Does Fixing Bug Increase Robustness in Deep Learning?

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ABSTRACT

Deep Learning (DL) based systems are utilized vastly. Developers update the code to fix the bugs in the system. How these code fixing techniques impacts the robustness of these systems has not been clear. Does fixing code increase the robustness? Do they deteriorate the learning capability of the DL based systems? To answer these questions, we studied 321 *Stack Overflow* posts based on a published dataset. In this study, we built a classification scheme to analyze how bug-fixes changed the robustness of the DL model and found that most of the bug-fixes can increase the robustness. We also found evidence of bug-fixing that decrease the robustness. Our preliminary result suggests that 12.5% and 2.4% of the bug-fixes in *Stack Overflow* posts caused the increase and the decrease of the robustness of DL models, respectively.

CCS CONCEPTS

• **Software and its engineering** → **Software defect analysis**; • **Computing methodologies** → *Machine learning*;

KEYWORDS

deep neural networks, bugs, bug fix, robustness

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1 RESEARCH PROBLEM AND MOTIVATION

Deep Learning (DL) is popular in various domains including various safety-critical ones i.e., self-driving [6, 9, 37], aviation systems [5, 18], medical systems [20, 29], etc. Deploying an autonomous system to these safety-critical domains need a vigorous validation. In the past, we had instances, e.g., the Tesla autonomous car accident [38] that took place as the autonomous driving system failed to identify a truck and the outcome resulting in the death of the driver. Such incidents have made us question the trustworthiness of these autonomous systems. There are various researches conducted over these challenges and they are broadly categorized into two types, first, the study of the robustness property that includes

creating synthetic vulnerabilities [1, 4, 7, 8] and building defense mechanisms [11, 22, 23, 25]. Second, studying the bugs, and corresponding fixing pattern [12–14, 43, 44] to understand the issues faced by developers. Our study fits in the latter category.

Though prior works in understanding the ML and DNN bugs and their fixing strategies have charted the course, they do not reflect how these bug-fixes impact the robustness. Do bug fixes increase robustness? Is there any evidence of decreasing the robustness by deteriorating the learning capability of the model? To venture these research questions, we manually studied the *Stack Overflow* posts using a published dataset by Islam *et al.* [14] in a recent study.

2 RELATED WORKS

Study on the robustness property: In DNN models, one of the ways to measure the robustness property is by perturbing the input images that affect the decision of the models. This property is called the adversarial attack [8]. A wide spectrum of studies has been performed, and those include the generation of the adversarial examples [4, 8, 16, 22, 23, 26, 36] and crafting defense [4, 10, 11, 21, 28, 34, 35, 42] against such synthetic attacks. Also, studying DNN models as software and utilizing SE techniques have been proven to be useful to validate and test the DNN model [2, 15, 17, 24, 27, 39, 40].

Study on developers' challenges: There are several studies conducted on identifying the challenges, bugs, and fixing strategies that developers faced and adopted in the deep learning domain.

Zhang *et al.* [44] has identified the bugs faced by the developers using the *Tensorflow* library and categorized them into the causes and the symptoms.

Islam *et al.* [12] has built the classification scheme on top of the study performed by [44] and [3] to understand the commonality and the variability of the bugs found in five deep learning libraries. The bug dataset has been utilized in their recent study [14] to understand the fixing patterns to address the bugs. This study has found a few findings that indicated that the bug fix pattern has a direct impact on the robustness of the model. While these studies have charted the course in the deep learning bugs, they do not shed light on the deeper relationship between the coding approach and the robustness of the model. Our study utilized the bug fixing dataset by [14] and study the *Stack Overflow* posts to understand the correlation among the bug fix patterns and the robustness.

3 METHODOLOGY

In this section, we discuss the classification scheme, which has been adopted to label *Stack Overflow* posts. While studying the *Stack Overflow* posts, we found three types of examples,

No Change. Fixing a bug does not affect the robustness, e.g., fixing versioning related bug that includes the changes needed to cope up with the new releases for the libraries. These bug fixing strategies do not impact the learning capabilities of the model.

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Increase. Fixing a bug that increases the robustness, e.g., adding a dropout layer to decrease the overfit that helps the DNN model to learn better.

Decrease. Fixing a bug that decreases the robustness, e.g., for matching the data format with the model input format, developers often use *resize* and downscale the input to fit the need. [14] has shown that it decreases the learning capability of the model and decreases the robustness of the model.

Based on the classification scheme, we labeled 321 *Stack Overflow* posts from the bug-fix dataset [14]. In this study, we did not execute the code; rather, we manually verified the code snippet and the discussion to understand how the changes affect the learning capability of a DNN model. Also, we referred to the root cause, bug type, and impact from the [12], which refers to the same dataset.

4 RESULTS

In this section, we discussed the relation between the bug-fix and the change of robustness. Our primary results suggest that 84.06% of the posts related to bug-fix do not impact the robustness. 12.50% of the *Stack Overflow* posts that fix a bug increases the overall robustness. However, 2.44% of the bug-fixes decrease the robustness, as discussed in Table 1. To understand the examples of the bug-fix that concerns about the robustness, we focused only on the posts with label *Increase* and *Decrease*.

Data Dimension. This genre of the bug fix regarding the shape change of the input data to align with the expectation of the model. As discussed by [14], three different types of

operations tune the shape of the input data, resize, reorder, and reshape. Reorder and reshape do not have an impact on the robustness. These operations change the structure of the data, not the features. Resize can be either upscaling or downscaling. According to Xie *et al.* [41], upscaling an input, especially an image to a higher size and randomly adding padding, can help to decrease the effect of the adversarial attack that eventually increases the robustness. Whereas downscaling compresses the input, and the model learns fewer features than the actual input. This results in a decrease in robustness.

Loss Function. Loss function plays a crucial role in the learning process. During the backward propagation, this particular operation identifies the gap between the learned and the actual output of the DNN model. Table 2 suggests that loss function helps to increase the robustness of the DNN model. E.g., *Stack Overflow* post [33] states that the accuracy of the DNN model has a direct connection with the loss function, especially while using the *Keras* library. E.g., loss function i.e., *categorical_crossentropy* and *binary_crossentropy* chooses the accuracy metrics as categorical accuracy and binary accuracy respectively as a default choice. This poses an issue while selecting the desired choice for both loss function and accuracy metric. Choosing a wrong parameter can lead to the wrong computation of the forward and backward propagation and eventually decreases the robustness. Also, loss function can help to alleviate

the effect of bias in the dataset as proposed by Lin *et al.* [19], where different classes of labeled data get different treatment based on the amount of bias and the proposed loss function regularizes the bias by maneuvering the loss value for the negative inputs.

Neural Connection. DNN model trains itself based on the architecture of the network provided. If there is any misconnection among the input nodes and output nodes, the model does not learn accurately. One such example in *Stack Overflow* post [31], where a simple dropout layer can remove the connection among two layers of the neural network that ends in achieving lower accuracy than expected. According to the implementation of the *Keras* dropout layer, the value can be of the range (0,1). While the developer added a dropout layer with value 1, the dropout does not perform and the model accuracy is $\sim 97\%$. Changing the value to 0.99 that removes 99% of the edges between two layers disconnects the learning process and the resulting accuracy becomes $\sim 11\%$ that decreases the robustness. Another way to increase the robustness for unbalanced dataset by reinitializing the weights such that the initialization punishes the classes of input having fewer examples.

Iteration. Iterating is similar to training a model robustly so that it learns the features from the input dataset more profoundly and increases the robustness. However, we have found evidence [32], where increasing the iteration can have a negative effect by exhausting the memory or overfitting the model that ends up remembering the features rather than learning the feature and decreases the robustness.

Activation. Activation functions play a key role in the robustness by helping the model to learn features by removing the connection among nodes and edges (ReLU) or transferring the value corresponding to the nodes into the intent of the layer, i.e., prediction of the input (Softmax). However, a wrong choice can halt the training process, e.g., *Stack Overflow* post [30] that discusses the bug-fix related to the change of the activation function from Softmax that is primarily built for utilizing at the last layer of the classification problem. Using Softmax other than the last layer restricts the learning process and deteriorate the robustness.

5 FUTURE WORKS AND CONCLUSION

In this study, we manually verified the *Stack Overflow* posts and understand how the learning capabilities of the model changes with bug-fix. Studying the robustness property by including the effect of data bias, adversarial attacks by executing the model, and how different settings of the DNN model affect the decision taken by the DNN model, can be the extension of this study. Our preliminary study indicated that there is a direct impact on robustness with different fixing strategies. Understanding the relationships among the bug-fix strategies and the robustness can help the developers to opt for the fixing strategy that could increase the robustness.

Table 2: Distribution of the bug-fix

Bug-Fix Pattern	Increase	Decrease
Activation	12.5%	0.0%
Add Layer	7.5%	9.1%
Change Neural Arch.	2.5%	0.0%
Data Dimension	17.5%	63.6%
Data Wrangling	7.5%	0.0%
Iterations	12.5%	9.1%
Layer Dimension	5.0%	0.0%
Loss Function	15.0%	9.1%
Neural Connection	15.0%	9.1%
Optimizer	5.0%	0.0%

Table 1: Distribution of the change of robustness.

Label	# of Posts	% of the Posts
No Change	269	84.06%
Increase	40	12.50%
Decrease	11	2.44%

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