Towards Understanding the Faults of JavaScript-Based Deep Learning Systems

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ABSTRACT
Quality assurance is of great importance for deep learning (DL) systems, especially when they are applied in safety-critical applications. While quality issues of native DL applications have been extensively analyzed, the issues of JavaScript-based DL applications have never been systematically studied. Compared with native DL applications, JavaScript-based DL applications can run on major browsers, making the platform- and device-independent. Specifically, the quality of JavaScript-based DL applications depends on the 3 parts: the application, the third-party DL library used and the underlying DL framework (e.g., TensorFlow.js), called JavaScript-based DL system. In this paper, we conduct the first empirical study on the quality issues of JavaScript-based DL systems. Specifically, we collect and analyze 700 real-world faults from relevant GitHub repositories, including the official TensorFlow.js repository, 13 third-party DL libraries, and 58 JavaScript-based DL applications. To better understand the characteristics of these faults, we manually analyze and construct taxonomies for the fault symptoms, root causes, and fix patterns, respectively. Moreover, we also study the fault distributions of symptoms and root causes, in terms of the different stages of the development lifecycle, the 3-level architecture in the DL system, and the 4 major components of TensorFlow.js framework. Based on the results, we suggest actionable implications and research avenues that can potentially facilitate the development, testing, and debugging of JavaScript-based DL systems.

CCS CONCEPTS
• Software and its engineering → Software post-development issues; • Computing methodologies → Artificial intelligence.

KEYWORDS
JavaScript, Deep Learning, TensorFlow.js, Faults

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1 INTRODUCTION
Deep learning (DL) has been widely applied into various applications such as image classification [50], natural language processing [84], and speech recognition [44]. To support the DL-based applications, many DL libraries and frameworks such as TensorFlow [4], PyTorch [72], and Keras [1] have been developed and widely used. However, DL systems have been demonstrated to be vulnerable (e.g., adversarial attack [10, 11, 14, 24]), which can cause serious consequences when they are applied to some safety-critical applications such as healthcare [64] and autonomous driving [9]. Hence, quality assurance of DL systems is required.

Recently, extensive researches have been conducted from various communities including AI, software engineering, and security to study the quality issues of DL systems. For example, a lot of adversarial attack techniques [7, 25, 71] have been proposed to evaluate the model robustness. The quality of DL frameworks is also important for DL systems. Some works including bug analysis [16, 51, 53, 85] and framework testing [47, 73, 82] have been studied for DL frameworks. In addition to the model and DL frameworks, some studies are conducted on the programming bugs of DL applications (e.g., programming bugs with TensorFlow [87], bugs on the model architectures [86]). However, most of the studies focus on the native applications that can run on specific environments (e.g., Android and iOS) and DL frameworks.

A main drawback of the native applications is that they are often platform-specific (e.g., Windows, iOS, and Android) and device-specific (e.g., PC, mobile phones, and IoT devices). Considering the requirements for easy deployment and migration, JavaScript-based DL applications are becoming more and more popular. Compared to native DL applications, JavaScript-based applications are platform-agnostic and device-agnostic because they can easily run on major browsers such as Chrome, Firefox, and Safari on different platforms and devices [66]. Various JavaScript-based DL frameworks and
We also highlight the unique characteristics of JavaScript-based DL APIs. TensorFlow.js) into the applications. JavaScript-based DL applications that cover the 3-level architecture shown in Figure 1. We collected 700 faults in total from these repositories. Based on these 700 faults, we perform a comprehensive analysis to investigate their symptoms, root causes, and fix patterns. We also highlight the unique characteristics of JavaScript-based DL systems compared to the bugs of native applications.

From these 700 faults, we summarized 26 symptoms, 17 root causes, and 16 fix patterns. Furthermore, we study the distribution of symptoms on the 6 stages of the developing lifecycle; the distribution of root causes on the 3-level architecture, and 4 components of TensorFlow.js. The classification results (i.e., symptoms, root causes, and fix patterns) and the distribution results can help developers and researchers better understand the various faults and their characteristics, providing insights for developing different testing, debugging, and repairing techniques on JavaScript-based DL systems.

In summary, we make the following main contributions:

- To the best of our knowledge, this is the first empirical study towards understanding the characteristics of the faults in JavaScript-based DL systems. We constructed the taxonomies for fault symptoms, root causes, and fix patterns respectively, and further discussed the different characteristic of faults between the native DL systems and the JavaScript-based DL systems.
- We studied the fault distributions of symptoms and root causes on the 6 stages of the lifecycle of DL system, the 3-level architecture in the DL system, and the 4 components of TensorFlow.js.
- We provided a series of findings that benefit multiple stakeholders such as application developers, 3rd-party DL library developers, framework developers, and researchers in JavaScript-based DL ecosystems.
- We collected a dataset of real faults from a wide spectrum of sources, including the official TensorFlow.js repository, the 3rd-party DL libraries based on TensorFlow.js, and the high-level applications, which can be a valuable benchmark for further analyzing and testing the JavaScript-based DL ecosystems. We have made the fault dataset publicly available to facilitate the new research field. More details can be found on our website [3].

## 2 EMPIRICAL STUDY METHODOLOGY

### 2.1 Study Design

To characterize issues in JavaScript-based DL systems, we first collect and analyze relevant repositories from GitHub. As JavaScript-based DL systems can be built on top of various JavaScript-based DL frameworks, in this work, we mainly focus on the DL systems developed with TensorFlow.js [29], which is the most popular JavaScript-based DL framework. The overview of the methodology is illustrated in Figure 3. We first collect popular GitHub repositories through keyword search, including the official TensorFlow.js repository, the 3rd-party DL library repositories that wrap TensorFlow.js, and the repositories of DL-based web applications based on TensorFlow.js. For each repository, we crawl issues that may be related to fixing/discussing relevant problems and construct the candidate dataset for further analysis.

With the labeled issues, we study 4 research questions (i.e., the symptoms, root causes, fix patterns, and the differences from native DL systems). For the analysis of the symptoms in RQ1, we first summarize the taxonomy of fault symptoms and then analyze the distribution of symptoms on the 6 stages involved in the
development of JavaScript-based DL systems. The findings from RQ1 can provide insights for understanding and detecting bugs for JavaScript-based DL systems. The root cause analysis in RQ2 aims to characterize the fundamental reasons for these faults. We first summarize the different types of root causes, and further analyze the distribution of these root causes on the 3-level architecture and the components of TensorFlow.js, respectively. We summarize the fix pattern in RQ3 aiming to characterize the solutions to fix these faults. Finally, in RQ4, we analyze the different features of the fault symptoms and fault root causes between the native DL systems studied in the previous work and JavaScript-based DL systems.

2.2 Data Collection

Following existing work [15, 16, 45, 51, 53], we first use the GitHub search API [22] to collect repositories that are related to JavaScript-based DL systems, including the DL framework TensorFlow.js [29], 3rd-party DL libraries, and web applications using DL. In HTML and JavaScript code, TensorFlow.js is usually imported using the script tag\(^1\) and the statement import * as tf from @tensorflow/tfjs respectively. Therefore, we use “tfjs” and “TensorFlow.js” as the keywords to search the repositories. For each repository, we also collect the attributes such as links, number of stars [20], number of forks [21], number of issues, and language type. In total, we collected 924 candidate repositories. We filter out non-JavaScript-based and unpopular repositories based on the following criteria: 1) the language type is not HTML, JavaScript or TypeScript [67]; 2) there are no issues; and 3) the total number of stars and forks is less than 10. In addition, we manually check the remaining repositories to exclude irrelevant repositories that are not real DL systems, e.g., some tutorials, books, or repositories that contain the keyword but do not actually use the TensorFlow.js. In the end, 72 repositories are selected, including 1 official TensorFlow.js framework, 13 3rd-party DL libraries, and 58 web applications. The details of the repositories can be found on our website [3].

Based on the repositories, we then collect issues before Dec. 2021 for the following study because these issues contain more detailed information such as original reports, discussions between users and developers, and the fix strategy. Table 1 shows the number of issues collected under each type of repository, where AF and MF stand for Automatic Filtering and Manual Filtering, respectively. A total of 3,859 issues are crawled initially, of which 2,374 are from the official TensorFlow.js repository, 1,194 are from 13 3rd-party DL libraries, and 291 are from 58 web applications. We exclude the issues with the corresponding label (e.g., stat:awaiting response) or without answers. Note that, considering that manually analyzing bugs is time-consuming, we cannot analyze all the historical issues of TensorFlow.js. Therefore, to balance scale and cost, we filter out the issues related to deprecated versions of TensorFlow.js (before 2020-01-01).

For issues from 3rd-party DL libraries and web applications, we adopt the similar filtering strategies used in previous work [51] to discard the DL irrelevant issues. Specifically, in [51], a vocabulary of relevant words (e.g., “epoch”) related to native DL frameworks (e.g., TensorFlow) are defined, and all issues without these words are excluded. Considering the difference between TensorFlow.js and native DL frameworks, we update the vocabulary with TensorFlow.js-specific keywords (e.g., dispose, WebGL). The vocabulary finally contains 147 relevant words. As a result, 1,293 refined issues are selected as shown in column After AF of Table 1. Furthermore, during the manual labeling process (see Section 2.3), we discard issues with unclear descriptions and false positives. For example, some issues contain the keywords but are not errors. We finally obtain 684 issues, of which 359, 291, and 34 are from the TensorFlow.js, 3rd-party DL libraries, and web applications, respectively.

2.3 Manual Labeling

To answer the research questions, we manually label the faults in the 684 issues from 6 aspects: (1) symptoms, which show what the fault looks like, (2) development stages, which show at which stage the error happens, (3) root causes, which explain why the faults occur, (4) 3-level architecture, showing at which level of the DL system a root cause comes from, (5) components of TensorFlow.js, indicating which component the root cause of a framework-related failure comes from and (6) fix patterns, which describes how a fault is resolved. Note that we need to construct the labels for the symptoms, root causes and the fix patterns in our study. The labels about development stages, 3-level architecture and components of TensorFlow.js are fixed (see details in Figure 1), which are used to perform the distribution analysis of the symptoms and the root causes. The classification and the distribution analysis can help researchers and developers better understand, detect and fix different kinds of faults.

Regarding the labeling, we first randomly sample 50% of issues for pilot labeling. The first two authors label each fault of the issue following an open coding procedure [74]. Specifically, they carefully read each issue’s title, descriptions and inter-developer discussions to understand the context, and construct the taxonomies
for symptoms, root causes and fix patterns by grouping similar
faults together into categories. The taxonomies are adjusted con-
tinuously in the construction process. During the labeling process,
any disagreement is resolved by an arbitrator, who has more than
five years of experience in DL-relevant research. All labels and
taxonomies are finally discussed and finalized by all participants.

Second, the first two authors independently label the faults in
the remaining issues based on the taxonomies generated in the
pilot labeling. The issues that cannot be classified into the current
taxonomies are labeled with a new category. The labeling process
involves five rounds, and 20% of the remaining issues are labeled
in each round. Following existing work [13, 45], we adopt the Cohen’s
Kappa coefficient [17] to measure the inter-rater agreement of the
independent labeling. After the first round, the Cohen’s Kappa co-
efficient is just about 39% and then the two authors discuss all these
inconsistent results with the arbitrator. After the second round, the
Cohen’s Kappa coefficient reached 70%. Through further discussion
with the arbitrator on inconsistencies, the Cohen’s Kappa coeffi-
cients are over 90% after all the subsequent rounds. After manual
labeling, we identify 790 faults from 684 issues collected, of which
16 issues contain 2 faults.

3 SYMPTOMS (RQ1)
3.1 Symptom Classification Results
Figure 4 shows the hierarchical taxonomy of fault symptoms in
JavaScript-based DL systems. It is grouped into 5 high-level cate-
gories (i.e., Crash, Build & Initialization Failure, Poor Performance,
Incorrect Functionality, and Document Error), 15 inner categories,
and 15 leaf categories specific to Reference Error, Data & Model Error,
and Poor Performance. Note that the blue and pink rectangles indi-
cate symptoms specific to JavaScript-based and native DL systems
respectively, which will be further detailed in Section 6.1.

3.1.1 Crash (A). This category indicates the functionality of DL
systems is terminated unexpectedly with error messages like “un-
defined” or “uncaught Error”, accounting for the largest proportion
(45.43%) of faults in this study, including 318/700 faults and 5 sub-
categories. Note that non-functional terminations like performance
issues (e.g., out of memory) are not included in this category.

Among them, Fetch Failure (A.3) and Browser & Device Error
(A.4) mainly appear in the browser-based DL tasks, accounting for
26.42% of all crashes in this study. Browser & Device Error refers to
the crashes showing messages that browsers or devices are prob-
lematic. For example, WebGL (i.e., a JavaScript API for rendering
high-performance graphics on browsers, which can be used to ac-
celerate DL tasks) is not supported on a Macbook Pro 2018 [30].
JavaScript-based DL systems need to request model files or data
via the web API (i.e., Fetch [68]). Fetch Failure occurs during this
process, which refers to crashes with error messages showing the
fetch failure, i.e., it cannot directly access the local file system due
to the same-origin policy [69] that browsers follow. These 2 subcat-
egories jointly reveal that JavaScript-based DL systems are affected
by the limitations of browsers and devices.

Reference Error is the most common crash type with 154 faults
(see A.1 in Figure 4, referring to that certain objects (i.e., function,
variable, and training argument) are not implemented, defined, or
found. Specifically, the function reference errors include DL-related
function exceptions (i.e., A.1.1) and traditional function exceptions
(i.e., A.1.2). Variable reference errors refer to disposed tensors and
undefined variable properties/function return values are accessed
by program (i.e., A.1.3 and A.1.4). The remaining 24 faults are Train-
ing Argument Exception (A.1.5). Among them, A.1.1 (DL Operator
Exception) is the most common, indicating the implementations
of current JavaScript-based DL systems are still in fragile status,
which can easily bring errors when using a lot of DL functions.

The Data & Model Error (A.2) refers to the crashes that data or
model is reported to be problematic. Specifically, data errors rep-
resent the incorrect data types, shapes, and values, involving both
DL-related tensors (see A.2.1 in Figure 4) and JavaScript variables
(see A.2.2 in Figure 4). For example, the invalid data shape reports
"tensor should have 131072 values but has 14636" [77], and the invalid
data type reports “expected input to be of type HTMLImageEle-
ment” [57]. The model errors usually show failure occurs on model
usage or structure construction with messages like “model needs to
be complied before used”. The remaining 14 crashes with low
frequency (occurring only once or twice) are thus categorized in
Others.

Finding: Crash is the most common symptom, accounting for
45.43% of all faults. In particular, Fetch Failure and Browser & Device Error mainly appear when performing DL tasks on the
browsers. Meanwhile, the 154 Reference Error indicates that the
JavaScript-based DL systems are still in fragile status.

3.1.2 Build & Initialization Failure (C). At the start of develop-
oping JavaScript-based DL applications, developers need to build
and initialize the necessary environments. 141/700 (20.14%) faults
occurred in this process, which consists of 3 typical symptoms.
Specifically, 63 faults belong to the building failure when develop-
ers compile TensorFlow.js from source code and further compile the
DL applications (i.e., C.1 in Figure 4). Alternatively, developers can
install compiled TensorFlow.js via NPM (i.e., the package manager
for JavaScript), during which 27 faults were found (C.2 in Figure 4).

Apart from the explicit building errors mentioned above, there
may still be exceptions even after the application has been success-
fully compiled. Consider the Multi-backend Initialization Failure
(C.3), 51 faults show that JavaScript-based DL systems fail to ini-
tialize certain DL backends (e.g., Wasm) even though they have
already installed TensorFlow.js successfully [31]. The main reasons
include: the device/browser used is incompatible with the backend,
and some errors in the implementation of TensorFlow.js. More than
20% of the faults occurring during the building or initialization
process indicate the complexity of the JavaScript-based DL system.

Finding: 20.14% of all faults are introduced when building and
initializing the necessary environments for JavaScript-based DL
systems, which is the second most common symptom.

3.1.3 Poor Performance (B). Poor Performance is another typi-
cal symptom for JavaScript-based DL systems, which slow down the
execution processes, consume excessive resources, and bring bad
user experiences. 117/700 faults belong to this category, covering
16.71% of all faults. It is organized into 3 inner categories (i.e., Time,
Memory, and Others) and 7 leaf categories, as shown in Figure 4.

Time (B.1). This category covers the performance faults ex-
hibiting high time cost, which accounts for the largest portion of
Poor Performance, i.e., 57.26%. Particularly, 38.46% of performance faults show Slow Execution Time when performing DL tasks, including data processing, model building, training, and prediction. The systems can still work but are extremely slow. 13.68% of the performance faults result in a more severe symptom (i.e., Browser Hangs) that JavaScript-based DL systems cease to respond to inputs. For example, the desktop browsers hang and cannot respond over a long period of time [58].

Memory (B.2). This category covers 29.06% of the performance faults which consume RAM/GPU memory abnormally. It contains 3 subcategories: the Memory Leak (B.2.1), Out of Memory (B.2.2), and Abnormal GPU Memory/Utilization (B.2.3). Specifically, B.2.2 is the most severe symptom and can cause the JavaScript-based DL systems to terminate unexpectedly. Moreover, B.2.1 is the most common symptom in this category, which can lead to out of memory in severe cases. The remaining 3 memory faults show unexpectedly high or low GPU memory usage, i.e., B.2.3.

Others (B.3). We also summarize two special types of performance faults, i.e., the Regression and Unstable, covering 18.80% of all performance faults in this study. Specifically, Regression refers to the faults occurring after the TensorFlow.js upgradeation. For example, the fragment shader compilation fails after Tensorflow.js upgrading from version 3.5.0 to 3.6.0 [79]. Unstable means the inference results of JavaScript-based DL systems are unstable. For example, when the portrait in front of the camera remains still, the face recognition results are constantly changing [59].

Poor Performance accounts for a considerable proportion of all faults in this study, and it can directly affect the user experience. There are two main reasons for the poor performance: 1) Web applications inherently suffer from low performance due to the use of DOM [83] tree in the browser. 2) The explicit memory management can easily introduce memory performance issues, e.g., manually releasing memory. It is especially required on the WebGL backend, because the browser does not automatically recycle WebGLTextures, a variable where tensor data is ultimately stored.

Finding: As a kind of non-functional fault, Poor Performance covers 16.71% of all faults in this study. It has various symptoms, e.g., more than one-third of the performance faults slow down JavaScript-based DL systems, and nearly 30% of the performance faults consume extremely high memory.

3.1.4 Incorrect Functionality (D). We find another kind of faults that can run normally without crashes/failures, but the final results are incorrect. We refer to these faults as the Incorrect Functionality, covering 111/700 (15.86%) faults in this study. Specifically, 38 faults show that JavaScript-based DL systems produce different results under multiple DL backends, platforms, or devices (D.1). Models may give wrong inference results under some data in 28 faults (known as Poor Accuracy (D.2)) and even non-numerical outputs in 9 faults, such as the infinity and NaN results (D.3). Besides, there are other discrete cases (36 faults) that JavaScript-based DL systems provide incorrect functionality. For example, TensorFlow.js can not properly switch the WebGL backend to the CPU backend [78].

Notably, we clarify the incorrect functionality involves two levels. 1) The DL system level. That is, JavaScript-based DL systems give an incorrect inference result. For example [23], when there is a hand/phone in the camera, the blazeface infers that there is a face, indicating the inference of the DL system is not robust. 2) The DL operator level. Namely, the DL operators in TensorFlow.js give wrong calculation results without crashing. For example [32], with an input NaN, the operator tf.jluNaN outputs FALSE, indicating the implementation of this operator is incorrect. We emphasize this is a severe symptom that should arouse more attention from TensorFlow.js vendors. Due to the statistical characteristics of DL models in decision-making, the inference outputs show more uncertainty and uninterpretability than traditional software, which require carefully-designed oracles to capture the unexpected results.

Finding: Incorrect Functionality accounts for 15.86% of all faults in this study. This symptom category appears not only in the DL system but also in the specific operator. Moreover, we need to design test oracles for capturing these faults.

3.1.5 Document Error (E). Document Error refers to the faults related to TensorFlow.js official documents/tutorials, including invalid links, incorrect instructions, and missing tutorials. Although the 13 documental faults only account for 1.86% in this study, they will not only bring bad experiences to TensorFlow.js users but also may cause implementation bugs or even security vulnerabilities for the entire DL systems. Similar implementation problems caused by poor-quality docs have been extensively studied in other fields [12]. As the foundation of DL development in JavaScript ecosystems, the rigorousness and correctness of the TensorFlow.js guidance docs should also be seriously paid attention to.

Finding: Although the Document Error only accounts for a small proportion (i.e., 1.86%), it will bring bad experiences to the TensorFlow.js users.
4.1 Root Cause Classification Results

The root cause taxonomies of the studied faults are shown in Figure 6, which is organized into 5 high-level categories (i.e., Incorrect Programming, Execution Environment Error, Configuration & Dependency Error, Data/Model Error and Unknown) and 17 inner categories. The number of faults assigned to each category is in the top right corner. Note that, there are 46 (6.57%) faults that are difficult to analyze their root causes, and are therefore classified as Unknown. The blue and pink rectangles indicate root causes specific to JavaScript-based DL systems and native DL systems respectively, which will be further detailed in Section 6.2.

4.1.1 Incorrect Programming (A). This category covers faults caused by program code, which is the most common category and accounts for 357 (51.00%) of the faults. It contains 7 subcategories i.e., Unimplemented Operator, Inconsistent Modules in TF.js, Incorrect Code Logic, Incompatibility between 3rd-party DL Library and TF.js, API Misuse, Import Error, and Improper Exception Handling.

Incorrect Code Logic causes the most faults, accounting for 23.29% of all faults in this study, which can be divided into three subcategories based on the code functionality. ① Incorrect DL-specific algorithms due to incorrect implementation of DL-specific functions in TensorFlow.js (e.g., basic DL operators [33]), 3rd-party DL libraries (e.g., face recognition algorithm [60]), and incorrect code logic in web applications (e.g., [70]). The most Incorrect Code Logic faults (119 faults) belong to this subcategory. ② Incorrect memory management algorithm due to improper memory management, accounting for 24 (3.43%) of all faults. It mainly appears when explicit memory management is used on the WebGL backend. For example [34], there is a memory leak in operator tf . signal . stft, because some intermediate tensors are not released in time. The TensorFlow.js vendors explained it as "Complex components cannot be released if there are multiple references on the components and those references are disposed before the complex tensor is disposed." ③ Poor environmental adaptability due to the incorrect/missing condition checking (i.e., if-else blocks) required to handle different environments (e.g., specific browsers). It accounts for 20 (2.86%) of all faults. Such faults mainly occur in 3rd-party libraries and TensorFlow.js. For example [35], the application works well on Chrome and Edge but fails on Opera. The TensorFlow.js vendors explained that "In certain cases (e.g. in a webworker running in Opera), the window is not defined, which will fail the isMobile function. This PR adds a fallback check which uses navigator.userAgentData.mobile."

46 faults are caused by Unimplemented Operator, i.e., the DL operators used in DL systems are not yet supported or implemented by TensorFlow.js. For example [36], the operation tf . nod is not supported by the Wasm backend of TensorFlow.js. Besides, there are many modules in TensorFlow.js (e.g., the tf.js-core and tf.js-tf11te), which cooperate with each other to complete various DL tasks and adapt to various environments. Inconsistent implementations between these modules lead to 21 faults in this study (see A.2 in Figure 6). For example [37], tf.js-core does not support tensor of type Int8Array provided by another module tf.js-tf11te.

Apart from the faults caused by TensorFlow.js implementations, 43 faults are introduced by the flaws in 3rd-party DL libraries, i.e., A.5 in Figure 6. It refers to faults caused by the wrong TensorFlow.js versions, as the 3rd-party DL library requires the specific version of TensorFlow.js. For example [61], the 3rd-party DL library face-api.js executes based on outdated versions of TensorFlow.js (i.e., 2.x), resulting in an incompatibility error ‘t . toFloat not being a function’.

Finding: Incorrect Programming is the most common root cause category and covers 7 subcategories, accounting for 357 (51.00%) of all faults. Among them, Unimplemented Operator, Inconsistent Modules in TF.js, and Incorrect Code Logic are related to the implementations of TensorFlow.js. The most common subcategory is Incorrect Code Logic, especially the incorrect implementation of DL-specific algorithms.
The remaining 3 root causes are common in traditional software. Specifically, API Misuse refers to the faults due to the users’ misunderstanding of APIs, including missing or redundant calls to an API, wrong API names, and invalid API input/parameters (i.e., type/shape/value error). It contains 57 faults, accounting for 8.14% of all faults. Our further analysis finds 52.63% (30/57) of API Misuse faults are due to invalid usage of inputs/parameters, indicating that in JavaScript-based DL systems, developers are confused about the types and shapes of parameters/inputs supported by the APIs, especially for data types that can only be used in specific environments. Import Error refers to the faults (21 faults) caused by the missing/incorrect import of TensorFlow.js, and the import of multiple versions of TensorFlow.js at the same time. The remaining 6 faults are due to Improper Exception Handling, including missing exceptions, suspicious exceptions, and confusing error messages.

**Finding**: For the root causes that are also common in traditional software, API Misuse accounts for a considerable amount, especially the invalid API input/parameters.

### 4.1.2 Configuration & Dependency Error (B)
116/700 (16.57%) faults are caused by the incorrect configuration and dependencies, which is the second most common category. In particular, 28 Multi-environment Misconfiguration faults are specific to JavaScript-based DL systems. They are caused by incorrect bundler configurations that are used to ensure the same implementation of a JavaScript-based DL system can be deployed on heterogeneous environments (e.g., browser and Node.js), regardless of the underlying hardware types (i.e., PC, smartphones, and wearable devices) and the operating systems (e.g., Windows, iOS, and Android). For example, a fault is caused by not marking “os” as the external attribute in the bundler configuration for the browser target [38].

74 faults are caused by dependency-related problems, of which 61 faults suffer from the missing/redundant dependency, the dependency version mismatch, and dependencies with security vulnerabilities [39] (see Dependency Error); the remaining 13 faults are caused by the untimely updates of tensorflow.js [40] and npm packages (see Untimely Update). These dependency faults are closely related to the characteristics of TensorFlow.js, which relies on various libraries. For example, XNPNAC [43] is a highly optimized library for floating-point neural network inference that can be used on ARM, WebAssembly, and x86 platforms. Such complicated dependencies will inevitably introduce fragility during the configuration and runtime. The dependencies that are not updated in time or the relevant properties are not given correctly may cause serious problems in the entire system. Another 14 faults in this category are due to Confused Document in TensorFlow.js. Although the number is small, it brings bad experiences to users.

**Finding**: Configuration & Dependency Error is the second most common root cause, covering 116 (16.57%) of all faults. Multi-environment Misconfiguration and Dependency Error constitute two notable root causes, which are closely determined by the characteristics of TensorFlow.js (i.e., it depends on various libraries and can be used on multiple environments/platforms).

### 4.1.3 Data/Model Error (C)
55/87 faults are caused by the Data/Model Inaccessibility, due to 1) the browser limitations, i.e., local data/model cannot be accessed because of the same-origin policy [69] that browsers follow; 2) the UI framework limitations, i.e., model is not placed in specified folders (e.g., public/asset) as required by the UI framework; 3) the incorrect model path or extension. If developers are unfamiliar with the features of browsers and UI frameworks, it is easy to introduce the inaccessibility of models or data.

The remaining 32 faults are caused by Improper Model/Tensor Attribute, including the poor model design (e.g., incorrect inference due to the poor quality of models provided by the 3rd-party DL libraries [52]), improper model parameter (e.g., long inference time due to the large input size [62]), and improper model size (e.g., ssd mobilenetv1 model cannot run on Android because it requires a lot of resources [63]). This shows that the quality of the pre-trained models provided in the 3rd-party DL libraries needs to be improved, and some models with large size cannot work well due to the limited computing power of the web platform.

**Finding**: 63.22% of Data/Model faults are caused by the Data/Model Inaccessibility. Such faults are mainly related to the limitations of browsers and UI frameworks.

### 4.1.4 Execution Environment Error (D)
As stated before, TensorFlow.js is designed to execute on various environments, such as different backends (e.g., WebGL and Wasm) for browsers, and cross-platform applications [29]. In this study, 94/700 (13.43%) faults are caused by imperfect support of TensorFlow.js for some hardware/software environments, which can be further divided into 4 subcategories, i.e., the Device Incompatibility, Browser Incompatibility, Cross-platform App Framework Incompatibility, and WebGL Limits.
Device Incompatibility is the most environmental root cause, covering the largest number of faults (41/94 faults). Such issues persist when TensorFlow.js executes on specific hardware (e.g., graphics card) and operating systems (e.g., Android). For example, the DL system gives abnormal results on devices equipped with Intel HD Graphics. Compared with native DL frameworks [13], such faults are more prominent in JavaScript-based DL frameworks, indicating the implementation of DL backends specific to JavaScript usage needs to be improved in order to fit more diverse devices.

Browser Incompatibility (i.e., PC browser and mobile browser) is another major cause, covering 28 faults. Such faults are reasonable because the DL inference on browsers is executed in JavaScript and relies on the browser engine for interpretation. There are also 14 faults caused by Cross-platform App Framework Incompatibility. Specifically, TensorFlow.js can be integrated into mobile/desktop applications via cross-platform application frameworks (e.g., React Native). However, some of them are not compatible with the underlying libraries (e.g., expo-gl) on which TensorFlow.js depends. Apart from the incompatibility factors mentioned above, the inherited limitations of WebGL (a set of JavaScript APIs which can be used for accelerating DL tasks) can also bring faults in some browser-based DL scenarios (14 faults). For example, the GUI is blocked due to the management of GPU resources in WebGL [41].

Finding: Execution Environment is a common root cause that is quite specific to JavaScript-based DL systems, due to the complex software/hardware environments they execute on. Device Incompatibility and Browser Incompatibility are top two environmental causes, accounting for 73.40% of this category.

4.2 Root Cause Distribution

4.2.1 Distribution on the 3 levels of DL systems. We further analyze the distribution of root causes to understand how these faults present on the 3 levels of JavaScript-based DL systems (i.e., Web application, 3rd-party library, and Tensorflow.js). As shown in Figure 7, the top 6 common root causes (425/700 faults, 60.71%) are considered due to the space limit. Note that the TF.js Incompatibility stands for A.5 in Figure 6.

In terms of root cause, Incorrect Code Logic is the most common type, which distributes over all of the 3 levels. Such faults should be a concern for all developers and researchers. The remaining root causes are distributed over a specific level. For example, 85.25% of Dependency Errors and all of the TF.js Incompatibility faults appear in TensorFlow.js and 3rd-party library, respectively. In terms of system levels, most faults are caused by TensorFlow.js. Different levels present different fault distribution tendencies. Specifically, faults on TensorFlow.js are closely related to low-level implementation, e.g., Incorrect Code Logic and Unimplemented Operator, indicating that TensorFlow.js is still at the early stages of development. The vendors need to enrich DL operators and check the libraries on which TensorFlow.js depends in time. As a comparison, faults on 3rd-party libraries are mainly caused by TF.js Incompatibility, and faults on web applications are more about the high-level usage of TensorFlow.js, e.g., the API Misuse and Data/Model Inaccessibility. In these cases, the 3rd-party library vendors need more effort to keep compatible with TensorFlow.js, and web application developers should carefully use DL-related APIs and handle model/data.

4.2.2 Distribution on the framework components. TensorFlow.js contains 4 components (see Figure 1), i.e., API, Platform, Backend, and Device. To evaluate the quality of them, we further analyze the distribution of faults on each component, as shown in Figure 8. The inner layer represents the 4 components and corresponding faults number. The outer layer represents the sub-component corresponding to the component (the inner node of the same color) and the number of errors caused by each sub-component.

As we can see, 389/700 (55.57%) faults are introduced by the 4 TensorFlow.js components. DL-backend-related faults cover the most faults (i.e., 185/389 faults), of which the JavaScript-specific backends (i.e., WebGL, Wasm, WebGPU, and Pure-JS CPU) account for the majority of cases (141 faults), especially the WebGL (68/141) and Wasm (52/141). A large scale of faults brought by DL backends indicates that JavaScript-based DL systems are still at dawn for the goal of conducting DL across multiple environments. In particular, JavaScript-specific backend (e.g., WebGL) are more fragile than the native backend. API component introduces the second most faults (104/389 faults), which consists of 3 levels of APIs, i.e., the operator-level, layer-level, and model level. Among them, the operator-level APIs bring the most faults (65 faults). Since existing testing techniques [13, 47, 73, 82] suffer from low operator coverage, we emphasize this is a challenge for detecting API errors on JavaScript-based DL systems. Regarding the Platform component, it causes 59 faults, which mainly occur on browsers and mobile applications. The remaining 41 faults are due to device components.

Finding: In terms of the 3 system levels, the root causes present certain tendencies on different levels. Incorrect Code Logic is the most common one that affects all of the 3 levels. In terms of the components in TensorFlow.js, most faults are caused by the DL backends, especially the JavaScript-specific backends (e.g., WebGL), which calls for new testing techniques and debugging methods for detecting such errors.
5 FIX PATTERNS (RQ3)

A fix pattern means that the subject fixes these faults by using them to modify the object. Table 2 shows the 16 common fix patterns with 539 faults, which involve 4 major objects (i.e., Environment, Model, Data, and Program & API) and 2 subjects (i.e., application developers and framework/3rd-party library vendors). Note that we consider the subject to be the framework/3rd-party library vendors if the fault is fixed via PR in the framework/third-party library repository, otherwise it is the application developers.

**Environment.** Modifying the environment configuration is the most common, which resolve 264 faults and is typically used by developers. Specifically, changing versions of the TensorFlow.js, 3rd-party DL libraries, and compiler/installer (e.g., Typescript, Node.js, and NPM) can solve most faults (i.e., 99). 89 faults can be resolved by changing the browser/device, backend, and values of environment variables. Besides, 13 import confusion in the program can be fixed by adding/removing imports and changing import statements. Note that the pattern of modifying the dependency configuration includes adding dependencies, removing dependencies, replacing mismatched dependencies, and modifying related configuration options, which can be used by both developers and vendors.

**Model.** Developers fix 69 faults by modifying the models. Specifically, modifying the model file path/extensions solves 37 faults, which are mainly model inaccessibility faults. Another 32 faults are fixed by model reconstruction, including retraining the model, reconverting the model, and replace with another similar model.

**Data.** There are two patterns that act on the data, including adding data processing and replacing data shape/types. Specifically, developers fix 27 faults by adding preprocessing of inputs and post-processing of model predictions. Another 27 faults are fixed by developers and vendors by replacing the shape/type of related data.

**Program & API.** 152 faults are resolved by modifying the related programs and API usage. For this object, there are 6 fix patterns, 1 of which is typically used by the vendors (i.e., add unsupported operator), 1 by the developer (i.e., modify API parameter usage), and the remaining 4 can be used by both the developers and the vendors. Specifically, vendors solve 40 faults (i.e., unimplemented operators) by adding unsupported operators. Developers solve 25 API Misuse faults by modifying the usage of the API parameters. The remaining 4 patterns resolve 87 faults that can be introduced by any of TensorFlow.js, 3rd-party library, and web application.

Note that, the fix pattern applied to one object can also repair faults caused by other objects. For example, for the pattern of changing versions in the environment, developers can also use it to resolve incorrect program logic errors in TensorFlow.js in addition to faults caused by the environment, because vendors fix bugs inside TensorFlow.js and update the TensorFlow.js version frequently. Additionally, faults caused by the same root cause can be fixed by different patterns. For example, for an error caused by the Wasm backend not supporting a certain operator, the developer can bypass the faults by changing the backend into WebGL backend, however, the vendor can add support for the operator to solve the faults. Although both methods can solve the faults, adding support for the operator is the most direct and effective method.

### Finding
We summarize 16 common fix patterns based on 2 subjects and 4 objects. Modifying the environment is the most common pattern, especially changing versions of the TensorFlow.js, 3rd-party DL libraries, and compiler/installer. We find that faults caused by the same root cause can be fixed by different patterns in practice.

6 DIFFERENCES FROM NATIVE DL SYSTEMS (RQ4)

In this section, we discuss the differences between the taxonomies proposed in this study and that proposed by previous work on native DL systems from 2 aspects: the symptom and the root cause.

6.1 Differences Based on Symptom

As highlighted by the pink rectangles in Figure 4, 5 symptoms (e.g., **DL Operator Exception**) involving the characteristics of DL are shared with the existing symptom taxonomies for native DL (e.g., TensorFlow and TensorFlow Lite) faults [13, 16, 45, 51]. Despite all this, their symptoms on different DL frameworks are not exactly the same. For example, we found some cases where a basic DL operator/training argument is problematic in TensorFlow.js, but it is supported in TensorFlow (see [42]). This shows that TensorFlow.js needs to be aligned with the native framework in providing complete implementations of DL operators and training parameters.

Moreover, 8 symptoms are closely related to the characteristics of JavaScript-based DL systems, as shown by the blue rectangles in Figure 4, covering 35% faults. In Particular, the **Multi-backend Initialization Failure** and **Inconsistency between Backends/Platforms/Device** are determined by the characteristics of TensorFlow.js, which provide several parallel DL backends (e.g., WebGL and Wasm) specific to the different JavaScript execution environment. Similarly, the **Fetch Failure and Browser&Device Error** are determined by the fact that JavaScript-based DL systems mainly run on heterogenous browsers, including both PC browsers and mobile browsers. Such new symptoms cover more than one-third of the faults in this study, indicating that the quality of JavaScript-based DL systems deserves a comprehensive investigation.

The remaining symptoms are similar to traditional software, as shown by the white rectangles in Figure 4. The performance faults account for a large proportion in this study. Considering the low performance of JavaScript DOM manipulation and the explicit memory management of the WebGL backend, JavaScript-based DL
systems are more prone to performance issues, which should arouse developers’ attention and be analyzed exclusively in the future.

6.2 Differences Based on Root Cause

JavaScript-based DL systems experience some common issues as is for native DL systems, which have been extensively studied in prior work [13, 56, 85]. As shown by the pink rectangles in Figure 6, these issues are primarily caused by incorrect code logic (163 faults), unimplemented operators (46 faults), improper model/tensor attribute (32 faults), and inconsistent implementations between different modules in TensorFlow.js (21 faults). Although the aforementioned problems are expected, it is crucial to stress that a total of 262 faults (over 37%) brought on by typical DL-specific problems illustrate the incompleteness of JavaScript-based DL systems in supporting core DL functionalities.

Besides, we summarized 220 faults (31.4% of all faults) whose root causes are specific to JavaScript-based DL systems, covering 7 major subcategories. As shown by the blue rectangles in Figure 6, 126 faults are caused by the incompatibility problem. These compatibility issues can be summarized into two levels: 1) the 3rd-party DL library level, i.e., the incompatibility between TensorFlow.js and the 3rd-party DL libraries that wraps TensorFlow.js (43 faults); 2) the environment level, i.e., the incompatibility of TensorFlow.js with various execution environments, including the devices (41 faults), browsers (28 faults), and cross-platform applications (14 faults). Notably, another 28 faults are caused by the unique multi-environment characteristic of JavaScript-based DL systems. Compared with other single-environment DL systems (e.g., mobile DL apps), the JavaScript-based DL systems are designed to run in a variety of environments that rely on different configurations (e.g., browsers and Node.js). In addition, 55 faults are mainly caused by the limitations of the browser and UI framework (e.g., Local data/models inaccessible due to the same-origin policy [69 in browsers], and 11 faults are caused by WebGL limitations (e.g., GUI block due to the WebGL management mechanism of GPU resources). Such new root causes introduce more than 30% faults, suggesting the differences between the JavaScript-based systems and others.

The remaining categories in Figure 6 are common causes in traditional software, as shown by the white rectangles. The dependency-related error (61 faults) and API misuse (57 faults) are two leading factors. Particularly, as for API Misuse, 52.6% API-misuse cases are due to the invalid inputs/parameters in JavaScript-based DL systems, which is quite different from traditional software [5, 6] and even native DL framework [13], where the API missing/redundancy, and incorrect API names are uppermost cases. Therefore, for the JavaScript-based DL systems, some existing problems in traditional software are still worth exploring in combination with the characteristics of these systems.

**Finding:** 8 symptoms (35% of all faults) in our study are specific to the JavaScript-based DL systems, suggesting that the quality of JavaScript-based DL systems deserves a comprehensive investigation. 7 root causes (nearly one-third of all faults) in our study are specific to the JavaScript-based DL systems. Particularly, the incompatibility issues are prominent (18%) in TensorFlow.js usage. More efforts are needed for TensorFlow.js vendors to adapt to more environments.

7 DISCUSSION

7.1 Implications

7.1.1 For Application Developers. Data/Model Inaccessibility and API Misuse are major fault causes for the JavaScript-based DL applications, as shown in Section 4.2.1. Therefore, we conclude some tips: 1) Avoid data/model inaccessibility. Since data and models are the foundation of DL applications, developers should first ensure their accessibility. Depending on the causes of such issues, we recommend that developers avoid such errors by ① putting the model on the Internet and using TensorFlow.js to load the online model via the URL to bypass the limitation that the browsers cannot directly access local files; ② checking if the model is placed in the folder required by the UI frameworks (e.g., Angular); ③ checking if the model path and extension are correct. 2) Use API carefully. Quite a few faults are caused by the confusion on the API parameters/inputs in TensorFlow.js. Therefore, developers should use the APIs carefully, such as understanding the usage of the API based on the official documentation before programming.

7.1.2 For 3rd-party DL Library Developers. 1) Improve the environmental adaptability. Section 4.1.1 reveals that faults caused by poor environmental adaptability mainly appear in 3rd-party DL libraries. Developers are expected to conduct cross-platform testing before releasing a library, ensuring the library adapts to any platform, especially the browsers and Node.js. 2) Enhance compatibility with TensorFlow.js. Only a specific version of TensorFlow.js can work with 3rd-party DL libraries, which brings great inconvenience to users. Such issues should arouse the attention of developers.

7.1.3 For Framework Developers. 1) Enhanced testing of the implementations of DL backends specific to JavaScript (e.g., WebGL). JavaScript-specific DL backends present more faults compared to native DL backends (see Section 4.2.2). Such faults should be noted and detected promptly. 2) Do more unit testing. Incorrect Code Logic is the most common root cause (see Section 4.2.1). It causes various fault symptoms and is difficult to locate, so developers should focus on detecting such faults before releasing a new version to ensure that the implementation logic of each module is correct. 3) Check and update dependencies in time. Many faults in TensorFlow.js are related to the libraries on which it depends, especially the libraries with real vulnerabilities. To avoid these errors, we recommend that developers check and update dependencies in time. 4) Expand DL operators. Many operators have not been supported by TensorFlow.js, developers should support as many operators as possible to align with the mature native frameworks (e.g., TensorFlow).

7.1.4 For Researchers. 1) Call for testing techniques for performance faults. In terms of symptoms, poor performance faults are prominent in JavaScript-based DL systems and the reasons for such faults are difficult to analyze. Therefore, testing and debugging techniques for such faults are desired. 2) Focus on testing the framework. For the 3 levels in the JavaScript-based DL system, framework introduces the most faults. Particularly, JavaScript-specific DL backends present more faults compared to native DL backends, but there is currently no testing techniques for such errors. Thus, how to design effective testing methods according to the characteristics of JavaScript-based DL framework is a challenge for future research.
7.2 Threats to validity

The external threat to validity lies in the dataset. First, the selection of our study subjects (i.e., TensorFlow.js, 3rd-party DL libraries, and web applications) may be biased. To mitigate this threat, we choose the most popular and representative JavaScript-based DL framework (i.e., TensorFlow.js) as a base. The selected 3rd-party DL libraries and web applications are all built on TensorFlow.js. The findings based on TensorFlow.js-related systems can be largely applied to other JavaScript-based DL frameworks (e.g., Paddle.js [27] and WebDNN [28]) as most of them can run on DL backends (e.g., WebGL) specific to JavaScript like TensorFlow.js. Second, we identify relevant GitHub repositories and issues related to TensorFlow.js based on keyword matching. Some candidates may be ignored due to the predefined keywords, which would introduce bias in the data construction. To mitigate such a threat, we follow the previous work [51] to carefully select effective keywords to ensure most of the relevant repositories and issues can be identified. The internal threat to validity lies in our manual labeling process. To minimize the subjectivity of researchers, two authors conducted the labeling process independently, and another arbitrator with 3-year DL development experience helps to reach an agreement through discussions. Moreover, we leveraged Cohen’s Kappa coefficient to measure the inter-rater agreement of independent labeling. The high kappa value indicates a high agreement between researchers.

8 RELATED WORK

A number of empirical studies have emerged recently on analyzing the bugs relevant to DL/ML frameworks. Thung et al. [80] first targeted ML systems (i.e., Apache Mahout, Apache Lucene, and Apache OpenNLP) and analyzed 500 bug reports. They focused on the frequencies, types, severity & impact, fixing effort & duration of these bugs. Sun et al. [75] focused on ML frameworks (i.e., ScikitLearn, Paddle, and Caffe) and manually analyzed 329 real bugs to study the bug types and bug evolution. Several studies focused on the bugs in DL frameworks and applications, which generally collected real faults from Stack Overflow and GitHub, and applied taxonomic methods for fault summarizing. Specifically, [49, 51, 53, 54, 65, 87] studied the bugs symptoms, root causes, and effects of DL applications under PC platform, which rely on popular native DL frameworks (e.g., TensorFlow, Keras, and PyTorch). [19, 55, 56] analyzed the implementation bugs of TensorFlow itself in terms of the symptom, root cause, and fix pattern. Chen et al. [13] extended to four DL frameworks (i.e., TensorFlow, PyTorch, MXNet, and DL4J), and analyzed the current testing status of DL frameworks. Moreover, there are also some empirical studies focusing on specific bug types. For example, Gu et al. [45] studied the training issues of developers in DL software. Cao et al. [8] characterized the performance bugs in DL systems. Tambon et al. [76] studied the silent bugs existed in DL frameworks. Deploying DL techniques onto mobile platforms has currently become another trend. Chen et al. [15] built a taxonomy of specific challenges that developers encounter during the deployment of DL software. They further studied the deployment faults of mobile DL applications in terms of the symptoms and fix patterns [16].

The aforementioned studies target the DL systems on the PC or mobile platforms, which are built on top of native DL frameworks (e.g., TensorFlow and TensorFlow Lite). Different from them, firstly, we target the JavaScript-based DL systems built on TensorFlow.js, which is totally different from native frameworks in terms of the implementations of DL backends and the execution environments. Secondly, previous studies analyzed the faults on a specific level (i.e., framework-level or application-level), while this study analyzes the faults over a 3-level architecture of JavaScript-based DL systems, including the web applications, 3rd-party DL libraries, and TensorFlow.js. Thirdly, different from the existing studies [15, 16] that are related to the deployment faults of DL models on mobile devices, we mainly focus on the faults related to both the deployment (e.g., model training) and deployment of DL models on multi-environments (i.e., browsers, Node.js, and cross-platform apps). Apart from the symptom and fix pattern analyzed in [16], we also classify the root cause in detail and analyze the fault distribution on the 3 levels of JavaScript-based DL system and 4 major TensorFlow.js components. We further detail the different features of fault symptoms and root causes between other DL systems [16] and JavaScript-based DL system in Section 3.

Moreover, various JavaScript-based DL frameworks have been released to enable DL tasks on browsers. To understand how well these frameworks behave in practice, Ma et al. [66] measured the performance gap of 7 JavaScript-based frameworks when running different DL tasks on Chrome. Guo et al. [46] aimed at the DL software deployment across different platforms, and investigated the performance gap when the trained models are migrated from the PC platform to mobile devices and Web browsers. Instead of focusing on the performance problems, we focus on the characteristics of faults in TensorFlow.js, 3rd-party DL libraries, and the web DL applications built on top of TensorFlow.js.

9 CONCLUSION

In this work, we conducted the first comprehensive study on faults in JavaScript-based DL systems by manually inspecting 700 related faults from 3 levels of GitHub repositories (i.e., TensorFlow.js, 3rd-party DL libraries wrapping TensorFlow.js, and web DL applications based on TensorFlow.js). We constructed taxonomies for fault symptoms, root causes, and fix patterns, respectively. Besides, we also analyzed the distribution of symptoms from the 6 stages involved in the lifecycle of JavaScript-based DL systems and analyzed the distribution of root causes based on the 3 levels in JavaScript-based DL systems and the 4 components of the TensorFlow.js. Additionally, we highlighted the different fault features between JavaScript-based DL systems and native DL systems. The symptoms, root causes, and fix patterns discovered by our study can be adopted to facilitate fault fix in JavaScript-based DL systems. Finally, we discussed the implications for different stakeholders based on our findings.

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