Temporal Analysis and Repair of Flaky Dockerfiles

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***Abstract*—Dockerfile flakiness, characterized by inconsistent build behavior without Dockerfile or project source code changes, poses significant challenges in Continuous Integration and Delivery (CI/CD) pipelines. This issue can lead to unreliable deployments and increased debugging efforts, yet it remains underexplored in current research. We conduct a systematic analysis of Dockerfile flakiness, presenting a comprehensive taxonomy of common flakiness categories, including dependency-related errors and server connectivity issues. Furthermore, we introduce FlakiDock, a tool leveraging large language models and retrieval-augmented generation techniques with dynamic analysis and an iterative feedback loop to automatically repair flaky Dockerfiles. Our evaluation shows that FlakiDock achieves a 73.55% repair accuracy, outperforming existing tools such as PARFUM by 12,581% and GPT-4-based prompting by 94.63%. These results underscore the effectiveness of FlakiDock in addressing Dockerfile flakiness and improving build reliability.**

***Index Terms*—Large Language Models, Few-shot Learning, Docker, Flakiness, Automated Program Repair**

I. Introduction

Docker[1] is a set of platform-as-a-service (PaaS) products that utilize OS-level virtualization to automate the building, deployment, and delivery of applications in environments known as containers. Docker images, created based on instructions specified in a Dockerfile, act as the blueprints for these containers. These images include all necessary components to execute an application, such as the code, runtime environment, libraries, and system tools. This approach allows developers to package their applications once and deploy them across various systems, streamlining the software deployment process. Dockerfiles play a pivotal role in the Continuous Integration and Continuous Delivery (CI/CD) pipeline, making it essential to ensure their reliability during the build stage to maintain software dependability.

Given the extensive reliance of Dockerfiles on various dependencies, packages, and configurations, ensuring their reliability becomes a critical concern. Existing academic [1]–[8] and industrial efforts mainly focus on identifying Dockerfile smell or bug patterns. Dockerfile smells refer to an indication of potential issues or violations of best practices within a Dockerfile. Static analysis studies such as [2], [7], [9], [10] offer a linter to detect smells inside Dockerfiles. While these tools pinpoint a variety of Dockerfile smells, they rely on a set of pre-defined rules, often not well-maintained [10], to detect issues. A more recent tool called PARFUM [4] takes a step further and enriches Dockerfile AST by incorporating structural information from the command lines to automatically detect and repair smells.

Despite the extensive investigations on Dockerfile smells, a notable gap exists in the current body of research: *flakiness* in Dockerfiles has not been comprehensively explored. The term flakiness has been widely used in research and industry to refer to tests with inconsistent results, alternating between passing and failing without any changes to the underlying code or environment. A *flaky test* can be considered as a bug in the test code, prone to generating unpredictable outcomes [11]. While flakiness is commonly used to illustrate non-deterministic behaviors in software testing, its scope can extend beyond this context. Similar to test flakiness [11], we define *Dockerfile flakiness* as the unpredictable behavior of the Dockerfile build process, where builds may succeed or fail overtime under identical Dockerfile context.

Existing Dockerfile-related studies [1]–[7], [9], [10] assume the reliability of the Dockerfiles and their build output over time, so that a build failure indicates the changes applied directly to the source Dockerfile. Flakiness in Dockerfiles can cause several problems during the build and deployment of the projects such as disrupting CI/CD cycles by impeding automatic builds which causes delays or wasting time and effort of developers working on pinpointing and rectifying the cause of Dockerfile build flakiness.

In this work, we examine the consistency and reliability of Dockerfile builds over time. In a longitudinal study, which spanned over a nine-month timeframe, we analyzed the build of 8,132 Dockerfiles and observed that 798 (9.81%) exhibits flakiness. Based on the observed instances of flakiness, we developed a taxonomy for characterizing Dockerfile flakiness. Our findings indicate that the most common types of flakiness are related to dependencies, web server connectivity, and security/authentication issues. Furthermore, we found that

[1] https://www.docker.com

existing techniques, such as PARFUM [4] an automated tool for repairing Dockerfile smells, can repair less than 1% of the occurrences of flakiness. To overcome the limitations of current tools, we propose a technique called FLAKIDOCK to automatically repair Dockerfile flakiness.

In this work, we make the following contributions:

- We conduct the first study to characterize Dockerfile flakiness. We develop the first taxonomy of Dockerfile flakiness by building Dockefiles and analyzing build outputs of 8,132 Dockerized projects.
- We create a dataset called FLAKE4DOCK including 798 and 7,325 flaky and non-flaky Dockerfiles. Flaky Dockerfiles are accompanied by categorization and build errors. We also provide repair information for 100 flaky Dockerfiles, specifically designed to evaluate flakiness detection and repair tasks.
- We present a technique called FLAKIDOCK that leverages both static and dynamic information from Dockerfiles to repair flakiness.
- We perform an empirical evaluation of FLAKIDOCK, assessing its effectiveness with large language models (LLMs) such as GPT-4 and analyzing the contribution of its components. Additionally, we compare FLAKIDOCK with existing automated Dockerfile repair tools.

Our results show that FLAKIDOCK achieves a 73.55% repair accuracy in resolving Dockerfile flakiness, significantly surpassing existing tools such as PARFUM [4], which only achieves a 0.58% success rate. FLAKIDOCK effectively addresses complex flakiness issues by employing static and dynamic information, similarity retrieval techniques, as well as an iterative feedback loop for refinement.

II. MOTIVATION

Docker containerization aims to deliver a consistent and portable image build process. However, in practice, the Dockerfile build process often exhibits flakiness, posing a significant challenge to achieving these goals. This inconsistency can lead to several problems, such as unreliable deployments, increased debugging efforts, and unwanted delayed software delivery. Flakiness refers to the unpredictable nature of build failures in Dockerfiles over time, where a previously error-free Dockerfile may suddenly fail to build without any changes to the file or the project source code. This issue introduces challenges in maintaining reliable and efficient workflows. Despite the significance of this problem, there is a lack of comprehensive studies specifically addressing Dockerfile flakiness, which underscores the need for further research in this area.

As an illustrative example, Listing 1 represents a flaky Dockerfile, the corresponding build failure, and a subsequent repair based on the build error. According to the build output (lines 95 to 114), using a virtual environment is required to install `pip` for the specified `alpine` base image in Dockerfile (line 1) due to the adaptation of `Python Enhancement Proposal (PEP) 668` [2], which addresses Externally Managed Environments. This specification prevents package managers such as `pip` from modifying packages in the interpreter's default environment, ensuring compatibility and reducing the risk of breaking the underlying operating system managed by external package managers. As a result of this adaptation, this Dockerfile fails to build, whereas previous builds prior to this adaptation were all successful. Thus, the solution here is to create and activate a virtual environment, as shown in the Dockerfile context (lines 11 and 12).

Existing Dockerfile static and dynamic analysis approaches assume the determinism of the Dockerfile behavior. Static analysis techniques [2], [4], [7], [9], [10] consider Dockerfile context to provide a set of smell patterns coherent with Docker best practices [3]. The only Dynamic analysis approach [6], primarily focuses on the Dockerfile build output as an invariant to introduce and expand the error patterns. While adhering to best practices is essential to mitigate errors and vulnerabilities in Dockerfiles and in some cases to prevent potential failures from happening, we argue that this alone is insufficient to address flakiness. For example, existing tools such as HadoLint [9] recommend pinning the exact version of the base image (e.g., rule: DL3006) or dependencies (e.g., rules: DL3007, DL3008, DL3013, DL3016, DL3018) to prevent errors caused by their internal changes. This practice can be applied to Listing 1 by using old or outdated `alpine` images as a solution. However, it does not provide a viable solution for the problem; applying such rules without considering the static and dynamic nature of Dockerfiles can introduce other types of flakiness, such as outdatedness and compatibility issues in the future.

Build Output

```
1   ...
87  > [5/5] RUN pip3 install -r requirements.txt:
88  error: externally-managed-environment
95      If the package in question is not packaged already (
          and
96      hence installable via "apk add py3-somepackage"),
          please
97      consider installing it inside a virtual environment,
           e.g.:
98      ...
114 hint: See PEP 668 for the detailed specification.
115 ERROR: process "/bin/sh -c pip3 install -r requirements.
        txt" did not complete successfully: exit code: 1
```

Repaired Dockerfile

```
1  FROM alpine:latest
2  RUN apk add --update python3 py3-pip git tcpdump
3  RUN git clone https://github.com/649/Memcrashed-DDoS-
       Exploit.git Memcrashed
4  WORKDIR Memcrashed
5  ...
10 - RUN pip3 install -r requirements.txt
11 + RUN python3 -m venv venv
12 + RUN . venv/bin/activate && pip install -r requirements
       .txt
```

[2] https://peps.python.org/pep-0668/

[3] https://docs.docker.com/build/building/best-practices/

```
ENTRYPOINT ["python3", "Memcrashed.py"]
```

Listing 1: Base Image Internal Change

Listing 2 demonstrates another flaky Dockerfile that clings to the version pinning rule for the base image. As depicted in the Dockerfile (line 1), although the base image version is explicitly mentioned, inconsistent behavior is plausible due to using a relatively old base image. This flakiness is evident inside the build output (line 132), where the expression `pre_go17` is located. The error stems from the compatibility issue of a stale `GOLANG` base image, i.e., older than 1.17, with existing dependencies utilized in the Dockerfile (line 8), failing the compilation and build of the project. Accordingly, a base image version upgrade is required (line 2). Furthermore, updated `GOLANG` images require a different approach for handling executables (lines 3 and 4) due to the adoption of new techniques.

Build Output

```
1   ...
130 > [build-env 4/4] RUN cd /src && go build -ldflags "-
        linkmode external -extldflags -static" -o proxy:
132 /go/src/golang.org/x/net/context/pre_go17.go:47:2:
        background redeclared in this block
133 ...
153 ERROR: process "/bin/sh -c cd /src && go build -ldflags
        \"-linkmode external -extldflags -static\" -o proxy
        " did not complete successfully: exit code: 2
```

Repaired Dockerfile

```
1  - FROM golang:1.9.1 AS build-env
2  + FROM golang:1.22 AS build-env
3  + WORKDIR /src
4  + RUN go mod init my_module
5  RUN go get -d -v github.com/armon/go-socks5
6  ...
8  RUN cd /src && go build -ldflags "-linkmode external -
       extldflags -static" -o proxy
9  # final stage
10 FROM scratch
11 WORKDIR /app
12 ...
15 CMD ["./proxy"]
```

Listing 2: Compatibility Issues With Stale Base Image

Dockerfiles rely on various elements such as operating systems, packages, environments, commands, and project source code, which can result in different forms of flakiness. Examples in Listing 1 and Listing 2 illustrate that understanding and resolving such flaky behavior requires analyzing both the static context (Dockerfile) and dynamic context (build output) along with its temporal changes. Currently, no existing study examines flakiness in Docker builds. To characterize the extent and causes of Docker build flakiness, we first conduct a longitudinal study of 18,055 Dockerized repositories over a period of nine months (section III). Second, we propose FLAKIDOCK an automated approach for repairing Dockerfile flakiness utilizing both static and dynamic information (section IV).

III. CHARACTERIZATION OF DOCKERFILE FLAKINESS

In this section, we delve into our empirical investigation of Dockerfile flakiness. We begin by detailing our data collection method and the setup for analyzing Dockerized projects for flaky behavior. Subsequently, we address two important research questions:

- **RQ1**: How prevalent is flakiness in Dockerfiles?
- **RQ2**: What are the categories of Dockerfile flakiness?

The entire analysis, including project checkouts and Dockerfile builds, is performed on an infrastructure consisting of 4 Intel(R) Xeon(R) CPU 2.50GHz machines with 62 GB RAM each.

A. Data Collection

For our study, we started with the `Shipwright` dataset [6], which contains 20,526 Docker projects with ten or more stars from GitHub repositories. The dataset includes Docker projects created up to June 2020 and focuses exclusively on projects with a single Dockerfile located in the root directory. This approach aims to facilitate analysis and mitigate challenges associated with multiple Dockerfiles within a repository.

Initially, we attempted to clone the most up-to-date version of all the repositories from the `Shipwright` dataset. However, some repositories were no longer publicly accessible, had been removed from GitHub, or no longer contained the root Dockerfiles. Consequently, our final dataset comprised 18,055 repositories that met the criteria and were available for analysis.

In our study, we analyze Dockerfiles along with their build outputs, which we generate by building the Dockerfiles within our infrastructure systems. Given that some Docker projects can be time-consuming to build, we set a 30-minute build timeout for each repository. This resulted in 93% of builds completing without a timeout. To ensure the reliability and efficiency of our large-scale Docker build system, we use the `docker build` command with the `--no-cache` option to eliminate failures stemming from cached Docker data. Additionally, we develop a systematic Docker cleaning technique to prevent environmental and internal errors, ensuring a fresh Docker environment. To enhance time efficiency and prevent internal errors, we clean the Docker system after every four consecutive builds—a frequency determined through trial and error. The cleaning process involves removing all the cache, images, and any other peripheral leftover data during the builds alongside uninstalling and reinstalling Docker with a steady version to prevent working with a corrupted Docker system. This pipeline ensures the freshness of the Docker system throughout the builds. Using this approach, we stored 32 rounds of builds for the initial Docker projects, capturing Dockerfile build outputs in our infrastructure machines from April 2023 to December 2023.

B. Flakiness Extraction

The detection of flakiness within test suites has been extensively explored in the prior work [12], [13]. These efforts revolve around static and dynamic test code analysis, pattern recognition, rerunning tests multiple times, and checking code changes through times in repositories. Considering the complexity and variety of Dockerfile commands, external dependencies, and configurations, directly checking the Dockerfile context for flakiness detection would require an extensive endeavor. Furthermore, due to the dynamic nature of Dockerfiles, characterizing flakiness utilizing only the static analysis approaches would fail to address all aspects.

Filtering Phase. To uncover flakiness, we initiated an *in-context* Docker build for all the Dockerized GitHub projects in our dataset, of which (8,132 (45.04%)) were built successfully, and (9,923 (54.96%)) failed during the build procedure. We consider only the successful ones as valid candidates for our flakiness analysis due to their initial stability. Over nine months, we rebuilt the candidate projects 32 times (3.5 times per month on average). The reason for conducting builds over an extended timeframe was two-fold. First, building Dockerfiles is a time-consuming operation. The average time to build a single Dockerfile in our dataset is around eight minutes. Despite distributing our candidates across four different machines with similar operating systems and configurations and employing multiprocessing on each machine to enhance build speed, some degree of delay was unavoidable. Second, we expected that such an extended timespan could allow us to observe and investigate more fluctuations in project stability thoroughly.

Pre-Processsing Phase. The length of a Dockerfile build output varies based on the execution commands used, ranging from a few lines to tens of thousands, detailing the progress of each execution step. Therefore, diagnosing and extracting the important failure parts for further studies is essential. While extracting standard error logs can aid in understanding the root causes of issues, our extensive analysis revealed its inadequacy in capturing valuable insights in cases in which the error context is too long or the point of failure is far from the manifestation of error. To address such challenges, we implemented a rule-based pre-processing approach to extract error-related context from raw build outputs. In our method, we divide the build output into stages, each corresponding to an execution line in the Dockerfile. We examine each stage, capturing lines with error-related expressions alongside their adjacent lines with the same execution time to gather additional information about the captured errors.

C. Flakiness Categorization

Providing a taxonomy of Dockerfile flakiness serves as a vital step toward unraveling inconsistencies and complexities that come with flak Dockerfiles, thereby aiding in the identification and mitigation of the challenges developers face in practice. To achieve this, first, we use similarity-checking to remove duplicates or identical errors within each Dockerfile's build outputs. Afterward, we perform an extensive study on pre-processed build outputs, leveraging LLMs to interpret and summarize the results. Furthermore, we utilize manual analysis to correct issues stemming from LLM misunderstandings.

Clustering Phase. During the rebuild period, we encountered 12,964 failing build outputs while building the candidate projects. To streamline our analysis and minimize redundancy within Dockerfile build outputs, we conduct a clustering process using sentence similarity assessment within each project. To identify unique build errors in a single project, we measure the cosine similarity between the build output embeddings, extracted from the sentence transformer: `all-mpnet-base-v2` [4] which is trained over 1 billion sentences in different domains. Using the similarity scores, we cluster them into distinct groups. In our clustering approach, each new build output is evaluated for its similarity to existing clusters. Based on the average similarity with all current clusters, we decide whether to incorporate it into an existing cluster or create a new one. We apply this clustering method within individual projects rather than across all projects due to the intricate nature of Dockerfiles and their build outputs, which complicates the accurate clustering of errors when applied globally. To enhance accuracy, we use pre-processed build outputs for similarity comparison rather than raw outputs. This method resulted in an 87% reduction in failing build outputs, leaving 1,684 remaining, which in turn simplifies subsequent analysis steps.

Labeling Phase. We employed GPT-3.5 to extract error descriptions encountered during builds. Given the Dockerfile context alongside the corresponding build error, the model is prompted to extract a list of contributing factors to the error and an initial label indicating the category of error. We then used these build errors, alongside the information generated by the language model, to construct a taxonomy of Dockerfile build flakiness. Our objective was to create a comprehensive hierarchical classification that captures the diverse and dynamic behavior of Dockerfiles. To achieve this, a brainstorming session among authors was conducted to design a pipeline for analyzing context and refining the labels suggested by the language model. Two authors reviewed and resolved discrepancies in the labels generated by the model, based on the Dockerfiles and build errors. Any differences in interpretation were discussed among the authors to reach a consensus. This systematic analysis resulted in the generation of category hierarchies, requiring approximately 220 person-hours of effort.

D. RQ1: Prevalence of Dockerfile Flakiness

While categorizing, we selectively omitted failures stemming from our infrastructure, Docker servers, and project source code issues to hone in on genuine instances of Dockerfile flakiness. Infrastructure failures accounted for 38 of the 1,684 builds, highlighting the effectiveness of our systematic Docker cleaning method in ensuring reliability. Issues stemming from Docker servers and project-specific errors accounted for 431 and 241 failures, respectively, and were also excluded from the flaky build outputs.

[4]https://huggingface.co/sentence-transformers/all-mpnet-base-v2

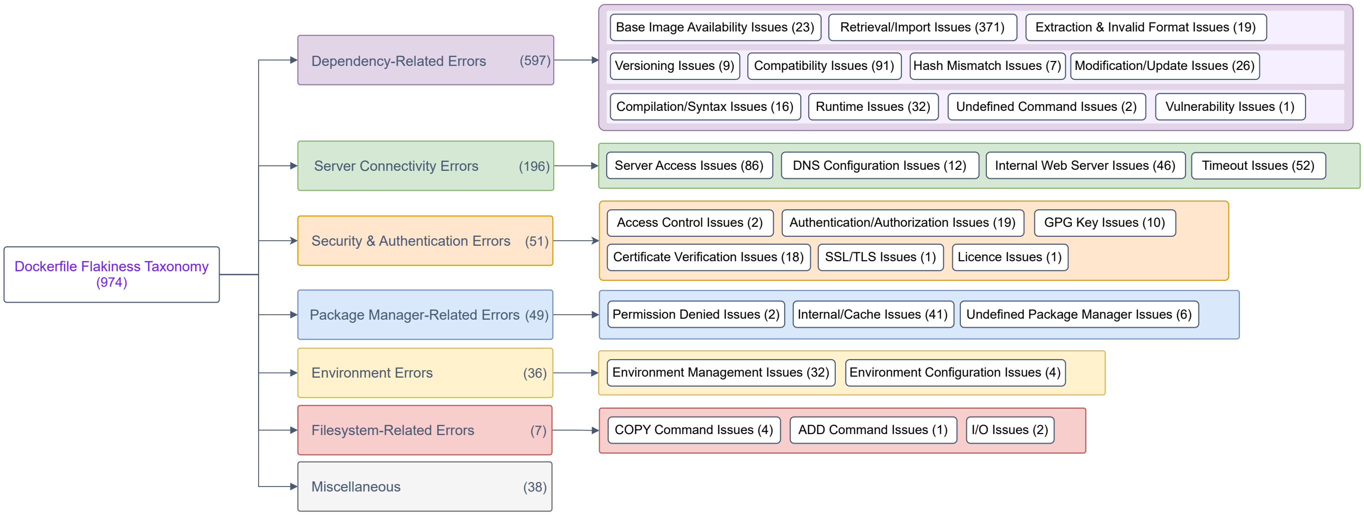

Fig. 1: Dockerfile Flakiness Taxonomy

After filtering out these non-flaky failures, we were left with 974 build outputs originating from **798 (9.81%)** Dockerfiles out of 8,132 candidate projects, as some Dockerfiles exhibited multiple distinct flaky behaviors throughout our longitudinal analysis. This number would likely be even higher in real-world scenarios, as our candidate Dockerfiles were sourced from high-quality projects.

This percentage is significant when compared to the prevalence of flaky tests in practice. According to an empirical analysis on Flaky tests [11], 4.56% of all test failures across test executions at Google's continuous integration (CI) system, named TAP, were reported to be due to flaky tests during a 15-month window. Another study by Microsoft [14] reported that 4.6% of individual test cases monitored over a month were flaky. Our finding of 9.81% flaky Dockerfiles aligns with the prevalence of flaky tests in other large-scale systems, highlighting the importance of investigating and developing tools to address Dockerfile flakiness.

E. RQ2: Taxonomy of Dockerfile Flakiness

Figure 1 illustrates our hierarchically structured taxonomy of Dockerfile flakiness. The left side shows the main categories of flakiness, while the right side lists the associated subcategories. The numbers within each box indicate the frequency of occurrences. The rest of this section provides an overview of the primary categories of flakiness identified in our taxonomy. Detailed information, including examples for each category and sub-category, can be found in our replication package [15].

Dependency-Related Errors (DEP). This is the most prevalent category, accounting for 61.29% of all errors. It encompasses 11 subcategories of errors that occur during the retrieval, installation, or post-installation operations of dependencies specified in Dockerfiles. These three steps of errors are shown in the first, second, and third rows of dependency-related error subcategories in Figure 1. We define a *dependency* as a Base image or any external software package or library explicitly mentioned in the Dockerfile.

Availability and Retrieval Errors: These errors happen when previously available dependencies are not found or cannot be accessed (e.g. RETRIEVAL/IMPORT ISSUES), or decompressed due to EXTRACTION & INVALID FORMAT ISSUES. As an example of BASE IMAGE AVAILABILITY ISSUES, one of the Docker projects we studied, `Mistserver`[5], uses `FROM phusion/baseimage:master`, leading to a failure because this specific version of the image is currently unavailable.

Installation Errors: During the installation phase, flaky errors can occur due to different reasons including VERSIONING ISSUES or COMPATIBILITY ISSUES, where specific dependencies with altered versions or configurations may conflict or be incompatible with one another, causing the build process to fail. These errors can also involve HASH MISMATCH ISSUES and MODIFICATION/UPDATE ISSUES, where changes in dependencies lead to inconsistencies. For instance, consider a scenario where package `p1` requires package `p2` with a version greater than or equal to `v2` to be installed properly, but the existing `p2` version is older than `v2`.

Post-Installation Errors: After installation, flakiness can arise from the dependencies themselves, such as VULNERABILITY ISSUES, COMPILATION/SYNTAX ISSUES, or RUNTIME ISSUES. Additionally, improper installations can lead to UNDEFINED COMMAND ISSUES in the Dockerfile, resulting in build failures. As an example, we have observed flakiness in a Dockerfile using `Symphony`—a PHP framework—which is known to have vulnerability issues within its CodeExtension filters [6], and using those filters may cause flakiness.

Server Connectivity Errors (CON). This category is the

[5]https://github.com/R0GGER/mistserver/blob/0fe477e4fb35755ad0852d46c91ed42e5b18e990/Dockerfile

[6]https://github.com/symfony/symfony/security/advisories/GHSA-q847-2q57-wmr3

second most prevalent among all the categories comprising 20.12% of the errors. These errors occur when there are issues while connecting to previously stable external servers. SERVER ACCESS ISSUES arise when the Dockerfile cannot reach the target server due to invalid URLs or server downtimes. TIMEOUT ISSUES occur when connections to servers take too long to establish or complete, often caused by overloaded servers or the massive size of transferred data. INTERNAL WEB SERVER ISSUES refer to errors within the accessed server, typically denoted with `HTTP` status codes `500s`. DNS CONFIGURATION ISSUES occur when the Dockerfile cannot resolve the server's domain name, leading to failed connections.

Security and Authentication Errors (SEC). This category contains errors related to changes or deprecation of previous security protocols and authentication processes, making up 5.24% of the total errors. ACCESS CONTROL ISSUES arise when the Dockerfile does not have the necessary permissions to access required internal resources caused by the base image's internal changes. AUTHENTICATION/AUTHORIZATION ISSUES manifest when there are problems verifying the identity of the user or service, which can result from incorrect or expired credentials or misconfigured authentication/authorization services. SSL/TLS ISSUES encompass a range of problems related to the secure transmission of data, including protocol mismatches and outdated cryptographic algorithms. GPG KEY ISSUES arise when there are problems with the cryptographic keys used to verify the integrity and authenticity of downloaded items, which can prevent the successful retrieval and installation of necessary dependencies. Lastly, LICENCE ISSUES occur when the Dockerfile attempts to use software with new licensing restrictions.

Package Manager-Related Errors (PMG). Package manager-related errors constitute 5% of the flakiness instances and refer to the changes applied to the package manager configuration during the build process. The most common subcategory of this class is INTERNAL/CACHE ISSUES with 4.2% of total flakiness. These errors arise from inconsistency or unreliability in the package manager's internal system during its installation or utilization, resulting in failed operations. As an example, the command: `RUN npm install --registry=r` where `r` is no longer a reliable registry for `npm` would cause an internal issue within the package manager. Another subcategory is PERMISSION-DENIED ISSUES, which occur when the Dockerfile does not have the necessary permissions to interact with the package manager to install or update packages. This sort of error can happen due to permission changes within the base images or other infrastructures within the Dockerfile. Lastly, UNDEFINED PACKAGE MANAGER ISSUES encompass errors caused by improper installation of package managers, resulting in a corrupted package manager within the system.

Environment Errors (ENV). ENVIRONMENT MANAGEMENT ISSUES and ENVIRONMENT CONFIGURATION ISSUES fall into this category, representing 3.7% of the errors corresponding to interactions with virtual environments. These environment errors often arise from changes made to the base images or other underlying infrastructures specified in the Dockerfile. Such changes enforce developers to strictly adhere to the new rules to minimize vulnerabilities and enhance the system's robustness. A detailed example of this type of error is illustrated in Listing 2 where an externally managed environment is required to alleviate the risk of disrupting the OS package management system.

Filesystem-Related Errors (FS). This category, representing the smallest portion of our study on Dockerfile flakiness, accounts for less than 1% of the total failures. These errors include challenges in handling file system operations within Dockerfiles such as COPY and ADD command errors, and I/O issues generally stemming from the base image internal file system updates.

Miscellaneous. During our analysis of Flaky Dockerfiles and their build outputs, we categorized 3.9% of the instances of flakiness as Miscellaneous. This group includes builds with highly complex errors or those executed in silent mode without informative execution logs, making it challenging to pinpoint the issues and classify them.

IV. FLAKIDOCK

As demonstrated in Section III, Dockerfile flakiness presents various complex symptoms in the build output. Leveraging the ability of LLMs to solve programming tasks across different domains [16]–[26], and the effectiveness of retrieval-augmented generation (RAG) techniques [27]–[29], we propose FLAKIDOCK, an automated approach using LLMs to repair Dockerfile flakiness. Our insight is that by providing LLMs with demonstrations containing *static* (Dockerfile) and *dynamic* (build outputs) information, along with repair patches from similar examples, the model can resolve flakiness in new Dockerfiles. Figure 2 provides an overview of our approach.

A. Demonstration Dataset Creation

We first need to create a demonstration dataset for our approach. To this end, we randomly sample 100 Dockerfiles from our dataset of 798 flaky Dockerfiles and manually provide repairs for them. To provide a robust demonstration of error categories in our repair dataset, we maintain a minimum of 30% coverage for categories that exhibit less than 5% distribution of Dockerfile flakiness, such as PMG, ENV, and FS categories. However, within each category, we randomly sample the Dockerfiles. If flakiness is not observed in a Dockerfile at the time of analysis, we randomly select another Dockerfile from our dataset for repair. We repair flaky Dockerfiles using static (Dockerfile), dynamic (build outputs), and extracted categorization information. If a repair solution is not apparent using this information, similar to `Shipwright` [6], we perform a human inspection of the top five web pages from search engine results, based on querying the error keywords, to find potential solutions.

Repairing Dockerfile flakiness is a complex and time-consuming task because it involves several intricate steps.

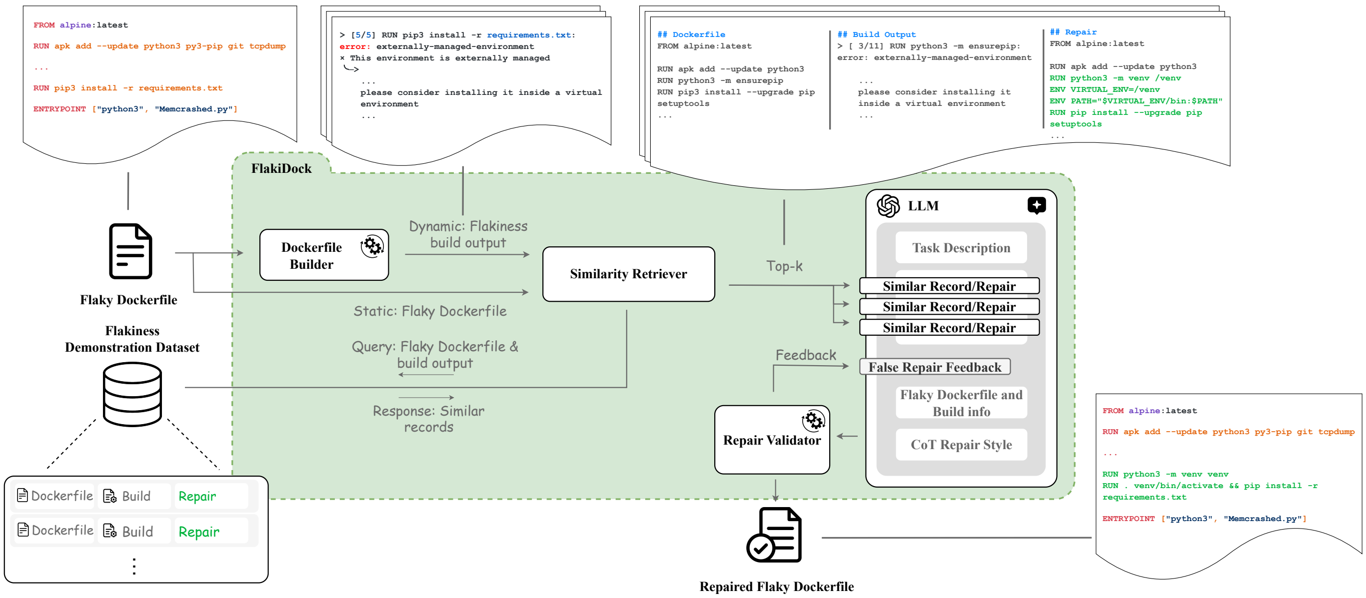

Fig. 2: An Overview of our proposed approach: FLAKIDOCK

First, one must understand the execution steps of the Dockerfile and the overall workings of the project. Then, the specific problem must be pinpointed, and finally, the suggested repair should be verified. We verified the suggested repairs using the `Docker build` command with the `--no-cache` option. To confirm the reliability of the proposed repairs, we test them as many times as the longest consecutive failure streak observed in our build history. Additionally, if a Dockerfile has exhibited different types of flakiness throughout the flakiness extraction phase III-B, we only consider the types of flakiness that can be observed during the repair step. Some instances of flakiness may be difficult to reproduce or may have been resolved due to external dependency updates.

Table I shows the distribution of repairs per category. We spent approximately 115 person-hours generating 100 Dockerfile repairs. Notably, the low occurrence in the server connectivity category is due to the fact that most errors in this category are temporary server issues resolved by the time of analysis.

Category	DEP	CON	SEC	PMG	ENV	FS	Total
Repairs	63	6	9	8	10	4	100

TABLE I: Number of Repairs by Category

In our demonstration dataset, a Dockerfile is denoted with d, and every record is defined as tuple $(S_d, D_d, C_d, R_d, I_d)$ containing several elements of the Flaky Dockerfile. The S_d component contains the static information, i.e., Dockerfile context. The identifier D_d indicates the pre-processed build output of the flaky Dockerfile, which is referred to as the dynamic information. C_d defines the category label for the current Dockerfile based on the taxonomy illustrated in Fig 1. Elements R_d and I_d denote the repair patch proposed for the Dockerfile and the number of iterations required for the repair to be tested to ensure its correctness, respectively. In case more than one repair is offered for a flaky Dockerfile, R_d and I_d form a list of values.

B. Dockerfile Building

The first step of FLAKIDOCK is to build a given flaky Dockerfile to elicit the failing build output. The purpose of this building stage is two-fold. First, based on the build output extracted, we classify the Dockerfile as *non-flaky* if no failure is detected over n iterations. Conversely, if a failure occurs, we identify it as flaky behavior and proceed to address it. n is determined based on our demonstration dataset, ensuring it is at least greater than or equal to 90% of I_d in our dataset, which corresponds to a minimum of two iterations. This approach is designed to encompass most flaky behaviors while optimizing time efficiency.

C. Static and Dynamic Similarity Retrieval Phase

Few-shot learning has shown remarkable efficacy when applied to LLMs [30]. While randomly selected examples can enhance performance, recent studies [27], [28] indicate that choosing examples based on their similarity to the input context can lead to even more significant improvements.

In the domain of Dockerfiles, we argue that both static and dynamic information are required to resolve flakiness. To this end, upon completing the build phase, the captured information along with the original Dockerfile is used to retrieve similar examples from the flakiness demonstration dataset. Formally, the input given to the similarity retriever is a tuple (S_q, D_q) where S_q and D_q represent the static (Dockerfile) and dynamic (build output) features respectively. Then, the retriever uses the pre-processing technique elaborated in Section III-B to extract error-related features from the build output.

The combination of S_q and D_q is the input query Q to the demonstration dataset. Given that our input encompasses both code segments and natural language descriptions, we utilize embedding-based search via `text-embedding-ada-002` embedding from OpenAI [31]. This model is pretrained on extensive datasets across various domains, can process up to 8,191 tokens, and outputs a vector of 1,536 dimensions. Using this transformer model, we compare Q with the records in our demonstration dataset (only S_e and D_e) by applying cosine similarity to retrieve the top-3 (S_e, D_e) combinations that are closest in embedded space to the input query, along with the corresponding repair snippets R_e for those retrieved Dockerfiles.

D. Repair Generation

This step contains the prompt design for Dockerfile flakiness repair generation. As shown in Figure 2, the prompt comprises a natural language task description, the flaky Dockerfile along with its build output, and a Chain-of-Thoughts (CoT) explanation to guide the model through the repair process. The prompt is then augmented with demonstration examples retrieved from the similarity retriever. Each example e consists of a triple: (S_e, D_e, R_e) represents the Dockerfile, build output, and repair/repairs suggested for the flaky Dockerfile.

If previous attempts have generated incorrect repairs for the current flaky Dockerfile, a feedback message is included in the prompt as false demonstrations to help the model avoid similar mistakes. It encompasses the history of proposed repairs, each recorded as a false repair: $fr = (R_{fr}, D_{fr})$. Here, R_{fr} element denotes the false repaired Dockerfile, and D_{fr} shows the pre-processed build output corresponding to the false repair.

E. Repair Validation

The validation phase serves as a heuristic approach to determine whether the repair suggested by the LLM is effective. The structure of this stage is elaborated in Algorithm 1. In the beginning, The repaired Dockerfile is built n times, and build outputs are captured, similar to the Dockerfile builder module described in IV-B. If all build outputs are successful, the validator confirms the repair's correctness and finalizes it as a result. Otherwise, it identifies the most common error type observed from the feedback generated thus far. The feedback comparison relies on the similarity of build outputs, assessed using sentence transformation models.

Through a manual evaluation of our demonstration Dockerfiles, we found that after three incorrect repair attempts with the same error, LLMs tend to continue proposing flawed repairs due to hallucination or model deficiency in addressing that specific problem even with the augmented information provided. Therefore, we establish a threshold, denoted by T, set at a constant value of 3, to determine the stopping point for repair generation. If a specific error type appears T times, we interpret it as an indication of the model's hallucination or inability to resolve the issue, resulting in the output `Unable to resolve!`. If no error occurs three or more times, new feedback—consisting of the false repair and its build output—is created, appended to the existing feedback list, and then incorporated into the LLM's prompt to generate a new Dockerfile flakiness repair.

Algorithm 1 Repair Validation

```
Input:
  r_d ← Repaired Dockerfile,
  f_d ← Previous feedbacks
  it ← n
  T ← 3                                                    ▷ Threshold
Output: Repair / Feedback / "Unable to Resolve!"
buildOutput ← getBuildResults(r_d, it)
if allSuccessful(buildOutput) then
    Return: r_d                                            ▷ Repair
else
    failures ← countSimilarFailures(buildOutput, f_d)
    if failures ≥ T then
        Return: "Unable to resolve!"
    else
        f_d ← appendNewFeedback(r_d, buildOutput)
        Return: f_d                                        ▷ Feedback
    end if
end if
```

V. Evaluation

To assess the effectiveness of FlakiDock we address the following research question:

- **RQ3**: How effective is FlakiDock and how does it compare to state-of-the-art techniques?

A. Implementation

FlakiDock is developed in Python. For running our experiments, we use GPT-4 model `gpt-4-0613` as our LLM. For all experiments, we set the temperature parameter to 0 to ensure deterministic and well-defined answers from the LLM. Chroma DB, which is an open-source embedding database[7], serves our need for vector similarity search. For embedding generation, we use `text-embedding-ada-002` from OpenAI [31]. The temporal analysis, including project checkouts and Dockerfile builds, is performed on an infrastructure consisting of 4 Intel(R) Xeon(R) CPU 2.50GHz machines with 62 GB RAM each. For repair, we use 8 AWS machines of type t2.2xlarge, each with 8 CPUs and 32 GB RAM.

B. Experimental Setup

We initially identified 798 Dockerfiles exhibiting flaky behavior. Out of these, 100 Dockerfiles were reserved for *repair demonstration* purposes. This left us with 698 Dockerfiles showing signs of flakiness during our nine-month longitudinal study. However, for the evaluation phase, we focused only on those Dockerfiles that continued to exhibit flakiness at the time of evaluation. Consequently, we evaluated FlakiDock on 344 Dockerfiles, as some causes of flakiness had been resolved over time.

[7]https://www.trychroma.com/

TABLE II: Results for Dockerfile Flakiness Repair

Tool and Strategy	DEP	CON	SEC	PMG	ENV	FS	Total
PARFUM	0/280 (0%)	1/9 (11.11%)	0/16 (0%)	1/16 (6.25%)	0/22 (0%)	0/1 (0%)	2/344 (0.58%)
GPT-4 Dockerfile	13/280 (4.64%)	2/9 (22.22%)	1/16 (6.25%)	4/16 (25%)	1/22 (4.55%)	0/1 (0%)	21/344 (6.10%)
GPT-4 Dockerfile & build output	105/280 (37.50%)	**4/9 (44.44%)**	2/16 (12.50%)	6/16 (37.50%)	13/22 (59.09%)	0/1 (0%)	130/344 (37.79%)
FLAKIDOCK (w/o feedback loop)	190/280 (67.86%)	2/9 (22.22%)	1/16 (6.25%)	6/16 (37.50%)	**18/22 (81.82%)**	0/1 (0%)	217/344 (63.08%)
FLAKIDOCK (w feedback loop)	**216/280 (77.14%)**	**4/9 (44.44%)**	**6/16 (37.50%)**	**9/16 (56.25%)**	**18/22 (81.82%)**	0/1 (0%)	**253/344 (73.55%)**

C. Baselines

We compare FLAKIDOCK with PARFUM [4] and LLM-only prompting to repair Dockerfile flakiness. We chose PARFUM as it is a recent work offering automated repairs for Dockerfile smells. In contrast, other techniques, such as `Shipwright` [6], Hadolint [9], and Binnacle [2] focus on detecting error patterns or smells and require manual intervention for their operation. For GPT-4 Dockerfile Only, we invoke the GPT-4 model to generate repairs based solely on the Dockerfile content. Following that, we include build output to provide more context for the LLM to generate repair.

We measure the effectiveness using the *repair accuracy* metric, which represents the percentage of genuine repairs produced. A proposed Dockerfile is considered a genuine repair if its build is successful across n builds.

D. Results

Table II shows *repair accuracy* for each method across various flakiness categories. Overall, FLAKIDOCK (With Feedback Loop) achieves the highest success rate of 73.55%, underscoring the advantage of iterative refinement in enhancing repair accuracy. PARFUM exhibits the lowest accuracy of 0.58%, indicating its limited ability to address complex errors. GPT-4 Dockerfile Only slightly improves this with a 6.10% success rate, while GPT-4 Dockerfile & Build Output significantly increases effectiveness to 37.79%, highlighting the value of additional context from build outputs.

Next, we present the results per error category.

Dependency-Related Errors (DEP). The repair accuracy for DEP errors with PARFUM is 0% because it fails to handle the complex and dynamic nature of dependencies effectively. It relies on predefined rules that do not accommodate the diverse issues that arise from dependency changes, such as version mismatches and missing libraries. On the other hand, GPT-4 Dockerfile Only achieves a 4.64% accuracy. GPT-4 Dockerfile & Build Output increases the success rate to 37.50%, demonstrating the value of incorporating build output information to provide context for the LLM to identify and resolve dependency issues more effectively. Without a feedback loop, FLAKIDOCK achieves a 67.86% repair accuracy, significantly outperforming the other methods by utilizing both static and dynamic information. With the inclusion of the feedback loop, FLAKIDOCK achieves the highest accuracy of 77.14%, highlighting the advantage of iterative refinement.

Server Connectivity Errors (CON). PARFUM manages a success rate of 11.11% for this error category. GPT-4 Dockerfile Only achieves a 22.22% success rate, providing moderate improvement over PARFUM by utilizing LLMs to interpret server connectivity issues directly from the Dockerfile content. GPT-4 Dockerfile & Build Output improves the success rate to 44.44%, as the inclusion of build output provides additional context, allowing the LLM to understand the specific nature of server connectivity errors more effectively. FLAKIDOCK without the feedback loop maintains the success rate at 22.22%, suggesting that the iterative feedback process is crucial for improving performance in this category. Finally, with the feedback loop, FLAKIDOCK achieves a 44.44% success rate, comparable to the best LLM-based method.

Security & Authentication Errors (SEC). PARFUM is unable to repair any issues as shown by a 0% repair accuracy. This highlights its inability to tackle the complexity of security and authentication problems, which often require more nuanced approaches than static rules can provide. GPT-4 Dockerfile only achieves a 6.25% success rate, showing a slight improvement by applying general LLM capabilities to security-related fixes, although its effectiveness is still limited due to the lack of detailed context. GPT-4 Dockerfile & Build Output sees a marginal increase in success to 12.50%, indicating some benefit from using additional build information to understand the security issues better. Furthermore, without a feedback loop, FLAKIDOCK remains at a 6.25% success rate, indicating that the iterative feedback process is essential for tackling these complex issues effectively. With the feedback loop incorporated, FLAKIDOCK achieves the highest repair accuracy of 37.50%.

Package Manager-Related Errors (PMG). PARFUM achieves a success rate of 6.25%, indicating a limited capacity to handle these flakiness category. GPT-4 Dockerfile Only performs better, with a 25% success rate. This improvement is due to the LLM's general knowledge of package management, which enables it to address some common package-related issues based on Dockerfile content. GPT-4 Dockerfile & Build Output further improves the success rate to 37.50% by leveraging build output data to provide a clearer understanding of package manager-related problems. FLAKIDOCK without a feedback loop maintains this 37.50% success rate. However, when the feedback loop is incorporated, the highest accuracy achieved is 56.25

Environment Errors (ENV). PARFUM fails to address any Environment Errors, resulting in a 0% success rate. We hypothesize that a static rule-based approach is inadequate for managing dynamic environmental issues, such as configuration changes and external environment dependencies. GPT-4

Dockerfile achieves a 4.55% success rate, reflecting a minimal ability to handle environmental factors due to its reliance solely on Dockerfile content without additional context. GPT-4 Dockerfile & Build Output significantly improves the success rate to 59.09%, benefiting from the extra context provided by build output data, which helps the LLM understand and resolve environmental errors more effectively. FLAKIDOCK achieves an 81.82% success rate even without a feedback loop, demonstrating its strong performance in addressing environmental errors. However, incorporating a feedback loop does not provide additional improvement.

Filesystem-Related Errors (FS). For this flakiness category, all methods, including FLAKIDOCK, fail to fix any flakiness. This consistent failure indicates that current techniques are inadequate in addressing the unique challenges posed by these errors.

VI. THREATS TO VALIDITY

Choice of Subjects. The choice of Dockerfiles for our study can inherently introduce a bias, potentially influencing the results of our research. To address this, we employed a dataset from a prior study [6], encompassing 8132 Dockerfiles. However, the dataset includes Dockerfiles from repositories with ten or more stars, which one might find in popular GitHub repositories, addressing the generalizability of our findings to a broader range of Dockerfiles.

Duration of the Study. The duration of our study could potentially influence our findings, especially with respect to detecting Dockerfile flakiness and temporal failures. To address this, we conducted our study over a nine-month period. This allowed us to observe the Dockerfiles over a significant period, during which updates and changes are likely to occur, potentially affecting their behavior. This extended period provided us with sufficient data to identify non-deterministic behaviors and temporal inconsistencies effectively.

Host Operating System. The choice of operating system for Docker can affect the results. We used a stable version of Redhat 9 to ensure consistency, but this may limit the generalizability to other systems. Different Linux distributions, or versions, might show varying flakiness due to differences in package management and system libraries. Non-Linux hosts such as Windows or MacOS could exhibit different flakiness not captured in our study. By focusing on Redhat, we minimized environmental variability, isolating Dockerfile-specific flakiness. Future research could explore Dockerfile flakiness across diverse operating systems and versions.

Repair Construction Bias. As we generate the repair dataset, we might be biased in providing the repairs in a way that helps with other repairs. This bias could stem from the tendency to create repair patterns that are more easily generalizable, potentially overlooking unique or less common solutions. To alleviate this bias, we used repairs found from existing knowledge-sharing websites such as Stack Overflow, GitHub discussions, and the official Docker website.

VII. RELATED WORK

Test Flakiness. There is a wide array of techniques that have been proposed focusing on characterizing, detecting, and repairing flaky tests [11]–[13], [32], [33]. Continuous integration research such as [34] has a strong overlap with test flakiness literature, evaluating the prevalence and impacts of test flakiness in systems that involve test executions. Flaky tests are also a concern in user interface testing [35]. We refer to a recent survey for a more comprehensive discussion on flaky tests [36]. In contrast, we are the first to examine flakiness from the perspective of Dockerfiles.

Studies on Dockerfiles. In Sections I and II, we presented the most recent works on Dockerfile analysis [1]–[10]. FLAKIDOCK differentiates itself from existing Dockerfile smell detection tools [2], [7], [9], [10] and repair tools such as [4] by not only addressing static issues within Dockerfiles but also targeting the dynamic errors caused by the flakiness of Dockerfiles. Unlike existing tools that primarily rely on predefined static analysis or require manual interventions while analyzing dynamic information [6], FLAKIDOCK uses LLMs and retrieval-augmented techniques, automatically analyzing both static and dynamic information. Furthermore, FLAKIDOCK employs a feedback loop to incorporate false repairs to alleviate LLM mistakes.

Learning-based Program Repair. Learning-based program repair has been extensively studied in the literature [37]–[43]. Unlike these approaches, which involve training task-specific models, FLAKIDOCK uses a general-purpose LLM without the need for model training.

LLM-based Program Repair. There has been increasing focus on applying LLMs to program repair tasks. Early studies focused on using prompts and error messages to generate source code repair in a single interaction with the model [27], [44]. More recent techniques involve iterative approaches, querying the LLM multiple times and refining repairs based on feedback from previous attempts to repair source code [45]. In contrast, in this work, we leverage both static and dynamic information from Dockerfiles to provide the LLM, enhancing its ability to repair flakiness more effectively. By integrating retrieval-augmented generation techniques, we further ensure that the LLM is equipped with relevant examples and contextual knowledge, leading to more accurate and reliable repairs.

VIII. CONCLUSION

This paper presents the first comprehensive study on Dockerfile flakiness, revealing that 9.81% of Dockerfiles exhibit flaky behavior, which impacts the reliability of CI/CD pipelines. We introduce the first taxonomy of Dockerfile flakiness and propose FLAKIDOCK, a novel tool that leverages large language models, retrieval-augmented generation, dynamic analysis, and an iterative feedback loop for automatic Dockerfile flakiness repair. Our evaluation shows that FLAKIDOCK achieves a 73.55% repair accuracy, outperforming existing tools like PARFUM by 12,581% and GPT-4 based prompting by 94.63%. These results highlight the effectiveness of FLAKIDOCK in addressing Dockerfile flakiness. As part of our future work, we plan to extend FLAKIDOCK to handle even more intricate build scenarios.

IX. Data Availability

We have made our dataset, model, comparison framework, and FLAKIDOCK's implementation available [15] for the reproducibility of results. We further provide instructions for replicating our experimental setup.

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