, in: *Proceedings of the IEEE International Conference on Computer Vision Workshops*, 2017, pp. 2798–2804.
- [112] M. Abdelaty, S. Scott-Hayward, R. Doriguzzi-Corin, D. Siracusa, Gadot: Gan-based adversarial training for robust ddos attack detection, in: *2021 IEEE Conference on Communications and Network Security (CNS)*, IEEE, 2021, pp. 119–127.
- [113] H. Wang, C.-N. Yu, A direct approach to robust deep learning using adversarial networks, arXiv preprint arXiv:1905.09591 (2019).
- [114] K. Sun, Z. Zhu, Z. Lin, Enhancing the robustness of deep neural networks by boundary conditional gan, arXiv preprint arXiv:1902.11029 (2019).
- [115] D. Hendrycks, K. Lee, M. Mazeika, Using pre-training can improve model robustness and uncertainty, in: *International conference on machine learning*, PMLR, 2019, pp. 2712–2721.
- [116] T. Chen, S. Kornblith, M. Norouzi, G. Hinton, A simple framework for contrastive learning of visual representations, in: *International conference on machine learning*, PMLR, 2020, pp. 1597–1607.
- [117] M. Caron, H. Touvron, I. Misra, H. Jégou, J. Mairal, P. Bojanowski, A. Joulin, Emerging properties in self-supervised vision transformers, in: *Proceedings of the IEEE/CVF international conference on computer vision*, 2021, pp. 9650–9660.
- [118] Y. Sun, E. Tzeng, T. Darrell, A. A. Efros, Unsupervised domain adaptation through self-supervision, arXiv preprint arXiv:1909.11825 (2019).
- [119] Y. Sun, X. Wang, Z. Liu, J. Miller, A. Efros, M. Hardt, Test-time training with self-supervision for generalization under distribution shifts, in: *International conference on machine learning*, PMLR, 2020, pp. 9229–9248.
- [120] F. Tramèr, A. Kurakin, N. Papernot, I. Goodfellow, D. Boneh, P. McDaniel, Ensemble adversarial training: Attacks and defenses, arXiv preprint arXiv:1705.07204 (2017).
- [121] C. K. Mummadi, T. Brox, J. H. Metzen, Defending against universal perturbations with shared adversarial training, in: *Proceedings of the IEEE/CVF international conference on computer vision*, 2019, pp. 4928–4937.
- [122] A. Shafahi, M. Najibi, M. A. Ghiasi, Z. Xu, J. Dickerson, C. Studer, L. S. Davis, G. Taylor, T. Goldstein, Adversarial training for free!, *Advances in Neural Information Processing Systems* 32 (2019).
- [123] Y. Wang, D. Zou, J. Yi, J. Bailey, X. Ma, Q. Gu, Improving adversarial robustness requires revisiting misclassified examples, in: *International conference on learning representations*, 2019.
- [124] J. Zhang, X. Xu, B. Han, G. Niu, L. Cui, M. Sugiyama, M. Kankanhalli, Attacks which do not kill training make adversarial learning stronger, in: *International conference on machine learning*, PMLR, 2020, pp. 11278–11287.

- [125] J. Zhang, J. Zhu, G. Niu, B. Han, M. Sugiyama, M. Kankanhalli, Geometry-aware instance-reweighted adversarial training, arXiv preprint arXiv:2010.01736 (2020).
- [126] R. Rade, S.-M. Moosavi-Dezfooli, Helper-based adversarial training: Reducing excessive margin to achieve a better accuracy vs. robustness trade-off, in: ICML 2021 Workshop on Adversarial Machine Learning, 2021.
- [127] X. Liu, M. Cheng, H. Zhang, C.-J. Hsieh, Towards robust neural networks via random self-ensemble, in: Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 369–385.
- [128] J. Cohen, E. Rosenfeld, Z. Kolter, Certified adversarial robustness via randomized smoothing, in: international conference on machine learning, PMLR, 2019, pp. 1310–1320.
- [129] J. Chen, Y. Cheng, Z. Gan, Q. Gu, J. Liu, Efficient robust training via backward smoothing, in: Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 36, 2022, pp. 6222–6230.
- [130] C. Mao, Z. Zhong, J. Yang, C. Vondrick, B. Ray, Metric learning for adversarial robustness, Advances in neural information processing systems 32 (2019).
- [131] J. Tack, S. Yu, J. Jeong, M. Kim, S. J. Hwang, J. Shin, Consistency regularization for adversarial robustness, in: Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 36, 2022, pp. 8414–8422.
- [132] A. Mustafa, S. H. Khan, M. Hayat, R. Goecke, J. Shen, L. Shao, Deeply supervised discriminative learning for adversarial defense, IEEE transactions on pattern analysis and machine intelligence 43 (9) (2020) 3154–3166.
- [133] D. Li, H. Zhang, Improved regularization and robustness for fine-tuning in neural networks, Advances in Neural Information Processing Systems 34 (2021) 27249–27262.
- [134] A. Chan, Y. Tay, Y. S. Ong, J. Fu, Jacobian adversarially regularized networks for robustness, arXiv preprint arXiv:1912.10185 (2019).
- [135] S.-M. Moosavi-Dezfooli, A. Fawzi, J. Uesato, P. Frossard, Robustness via curvature regularization, and vice versa, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 9078–9086.
- [136] D. Wu, S.-T. Xia, Y. Wang, Adversarial weight perturbation helps robust generalization, Advances in Neural Information Processing Systems 33 (2020) 2958–2969.
- [137] N. Papernot, P. McDaniel, X. Wu, S. Jha, A. Swami, Distillation as a defense to adversarial perturbations against deep neural networks, in: 2016 IEEE symposium on security and privacy (SP), IEEE, 2016, pp. 582–597.
- [138] N. Papernot, P. McDaniel, Extending defensive distillation, arXiv preprint arXiv:1705.05264 (2017).
- [139] E.-C. Chen, C.-R. Lee, Ltd: Low temperature distillation for robust adversarial training, arXiv preprint arXiv:2111.02331 (2021).
- [140] E. Grefenstette, R. Stanforth, B. O’Donoghue, J. Uesato, G. Swirszcz, P. Kohli, Strength in numbers: Trading-off robustness and computation via adversarially-trained ensembles, arXiv preprint arXiv:1811.09300 (2018).
- [141] N. Mani, M. Moh, T.-S. Moh, Towards robust ensemble defense against adversarial examples attack, in: 2019 IEEE Global Communications Conference (GLOBECOM), IEEE, 2019, pp. 1–6.
- [142] T. Jian, Z. Wang, Y. Wang, J. Dy, S. Ioannidis, Pruning adversarially robust neural networks without adversarial examples, in: 2022 IEEE International Conference on Data Mining (ICDM), IEEE, 2022, pp. 993–998.
- [143] J. Cosentino, F. Zaiter, D. Pei, J. Zhu, The search for sparse, robust neural networks, arXiv preprint arXiv:1912.02386 (2019).
- [144] Y. Yan, Q. Pei, A robust deep-neural-network-based compressed model for mobile device

- assisted by edge server, *IEEE Access* 7 (2019) 179104–179117.
- [145] H. Chen, J. He, K. Narasimhan, D. Chen, Can rationalization improve robustness?, arXiv preprint arXiv:2204.11790 (2022).
- [146] J. Gao, B. Wang, Z. Lin, W. Xu, Y. Qi, Deepcloak: Masking deep neural network models for robustness against adversarial samples, arXiv preprint arXiv:1702.06763 (2017).
- [147] V. Schwag, S. Wang, P. Mittal, S. Jana, Hydra: Pruning adversarially robust neural networks, *Advances in Neural Information Processing Systems* 33 (2020) 19655–19666.
- [148] S. Kundu, M. Nazemi, P. A. Beereel, M. Pedram, Dnr: A tunable robust pruning framework through dynamic network rewiring of dnns, in: *Proceedings of the 26th Asia and South Pacific Design Automation Conference*, 2021, pp. 344–350.
- [149] B. Sun, J. Sun, L. H. Pham, J. Shi, Causality-based neural network repair, in: *Proceedings of the 44th International Conference on Software Engineering*, 2022, pp. 338–349.
- [150] J. Sohn, S. Kang, S. Yoo, Arachne: Search-based repair of deep neural networks, *ACM Transactions on Software Engineering and Methodology* 32 (4) (2023) 1–26.
- [151] H. Wu, Z. Li, Z. Cui, J. Liu, Genmunn: A mutation-based approach to repair deep neural network models, *International Journal of Modeling, Simulation, and Scientific Computing* 13 (02) (2022) 2341008.
- [152] S. Tokui, S. Tokumoto, A. Yoshii, F. Ishikawa, T. Nakagawa, K. Munakata, S. Kikuchi, Neurecover: Regression-controlled repair of deep neural networks with training history, in: *2022 IEEE International Conference on Software Analysis, Evolution and Reengineering (SANER)*, IEEE, 2022, pp. 1111–1121.
- [153] P. Henriksen, F. Leofante, A. Lomuscio, Repairing misclassifications in neural networks using limited data, in: *Proceedings of the 37th ACM/SIGAPP Symposium on Applied Computing*, 2022, pp. 1031–1038.
- [154] M. Sotoudeh, A. V. Thakur, Provable repair of deep neural networks, in: *Proceedings of the 42nd ACM SIGPLAN International Conference on Programming Language Design and Implementation*, 2021, pp. 588–603.
- [155] F. Fu, W. Li, Sound and complete neural network repair with minimality and locality guarantees, arXiv preprint arXiv:2110.07682 (2021).
- [156] B. Goldberger, G. Katz, Y. Adi, J. Keshet, Minimal modifications of deep neural networks using verification., in: *LPAR*, Vol. 2020, 2020, p. 23rd.
- [157] S. H. Silva, P. Najafirad, Opportunities and challenges in deep learning adversarial robustness: A survey, arXiv preprint arXiv:2007.00753 (2020).
- [158] R. Geirhos, K. Narayanappa, B. Mitzkus, T. Thieringer, M. Bethge, F. A. Wichmann, W. Brendel, Partial success in closing the gap between human and machine vision, *Advances in Neural Information Processing Systems* 34 (2021) 23885–23899.
- [159] J. W. Vaughan, Making better use of the crowd: How crowdsourcing can advance machine learning research, *Journal of Machine Learning Research* 18 (193) (2018) 1–46.
- [160] B. Nushi, E. Kamar, E. Horvitz, D. Kossmann, On human intellect and machine failures: Troubleshooting integrative machine learning systems, in: *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 31, 2017.
- [161] J. Yang, A. Smirnova, D. Yang, G. Demartini, Y. Lu, P. Cudré-Mauroux, Scalpel-cd: leveraging crowdsourcing and deep probabilistic modeling for debugging noisy training data, in: *The World Wide Web Conference*, 2019, pp. 2158–2168.
- [162] Á. A. Cabrera, A. J. Druck, J. I. Hong, A. Perer, Discovering and validating ai errors with crowdsourced failure reports, *Proceedings of the ACM on Human-Computer Interaction* 5 (CSCW2) (2021) 1–22.
- [163] V. Nanda, T. Speicher, J. P. Dickerson, K. P. Gummadi, M. B. Zafar, Unifying model explain-

- ability and robustness via machine-checkable concepts, arXiv preprint arXiv:2007.00251 (2020).
- [164] K.-P. Ning, L. Tao, S. Chen, S.-J. Huang, Improving model robustness by adaptively correcting perturbation levels with active queries, in: Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 35, 2021, pp. 9161–9169.
 - [165] J. C. Peterson, R. M. Battleday, T. L. Griffiths, O. Russakovsky, Human uncertainty makes classification more robust, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 9617–9626.
 - [166] P. Ren, Y. Xiao, X. Chang, P.-Y. Huang, Z. Li, B. B. Gupta, X. Chen, X. Wang, A survey of deep active learning, ACM computing surveys (CSUR) 54 (9) (2021) 1–40.
 - [167] X. Wang, Y. Chen, W. Zhu, A survey on curriculum learning, IEEE Transactions on Pattern Analysis and Machine Intelligence 44 (9) (2021) 4555–4576.
 - [168] R. Hadsell, D. Rao, A. A. Rusu, R. Pascanu, Embracing change: Continual learning in deep neural networks, Trends in cognitive sciences 24 (12) (2020) 1028–1040.
 - [169] D. Jin, Z. Jin, J. T. Zhou, P. Szolovits, Is bert really robust? a strong baseline for natural language attack on text classification and entailment, in: Proceedings of the AAAI conference on artificial intelligence, Vol. 34, 2020, pp. 8018–8025.
 - [170] K. Hendrickx, L. Perini, D. Van der Plas, W. Meert, J. Davis, Machine learning with a reject option: A survey, arXiv preprint arXiv:2107.11277 (2021).