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# Robust<sup>★</sup>: Interactive Toolbox Supporting Precise Data Annotation for Robust Vision Learning

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## Abstract

We introduce the initial release of our software Robustar, which aims to improve the robustness of vision classification machine learning models through a data-driven perspective. Building upon the recent understanding that the lack of machine learning model’s robustness is the tendency of the model’s learning of spurious features, we aim to solve this problem from its root at the data perspective by removing the spurious features from the data before training. In particular, we introduce a software that helps the users to better prepare the data for training image classification models by allowing the users to annotate the spurious features at the pixel level of images. To facilitate this process, our software also leverages recent advances to help identify potential images and pixels worthy of attention and to continue the training with newly annotated data. Our software is hosted at the GitHub Repository <https://github.com/HaohanWang/Robustar>.

## 1. Introduction

Machine learning has achieved remarkable performances over *i.i.d* benchmarks in recent years, which has greatly encouraged the community to test the methods in other scenarios beyond the *i.i.d* settings, leading to multiple other

topics such as the study of cross-domain robustness including domain adaptation (Ben-David et al., 2007; 2010), domain generalization (Muandet et al., 2013), and the recent advances beyond the settings (Ye et al., 2021; Huang et al., 2022), as well as the study of robustness against predefined perturbations such as adversarial robustness (Szegedy et al., 2014; Goodfellow et al., 2015).

While there is a diverse set of topics regarding machine learning robustness over different directions, recently literature suggests that a central theme of these challenges is the existence of spurious features that are not semantics but associated with the labels (Wang et al., 2020). Correspondingly, a proliferation of machine learning robustness methods are designed by explicitly or implicitly countering the model’s tendency in learning spurious features (Wang et al., 2021).

While the central theme of countering the learning of spurious features can potentially guide the development of many robust machine learning methods (Wang et al., 2021), we nonetheless consider the repeated case-by-case design and implementation of machine learning methods over different applications might be inconvenient at certain scenarios.

Therefore, in this project, we aim to solve this problem in the scope of image classification with a model-free manner, by focusing on the data perspective at the image pixel level. We introduce a software that allow the users or domain experts to annotate the pixels that are associated with the label in the spurious manner. The annotation will allow the system to continue to train the model with established robust learning methods of data augmentation strategies.

In summary, we introduce the software Robustar with the following functions:

- Core Function: to allow users interact with the training samples, annotating features that are useless used potentially used by the models to help train a robust model to the request of the domain expert.
- Supporting Functions:
  - We use influence function to help identify the

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samples that need attention.

- We use saliency-map style interpretation to help the user identify the features need attention.
- We use segmentation models to help the user select certain pixels more efficiently.
- We use data augmentation and regularizations to help train models invariant to the identified pixels.

The remainder of this manuscript will be structured as follows. We will first offer an overview of our system and the main pipeline of the use case in Section 2. Then in Section 3, we will introduce the core functions presented in our software. Finally, we will offer some discussions before we conclude in Section 5.

## 2. System Overview

Figure 1 shows the overview of the software Robustar pipeline, which consists of five major steps.

1. The model can be trained elsewhere and then fed into the software.
2. With new test samples, the model can help identify the samples that are responsible for the prediction through influence function.
3. The software offers saliency map to help the user know which part of the features the model are paying necessary attention.
4. The users can use the drawing tools to brush out the spurious pixels.
5. New annotation of these images will serve as the role as augmented images for continued training.

The software can work with models trained elsewhere, as long as these are standard vision models and have the standard pytorch checkpoints available. If the influence function results are also calculated, the software can guide the users to the samples that are believed to be responsible for the incorrect classification of the images. Further, our software will also guide the user’s attention of the features by the saliency-style interpretation of the models. Then the users can use canvas tool to annotate the spurious pixels of the images. Finally, with the newly annotated spurious features, we can continue to update the model with data augmentation and consistency regularization to help us discard these spurious features.

## 3. Major Functions

In this section, we will introduce the functions our software offer following the natural order of the pipeline of our pack-

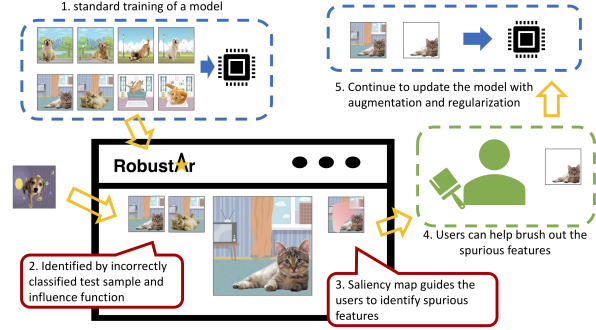


Figure 1. The major working flow of Robustar.

age will help the domain experts to annotate the spurious pixels in image classification.

**Image Browsing** Our system allows the users to examine every samples in the training set through the image browsing interface (Figure 2,(upper)).

Through the interface, the users can directly view the each image from either the training or the testing set. If the user click one image, the sidebar on the right-hand-side will display multiple relevant statistics of the image of interest. For example, the prediction summary will indicate what the model believes the current image to be, offering the users the information of whether the prediction align with the user’s p perception of the images well. The remaining statistics at the sidebar will be discussed later.

This interface allows the user to check every image in the training sample and identify the ones with spurious features for further annotation.

**Automatic Identifying Misleading Samples** Ideally, to achieve a robust learning system, the domain experts will scrutinize the training samples annotate any spurious pixel features. However, this examination process might potentially require an unrealistic amount of working load, despite it potentially significantly amount of robustness gain. Thus, to suit the need for some users’ concerns in devoting the efforts of examining every samples, we allow the system to propose the suspiciously misleading samples (samples with spurious features learned by the model) first.

The central assumption that enables the automatic proposal of misleading samples is that the spurious features are not shared between training samples and testing samples, so that when a test sample is misclassified, it is mostly due to the fact that the model learns a biased signal that accounts for the misclassification. This allows us to identify the samples with spurious features. Influence function (Koh & Liang, 2017) conveniently allows us to identify the samples that

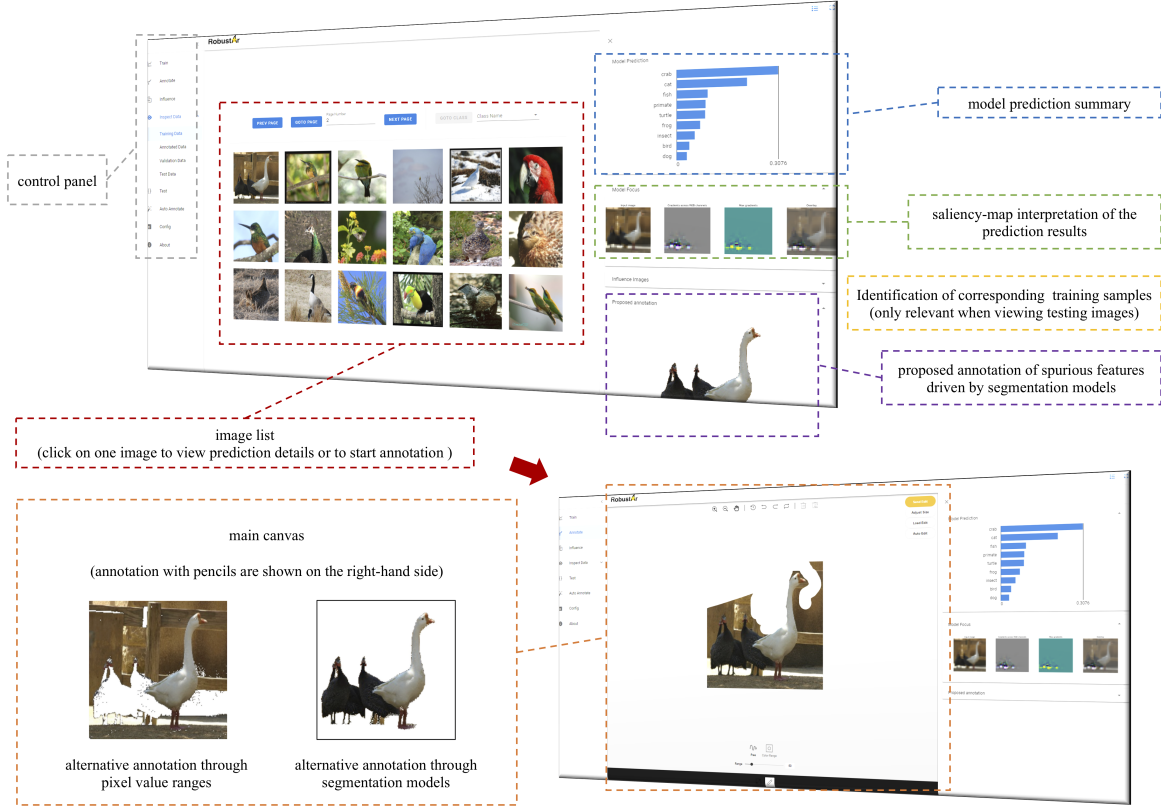


Figure 2. Screenshots of main functions of Robustar: above: the image list to view training images and their role in the model; below: the canvas to annotate the details of one image.

account for the misclassification: for every test samples, we calculate the most relevant training samples from the training set, and these samples are proposed to the users to pay particular attention especially when the test samples are misclassified.

**Annotation of Spurious Pixel Features** The user can choose to enter the annotation page (Figure 2 (bottom right)) by clicking on any images of interest. In the annotation page, the user can choose to use pencil to brush out the pixels that are considered spurious.

In addition, to reduce the efforts for user to identify and brushing out, the system offers two other alternative ways of annotating the images, as shown in (Figure 2 (bottom left)): the users can choose to directly filter out all the pixels with certain ranges, we also offer a pretrained segmentation model (He et al., 2017) that can automatically filter out the background pixels. In our experiments, we notice that the segmentation model can save significant efforts in natural images, although not perfect. However, we also notice that, in medical images such as X-ray, the segmentation model is not always able to reduce a significant amount of efforts.

**Interpret Model’s Decision** While it will be better to ask the user to identify all the pixels in the background, it might not be required for all the background pixels to be annotated for continued training: only the pixels that are learned by the machine learning model as spurious features need to be annotated and later countered through the continued training process. Therefore, to further reduce the users’ efforts in annotation, the system to show where the current model focuses on the images (Figure 2).

For the visualization of the model’s decision, we simply uses the pioneering model-interpretation methods, activation maximization (Erhan et al., 2009), and we notice that the method can fulfill our need well enough, especially when the model is already trained to be invariant to high-frequency signals of the images.

**Continued Training with Randomized Pixels** With annotation of spurious features all misleading samples, the users can directly use our system to update the model to improve its robustness against its tendency in learning the spurious features through our task center (Figure 3).

In particular, to sufficiently force the model to drop the

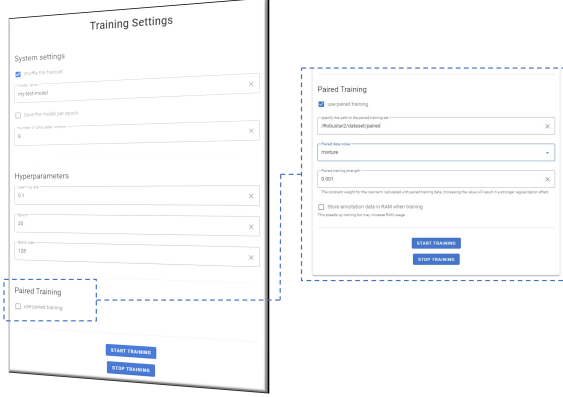


Figure 3. Task center and paired training

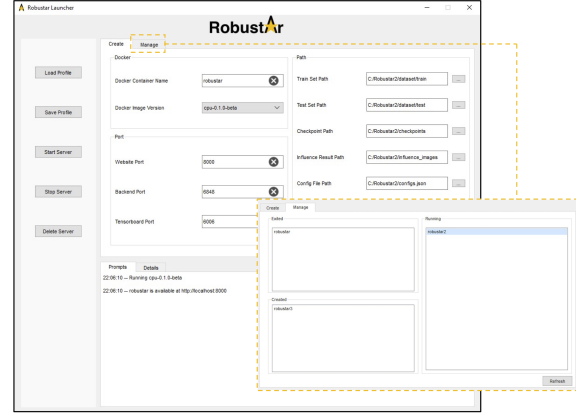


Figure 4. GUI console

learning of spurious features, we leverage the recent training paradigm with data augmentation and consistency regularization (Wang et al., 2022): to train the model with the original image and an augmented image whose spurious pixel features are replaced by random noises and a regularization forcing the model’s logits (pre-softmax embedding) to be the same from both set of images.

We refer to this training paradigm as paired training. Wang et al. (2022) showed that this generic training paradigm can efficiently improve the robustness of models empirically better than models specifically designed for the tested applications, with significantly less computing costs.

This software paper omits the demonstration of the machine learning performances through these techniques, but one can refer to (Wang et al., 2022) for the superior performances led by data augmentation and alignment regularization.

## 4. Usage Instructions

**Preparation** As the goal of this system is to counter the model’s tendency in learning spurious features, we recommend the users to start with a model with reasonably small training and testing errors. Users can either upload such a model to the system or use the functions offered by the system to start from scratch and train a new model. In either case, the whole training dataset is expected to be available for the annotation.

To take the most advantage of the system, we recommend the user to use out-of-domain test samples (*i.e.*, test samples from an independent data collection instead of from a cross-validated split), because the test data from the same collection (distribution) with training data tend to share the same spurious features with training data, thus may be inadequate to help identify the spurious features. As long as the test samples can represent a wider range of distributions, we do not need a large number of test samples.

**Setup and Run** With Docker installed, the users can run Robustar with a single-line command, if the user has pulled the relevant docker images with another command line, which is only required before the first run.

To run the system, the users need to feed in several path for the Docker to mount, including the folders of the data (with PyTorch ImageFolder structure), folder of influence images (precomputed or empty folder path), folder of checkpoints, and a configuration file with information such as number of classes and model configuration. Details of these information can be found at the Robustar GitHub Repository.

**GUI Console** For users not comfortable using command line, we also offer a GUI console for the users to setup the above the configurations and monitor the running of the system (Figure 4).

## 5. Discussion and Conclusion

We aim to improve machine learning robustness from its root at the data perspective by allowing the users to train a model with spurious features annotated. For this purpose, we offer a software for the users to inspect the training data and annotate the spurious image features. Our software can be found as <https://github.com/HaohanWang/Robustar>.

In addition to the facilitate machine learning robustness, we believe our system can also serve multiple purposes in the machine learning community from the data perspective. For example, we expect our system to also help the community to inspect the properties of the data to understand how to annotate and prepare the data better at the pixel level, and our software has the potential to generate massive amount of data along the interactive process between human and the model, leading to another possibility to automatically understand the properties of the data.

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