Few-Shot API Attack Anomaly Detection in a Classification-by-Retrieval Framework

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Abstract-Application Programming Interface (API) attacks refer to the unauthorized or malicious use of APIs, which are often exploited to gain access to sensitive data or manipulate online systems for illicit purposes. Identifying actors that deceitfully utilize an API poses a demanding problem. Although there have been notable advancements and contributions in the field of API security, there still remains a significant challenge when dealing with attackers who use novel approaches that don't match the well-known payloads commonly seen in attacks. Also, attackers may exploit standard functionalities in unconventional manners and with objectives surpassing their intended boundaries. This means API security needs to be more sophisticated and dynamic than ever, with advanced computational intelligence methods, such as machine learning models that can quickly identify and respond to anomalous behavior. In response to these challenges, we propose a novel few-shot anomaly detection framework, named FT-ANN. This framework is composed of two parts: First, we train a dedicated generic language model for API based on FastText embedding. Next, we use Approximate Nearest Neighbor search in a classification-by-retrieval approach. Our framework enables the development of a lightweight model that can be trained with minimal examples per class or even a model capable of classifying multiple classes. The results show that our framework effectively improves API attack detection accuracy compared to various baselines.

Index Terms—API Security, Anomaly Detection, Few-Shot Learning, ANN, Classification-by-Retrieval, NLP.

I. INTRODUCTION

PPLICATION Programming Interface (API) refers to a set of routines, procedures, resources, and protocols that permit the interaction between software systems and data exchange services [1]-[3]. APIs are an evolving technology for orchestrating applications utilizing web technology [4], [5]. Recently, it has been argued that we are currently living in an API economy [5] due to the growing interconnectedness of people, applications, and systems, all of which are powered by APIs. These interfaces now serve as the foundational framework of the digital ecosystem, establishing connections between industries and economies to foster value creation and cultivate innovative capabilities [2]. APIs find utilization across a broad spectrum of services, including Web applications, Operation Systems (OS), Databases, and Hardware [6]. The increasing ease of building web applications has led to a rise in agile development, where even inexperienced engineers can deploy applications. However, this approach often lacks strong security design or hardening planning. This can lead to vulnerabilities in application logic and inadequate consideration of security impacts. For instance, failure to properly constrain resources or access levels could lead to denial of service attacks [7]. As a result, the extensive adoption of web APIs has heightened the potential of user safety and privacy breaches, making APIs a prime target for cyber attackers [3]. In recent years, there have been several high-profile API attacks [8]–[11], such as the Zoom video conferencing platform in 2020.

To address these challenges, the Open Web Application Security Project (OWASP¹) provides resources, tools, and best practices to help organizations and developers enhance the security of their web applications and protect against malicious attacks. One of the most well-known contributions is the OWASP API Top 10, which outlines the ten most critical API security risks [12].

Despite the progress made in prior research on utilizing machine learning and deep learning models for protecting APIs against both known and unknown attacks [13]-[15], there are lingering concerns that remain unresolved. These concerns encompass several challenges, such as effectively detecting zero-day vulnerabilities, minimizing false positives, and addressing real-time and continuous protection requirements. Given that a zero-day API attack involves an unknown vulnerability that the security solutions, such as web application firewalls, are unaware of, it becomes necessary to employ few-shot learning techniques. The anomaly detection model needs to leverage its comprehension of previously encountered samples to make predictions on new, unseen samples. In light of the requirement to improve traditional methods for training binary anomaly classifiers, the utilization of Classificationby-Retrieval presents a solution [16]. This approach enables the construction of neural network-based classifiers without the need for computationally intensive training procedures. Consequently, it facilitates the development of a lightweight model that can be trained with minimal examples per class or even a model capable of classifying multiple classes [17]–[19].

The remaining sections of this paper are structured in the following manner. In Section II, we summarize the contributions made in this paper, Section III provides an overview of the relevant literature. The architecture of the FT-ANN solution is presented in Section IV. The experimental design is outlined in Section V. Section VI focuses on measuring the effectiveness of FT-ANN and presenting experimental results in comparison to various state-of-the-art benchmarks. Finally, we draw our conclusions, current research limitations, and suggestions for future work in Section VII.

¹The Open Web Application Security Project®, https://owasp.org/

II. OUR CONTRIBUTION

In this paper, we introduce a novel unsupervised fewshot anomaly detection framework, utilizing FastText embedding and Approximate Nearest Neighbor search (FT-ANN), which leverages a Classification-by-retrieval approach. We enable training of a single retrieval model capable of handling multiple baselines simultaneously. This approach not only saves computational resources but also simplifies the model deployment and maintenance processes. By reducing the number of models required, our methodology offers a more efficient and scalable solution for anomaly detection. Moreover, unlike traditional anomaly detection models, ANN supports incremental index updates.

Additionally, we define a novel tokenizer that specifically emphasizes the language factors present in APIs, addressing the unique challenges associated with API-based natural language processing. Unlike existing tokenizers, our approach takes into account the specific language characteristics of APIs, enabling more accurate and efficient processing of API-related text. APIs are defined by a URL-based syntax in which each URL corresponds to a particular resource or action. They also include fundamental actions such as GET and POST, which determine how requests and responses are structured. Additionally, APIs utilize standard structure of HTTP headers to transmit metadata pertaining to both the request and the anticipated response.

Furthermore, our language model is designed to be domainagnostic, eliminating the need for retraining when transitioning to different API domains. This flexibility allows our model to seamlessly serve various domains without sacrificing performance or requiring additional training efforts.

Lastly, its agnostic nature allows it to seamlessly adapt and address the unique requirements and challenges as also outlined in the OWASP Top 10 API vulnerabilities, posed by different API forms include REST, GraphQL, gRPC, and WebSockets, regardless of the emphasis on HTTP datasets during the demonstration.

III. RELATED WORK

Reddy et al. [20] proposed supervised sequence models based on Recurrent Neural Networks (RNN) to identify malicious injections in API requests in addition to a heuristic rule which classified 10% of each request sequence with a probability of 60% as valid to minimize the number of false positives. However, such rules can introduce subjective biases and limitations. They generated a custom-labeled dataset, but used only the request payloads. This presents a significant constraint in real-world scenarios, where malicious actor could potentially manipulate a majority of the request components, including headers [21]. They compared six unidirectional and bidirectional RNN models by evaluating various performance measures and showed a 50% decrease in false positive cases.

Jemal et al. [22] suggested the Convolutional Neural Network (CNN) method to detect web attacks. They concluded that appropriately adjusting hyper-parameters and employing a data pre-processing approach significantly impacts the detection rate.

Gniewkowski et al. [23] suggested an NLP-based semisupervised anomaly detection methodology that employs RoBERTa for embedding HTTP requests to detect anomalies. They evaluated the pipeline over the CSIC 2010 and CSE-CIC-IDS 2018 published datasets, in addition to UMP, a customgenerated dataset, achieving F1-scores of 96.9%, 92.6%, and 99.9%, respectively. A notable limitation in their method is the relatively long training and inference time, which presents a considerable drawback in real-time systems.

Jemal et al. [24] propose a supervised Memory CNN that combines a CNN and Long Short-Term Memory (LSTM) to identify patterns of malicious requests within sequences of requests. They evaluated the model using the CSIC 2010 dataset. Niu et al. [25] propose a technique for detecting web attacks based on a supervised CNN and Gated Recurrent Unit (GRU). They extracted statistical features and utilized a Word2Vec model to extract word embeddings, resulting in a 3-dimensional input for the suggested CNN-GRU method. A fully connected layer was used for classification, and the experiment was made on the CSIC 2010 dataset. Yu et al. [26] combined a CNN and Support Vector Machine (SVM) to detect malicious web server requests. The CSIC 2010 dataset was selected to validate proposed approach. Baye et al. [14] also utilized SVM with a Linear Kernel as a twoclass classifier to identify anomalous API requests. To form a training dataset that accurately represented authentic API logs, they employed a technique for outlier detection based on Gaussian Distribution, generating a synthetic dataset with labeled examples.

Moradi et al. [27] introduced an unsupervised anomaly detection technique utilizing Auto-Encoder LSTM for feature extraction and Isolation Forest for classification. They applied this model to the CSIC 2010 dataset, achieving an F1-score of 81.96%. Although, they faced limitations related to the choice of encoding method for HTTP data, the non-stationary nature of HTTP data, and the integration of multiple feature sets, which may impact the effectiveness of the proposed approach. In more recent research [28], they also proposed an unsupervised Deep Support Vector method. They conducted a comparison between two feature extraction approaches, namely bigram (2-gram) and one-hot. They evaluated it on the CSIC 2010 and ECML/PKDD 2007 datasets, achieving F1scores of 89% and 79.48%, respectively. They pointed out the limitation of lacking support for data streams in incremental learning, emphasizing the need for future research to address this aspect.

IV. FRAMEWORK

The analysis of API requests can be framed as a problem in NLP. One challenge lies in selecting a language model capable of generating a vector space representation. In our work, we decided to utilize the FastText [29] model. The primary aim of FastText embeddings is to factor in the internal structure of words rather than simply learning word representations. This feature is especially advantageous for morphologically complex languages, allowing representations for various morphological forms of words to be learned separately. FastText offers Skip-gram and Continuous Bag-of-Words (CBOW)

Ref Attack Method	Task	Technique(s)	Method(s)	Dataset(s)	Best Score
[20] SQL, XML and JSON a tacks in HTTP request	t- Supervised	RNN	Word embedding	Custom	98.13% F1-Score
[22] Attack in HTTP request	Supervised	CNN	Word embedding, Character embedding	CSIC 2010	97.65% Accuracy
				CSIC 2010	96.9% F1-Score
[23] Attack in HTTP request	Semi-Supervised	RoBERTa	BBPE	UMP	92.6% F1-Score
				CSE-CIC-IDS2018	99.9% F1-Score
[24] Sequences of HTTP reques	ts Supervised	CNN, LSTM	ASCII embedding	CSIC 2010	98.53% F1-Score
[25] Attack in HTTP request	Supervised	CNN, GRU	Word embedding, Statisti- cal features	CSIC 2010	98.77% F1-Score
[26] Attack in HTTP request	Supervised	TextCNN, SVM	Word embedding,t-SNE, Statistical features	CSIC 2010	99.3% F1-Score
[27] Attack in HTTP request	Unsupervised	Auto-Encoder LSTM	Character embedding	CSIC 2010	81.96% F1-Score
[28] Attack in HTTP request	Unsupervised	SVDD	Character embedding	CSIC 2010	89% F1-Score

TABLE I: Summary of Machine Learning NLP-based Techniques

models to compute word representations. Although CBOW learns faster than Skip-gram, Skip-gram outperforms CBOW on small datasets [30]. FastText adopts a character n-gram approach to tokenize words, which effectively tackles Out-ofvocabulary (OOV) problems. This method not only generates embeddings for common words but also for rare, misspelled, or previously unseen words in the training corpus. In the realm of API security, it is imperative to pay attention to the internal structure of words in order to grasp the intent and context behind API requests. API security entails scrutinizing the textual content within API requests to pinpoint potential threats or vulnerabilities [31]. These security threats could be concealed within apparently harmless text, which may involve the use of uncommon or previously unseen terms, or even attempts to obscure their intent through spelling errors [32]. Moreover, APIs might be required to accommodate a diverse range of languages, including those characterized by intricate morphological structures [33].

Prior works have proposed various methods for detecting anomalies. While the majority of these approaches focus on classic classification tasks, we propose the utilization of the ANN vector similarity method for identifying in-distribution records. The similarity search concept pertains to the process of identifying data points in a dataset that demonstrate similarities with a specific pattern, commonly referred to as a query [34]. To measure the similarity of a pair of data points, a distance function is used, where a small distance indicates that the two points are more similar or "closer" to each other [35]. The NN search is a specific type of similarity search used to identify data points that are nearest in distance to a provided query point [36]. The ANN allows search despite the possibility of not retrieving all neighbors in a metric space [36].

While both ANN and traditional NN are rooted in the fundamental concept of similarity search, traditional NN search involves an exhaustive examination of all data points to find the NN, which can be prohibitively time-consuming for large datasets [36]. In contrast, ANN employs techniques that trade off a slight loss in precision for substantial gains in speed, enabling the identification of ANN without examining every data point. This efficiency becomes especially crucial in real-world API applications where rapid response times are essential. Additionally, ANN methods are adaptable to high-dimensional spaces [34], [37], where traditional NN searches can suffer from the "curse of dimensionality", in which the computational requirements for exact NN search become prohibitively high as the dimensionality of the dataset increases [36].

The framework proposed (depicted in Figure 1) comprises a combination of a FastText embedding network and a retrieval layer, which includes an ANN matching component and a result aggregation component built upon it, forming the FT-ANN system. In Phase 1 (Figure 1), we initiate the process by training a generic language model to serve as a reliable baseline for the detection model. To gather a substantial dataset, we conducted web crawling on a random sample of websites from the Tranco top websites list, collecting over a million examples of normal web traffic. This language model now serves as a pre-trained baseline, applicable to any real-world API anomaly detection system.

Proceeding to Phase 2 (Figure 1), the unsupervised detection model is trained, consisting of a pre-processing step and a Classification-by-retrieval framework. The pre-processing step validates the HTTP headers against the standard structure. Additionally, a unique data transformation is applied to simplify the API vocabulary. The detection model is trained solely on normal API traffic, and constructs a single ANN model for all endpoints. The term "endpoint" refers to any data or metadata that may represent a type, an origin, or identification of a respective API request. Endpoint is defined as the combination of the method, host and path [38]. For each endpoint, a threshold is calculated and utilized during the detection stage.

Finally, in Phase 3 (Figure 1), the model's performance is validated by allowing an index search for every request. During validation, we standardize the request using the same preprocessing stages applied during the detection model training phase. The text is then transformed into a vector representation using our generic language model through inference. These embedding vectors are used in the ANN search, which returns the K-NNs from the specific endpoint index collection, followed by a maximum distance scaling layer. The final score obtained enables the model to ascertain whether the incoming API request is normal or an anomaly by comparing with the

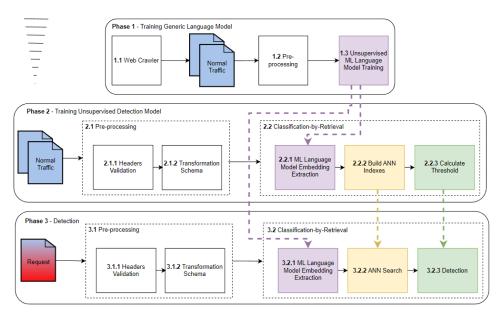


Fig. 1: Our FT-ANN Framework

pre-defined threshold for each API endpoint.

A. Data Pre-Processing

For both training and inferring the detection model, we employ a unique pre-processing technique consisting of three phases, as depicted in Figure 1 in steps 2.1 and 3.1. First, decoding URL special characters, decompressing request body content, and converting every character within the request data string into lowercase. Then, validating request headers to ensure they are formatted correctly and extracting the endpoint definition, as depicted in Figure 1 2.1.1 and 3.1.1. API request headers typically provide information about the request context, supply authentication credentials, and provide information about the client (e.g., a person, a computing device, and/or a browser application) that had initiated the API [39]. API request header fields are typically derived from a limited set of options. Accordingly, the data preparation also uses a fixed set of rules to validate the content of request headers and filter-out headers according to these rules. Headers that include valid or approved strings may be transferred to their destination as an API request and may be excluded from additional processing. For example, request headers may include host strings, which specify host or Internet Protocol (IP) addresses and/or port numbers of a server to which the API request is being sent. Valid IPv4 syntax should be in the format of: $(0 \le n < 256).(0 \le n < 256).(0$ n < 256): $(1 \le n \le 65535)$.

Lastly, as shown in Figure 1 2.1.2 and 3.1.2, we convert received requests into abstracted versions based on a conversion schema. For instance, we replace non-numeric single characters with the string "chr", which serves as a representative, abstract version of the original request string. Another example involves converting non-textual symbols into predefined textual strings. for instance, colons (":") may be converted to the string "colon". During the pre-processing stage, the API language has been refined to achieve optimally,

enabling it to describe various transactions in a consistent format without sacrificing their original meanings. In fact, in the majority of cases, these requests have been intelligently merged into a single text representation. This consolidation not only streamlines the data but also ensures that the essential information pertaining to different transactions remains preserved.

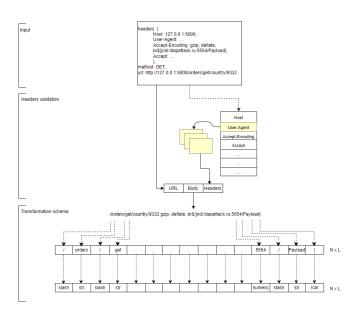


Fig. 2: Data pre-processing steps

B. Unsupervised ML Language Model

Our framework leverages FastText for unsupervised learning. FastText possesses the capability to encapsulate substantive knowledge about words while integrating morphology details, a crucial aspect for API attack detection. While deep learning models have excelled state-of-the-art results across

various NLP tasks, to the best of our knowledge, no previous NLP pre-trained model on the API traffic domain has been publicly published. In the training phase of the method, we built a single generic FastText language model (based on [29]) from scratch using the normal API traffic collected by crawling Tranco's list of the most popular websites, as can be seen in Figure 1 Phase 1. For training the generic language model, we used the default hyper-parameters of [29], which encompass a learning rate of 5%, a word vector size of 100, and a context window size of 5. The model was then trained for 5 epochs. We utilized the CBOW model as the dataset is relatively large, and CBOW embeddings are precise enough for anomaly detection and computed in a shorter time than skip-gram [40]. For training the detection model and inferencing, we extract the vector representation of words for every input line.

C. ANN

We obtained ANN to identify normal representation of an API endpoint. We train a single detection model, which is used to describe a normal representation of all endpoints. During the detection model training stage, each API request is represented as a vector in the textual embedding space, including endpoint information. We employ cosine distance to measure the similarity between data points as it has been applied in numerous text mining endeavors, such as text classification, and information retrieval [41]. Additionally, it has been proven to be effective for Out-of-Distribution (OOD) detection tasks [42], [43]. Cosine similarity is a widely used measure of similarity that calculates the angle formed by a pair of vectors. When measuring the similarity between two patterns, the Euclidean distance increases as they become less similar, while the cosine similarity increases as they become more similar. Unlike Euclidean distance, cosine similarity is unaffected by the magnitude of the vectors being compared [44]. The embedding vector feeds the Hierarchical Navigable Small Worlds (HNSW) graph [45] to build new indexes of data points. During the detection stage, the model compares new API vectors of incoming API requests in relation to API vectors of the same API endpoint information to evaluate normality or anomaly of the incoming API request. The comparison is made by querying the similarity between the input vector to the closest k objects.

The ANN search returns a set of IDs representing neighbors' points and the similarity score between the given point and its ID. Max distance scaling is employed to scale the ANN similarity score within the given range. For every score, the maximum value gets transformed into a 0, and every other value is divided by the maximum similarity score in the range and then subtracted from 1. We use this method to invert the relationship between the original and the normalized scores to emphasize higher scores for smaller values. As in the cosine space, a smaller distance indicates that the two points are closer to each other. Let X be the similarity score, the normalized score X' is: $X' = 1 - \left(\frac{X}{\max(X)}\right)$

Lastly, we suggest an adaptive search for the best threshold for each API endpoint. As part of the detection model training, the model iteratively evaluates thresholds between 0 and 1, with increments of 0.1. The model considers the balance between precision and recall, as captured by the F1 score, to determine the optimal threshold value. As described in Figure 3, in the detection stage, the first position score with the max normalized value is compared to the best threshold to determine anomaly.

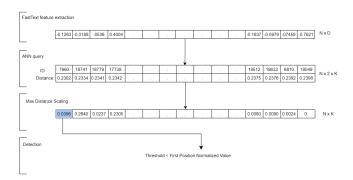


Fig. 3: Features extraction and classification-by-retrieval

V. EXPERIMENTAL DESIGN

API security papers are not as prevalent as the technology itself, despite being one of the most influential technologies [46]. This is particularly evident in the scarcity of ready-touse publicly available API datasets [47]. Several of these datasets are obsolete and unsuitable for usage, with some lacking traffic diversity and volumes, and others failing to encompass a variety of attacks, such as ECML/PKDD 2007 [48] and CSE-CIC-IDS 2018 [49]. Consequently, researchers resort to creating customized datasets by primarily utilizing open-source vulnerable web applications like DVWA, BWAPP, and Mutillidae, and employ automated penetration tools such as SQLMAP [50], SQLNINJA [51], and OWASP ZAP [52] to gather malicious payloads [53]. Therefore, this research is evaluated on two datasets: CSIC 2010 [54] and ATRDF 2023 [55]. The HTTP CSIC 2010 dataset [54] is widely [23]–[27], [33], [56]–[62] in the field of malicious web traffic detection. This dataset was created by the Spanish Research National Council (CSIC). It is a sample of the traffic occurring on the Spanish e-commerce web application. The dataset includes attacks such as SQL injection (Figure 4a), buffer overflow, information gathering, files disclosure, CRLF Injection, XSS, static attacks and unintentional illegal requests. While unintentional illegal requests lack malicious intent, they deviate from the typical behavior of the web application and exhibit a different structure compared to regular parameter values. For instance, as shown in Figure 4b, an invalid DNI (Spanish national ID number) was marked as an anomaly. We divided the dataset into two segments: the training portion, which included 36,000 normal requests and was exclusively utilized for representation learning, and the inference portion, which comprised both 36,000 normal and 25,000 anomalous traffic that was encoded by the model and employed for detection. It has 38 different endpoints, 8 of which have no normal representation and were excluded from our experiment.

The API Traffic Research Dataset Framework (ATRDF) [55] is a recently published HTTP dataset publicly available which

includes 18 different API endpoints. The dataset includes attacks such as Directory Traversal, Cookie Injection, Log4j (Figure 4c), RCE, Log Forging, SQLi, and XSS. The dataset contains 54,0000 normal and 78,000 abnormal sets of request and response.

In response to the unavailability of a publicly accessible pre-trained model specialized for the API domain, a generic language model was developed to establish a reliable baseline for various detection models. However, developing a robust language model necessitates a significant amount of training data. To address this requirement, an extensive dataset of 1,061,095 API examples was collected. This dataset was obtained by performing a comprehensive data collection process, involving the crawling of a random sample of websites from the Tranco top websites list². The Tranco list is an invaluable resource for cyber-security research as it provides a publicly available compilation of the top one million most popular domains, ranked based on a combination of four reputable lists: Alexa, Cisco Umbrella, Majestic, and Quantcast. Additionally, the Tranco list offers the advantage of being able to filter out unavailable or malicious domains, making it a valuable asset for our research [63].

VI. EVALUATION METRICS

In the realm of anomaly detection, it is commonplace to integrate a binary classification layer into the model architecture. This is due to the fundamental objective of distinguishing between normal and abnormal instances. To evaluate our architecture, we suggest using several performance measures in various experiments, including precision, recall, accuracy and F1-score. Actual values are represented as True and False by (1) and (0), respectively and predicted as Positive and Negative values by (1) and (0), respectively. Predicted possibilities of classification models are obtained through the expressions TP, TN, FP, and FN.

Precision: evaluates the accuracy of the positive predictions using the ratio of correctly predicted positive instances out of all instances predicted as positive. It is obtained by dividing the number of true positives by the sum of true positives and false positives.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

Recall: measures the proportion of actual positives identified correctly. It is obtained by dividing the number of true positives by the sum of true positives and false negatives.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

Accuracy: measures the overall correctness of the model predictions. It is obtained by dividing the total number of correct predictions by the total number of predictions made by the model.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

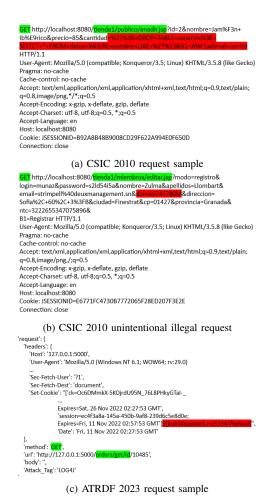


Fig. 4: An example of anomaly requests from CSIC 2010 and ATRDF 2023 datasets where endpoint definition is marked in green, abnormal payload is marked in red.

F1-score: measures the accuracy of the instances that were classified incorrectly by a model. It is obtained by taking the harmonic mean of precision and recall.

$$F1\text{-}score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

In the current problem, two classes are represented by Positive and Negative, where the positive class corresponds to an abnormal API request and the negative class corresponds to a normal API request.

VII. EXPERIMENTAL RESULTS

To understand better the two datasets, we use the t-Distributed Stochastic Neighbor Embedding (T-SNE) method for dimensionality reduction to graphically depict our high-dimensional datasets. The plots in Figure 5 indicate distinct separation among classes within a reduced dimensional space. This suggests that requests with similarities tend to be grouped together, enabling the exploration of a neighborhood for any given sample. Close records from different classes suggest that certain requests are quite similar, causing the embedding to overlap between the two classes. The result for ATRDF 2023

²https://tranco-list.eu/

shows no overlap and clear separation between the classes while for CSIC 2010, some records from the two classes were found to be similar. We identified that most of the anomalous requests which overlap with normal requests actually have no malicious payload and are categorized as unintentional illegal requests.

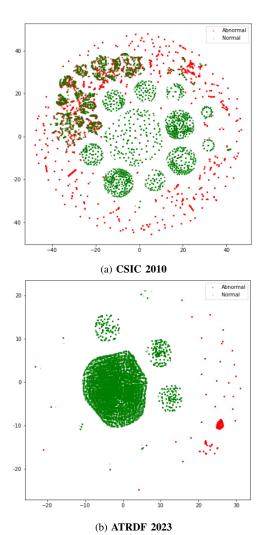


Fig. 5: Vector representations reduced to 2D with t-SNE

Then, we compare our method with fourteen detecting outlying objects in multivariate data baseline models [64]: Feature Bagging (FB), Histogram-based Outlier Detection (HBOS), Isolation Forest (IF), Local Outlier Factor (LOF), Minimum Covariance Determinant (MCD), One-class SVM (OCSVM), Principal Component Analysis (PCA), Copula-Based Outlier Detector (COPOD), Deep One-Class Classification for outlier detection (DeepSVDD), Clustering-Based Local Outlier Factor (CBLOF), Outlier detection based on Gaussian Mixture Model (GMM), Kernel Density Estimation (KDE), Linear Model Deviation-based Outlier Detection (LMDD), Quasi-Monte Carlo Discrepancy Outlier Detection (QMCD). We apply default hyper-parameters as provided by the original source code across all models for consistency and use the same pre-processed dataset to facilitate optimal comparison.

Furthermore, we conducted an ANN benchmark to effec-

tively contrast our framework with other nearest neighbor algorithms. This benchmark involved generating algorithm instances based on configuration file written in YAML format that defines the different methods and algorithms. At the top level, the point type is specified, followed by the distance metric, and finally, each algorithm implementation to be evaluated. Each implementation specifies the Python library, and additional entries provide the necessary arguments. For clarity, an illustrative example of this configuration file is presented in Figure 6, while the complete file is available in the project GitHub repository ³. Both the "space" and "run_groups" lists encompass arguments that should be included at the beginning of every invocation. Each algorithm defines one or more "run groups," each of which is expanded into several lists of arguments. The Cartesian product of these entries results in numerous argument lists. For instance, consider the hnswlib entry depicted in Figure 6. This expands into three distinct algorithm instances: Cosine (Cosine Similarity), L2 (Squared L2), and IP (Inner product). Each of these instances undergoes training before being utilized for various experiments. Initially, experiments are conducted with different values of k, representing the number of neighbors to return (e.g., [10, 50, 100, 300, 400, 500, 1000, 2000, 2500, 3000]). Subsequently, experiments are conducted with varying ef_construction values, which denote the size of the dynamic list used during index construction. A larger ef_construction value indicates a higher quality index but also results in longer build times (e.g., [10, 20, 40, 80, 120, 200, 400, 600, 800]). Throughout each run, pertinent information is recorded, including the algorithm name, the time taken to construct the data structure used for indexing, and the outcomes of every query. These query outcomes encompass the neighboring points returned by the algorithm, the duration required to locate these neighbors, and the proximity between the neighbors and the query point. We leveraged the query results to compute the corresponding confusion matrix, enabling us to thoroughly evaluate the classification-by-retrieval performance of each algorithm. We conducted our benchmarking analysis by assessing the performance of various algorithm implementations, including Nmslib, Hnswlib, Bruteforce Blas, Balltree, KDtree, CKDtree, Annoy, Faiss, and RPForest, all of which were evaluated using the publicly accessible ANN-Benchmarks tool as a reference framework [65]. In order to gain a deeper comprehension of how the embedding layer influences the detection outcome, we assessed all anomaly detection baseline models and the ANN benchmark using two additional prominent language models: BERT [66], and RoBERTa [67]. Each model was individually trained from scratch and subsequently subjected to evaluation. We employed the RoBERTa model, specifically the RoBERTaForMaskedLM class, with a language modeling head on top⁴. This model was trained with a maximum sequence length of 512, utilizing 12 hidden layers and 12 attention heads. The training process spanned 10 epochs, employing a batch size of 16, which aligns with a similar

³https://github.com/ArielCyber/FT-ANN-Journal/blob/main/ann_benchmark.yaml

⁴RoBERTa implementation by Hugging Face - https://huggingface.co/docs/transformers/model_doc/RoBERTa

approach in a prior study by [23]. Likewise, we employed the BERT model, specifically BertForMaskedLM, which also incorporates a language modeling head on top⁵. This model underwent training with a maximum sequence length of 512, utilizing 4 hidden layers and 4 attention heads, as was the case in a similar task outlined in [68].

```
- name: hnswlib
library: hnswlib
method: [hnswlib]
space: [cosine,12,ip]
run_groups:
  K:
      query_args: [[10,50,100,300,400,
      500,1000,2000,2500,3000]]
ef_construction:
      query_args: [[10, 20, 40, 80,
      120, 200, 400, 600, 800]]
```

Fig. 6: Example configuration for the hnswlib algorithm

We used Intel(R) Xeon(R) Silver 4214R CPU @ 2.40GHz to evaluate the effectiveness of each technique. Each endpoint was evaluated separately, and the average score for all endpoints was used to measure overall detector performance. We evaluate model performance by measuring both execution time and F1-score during training and testing. Training time is usually longer than testing time as it entails parameter optimization, a computationally intensive task. Conversely, testing time is relatively faster as it only involves applying the pre-trained model to new data and predicting their likelihood of being outliers. It is worth noting that detecting anomalies in real-time is critical in mitigating the effects of an attack. Therefore, it is advisable to analyze each phase separately to better understand each model's performance. Additionally, we aim to achieve better results compared to previous semi-supervised and unsupervised studies. Supervised studies should not be compared since they rely on labeled data.

In the context of ANN search, selecting the optimal value for K involves determining the number of nearest neighbors to consider for predictions. The model performance evaluation and the choice of the optimized value of K rely on the F1 score, which provides a balanced assessment of precision and recall. By systematically iterating through a range of K values and assessing the F1 score for each value, we can identify the K value that yields the highest F1 score and use it in our final endpoint evaluation. During this experiment, the performance of the model was validated by iteratively testing different values of K, ranging from 1 to 1000.

The results for the CSIC 2010 dataset, as can be seen from Table II, comparing against the conventional outlier detection baselines, NMSLIB-COS (FT-ANN) and PCA demonstrate the shortest times, with 0.0552 and 0.0575 seconds respectively, whereas AUTOENCODER and LMDD show significantly longer train times of 75.0644 and 225.8 seconds respectively. NMSLIB-COS achieves the highest F1 score of 0.9713, indicating its balanced precision-recall performance. Similarly,

in terms of precision and recall, NMSLIB-COS again outperforms other algorithms with scores of 0.9538 and 0.9954 respectively. LMDD appears to exhibit the comparatively weakest performance across multiple metrics. With an F1 score of 0.3017, a precision of 0.528, and a recall of 0.2293, LMDD lags behind the other algorithms. Furthermore, its training time of 225.8 seconds is considerably longer than most other methods. The poor performance and unfavorable tradeoff between training time and results for LMDD could be attributed to its reliance on a dissimilarity function that may not be well-suited to the complex and diverse anomalies present [69].

Several observations stand out when considering the framework performance using BERT and RoBERTa embedding compared to FastText. It's noticeable that BERT and RoBERTa introduce longer training times for all models. For instance, NMSLIB-COS with BERT takes around 0.446 seconds, while with RoBERTa, it's approximately 0.563 seconds, compared to the original 0.0552 seconds with FastText. This increase in training time could be attributed to the more computational complexity nature of BERT [70], [71] and RoBERTa [72] models. In terms of performance, when considering the BERT embedding, NMSLIB-COS framework continues to exhibit robust performance, achieving an F1-score of 0.9675. This result suggests that the framework effectively leverages the contextual information embedded within BERT's representations to identify anomalies. The high precision (0.947) and recall (0.9982) values further support the framework's ability to maintain a fine balance between detecting true anomalies and minimizing false positives. However, a noteworthy observation lies in the performance of NMSLIB-COS framework when using RoBERTa embeddings. Surprisingly, while RoBERTa is considered an even more advanced and powerful language model compared to BERT, the F1-score for NMSLIB-COS drops slightly to 0.9664. This outcome raises questions about why the transition to RoBERTa, which typically exhibits superior performance across range of natural language processing tasks [67], [73], [74], did not lead to an improved performance for this specific outlier detection method. Generally, both BERT and RoBERTa maintain performance comparable with FastText with some exceptions. NMSLIB-COS with BERT achieves an F1-score of 0.9675, a slight improvement over FastText's 0.9713. Similarly, GMM, MCD, CBLOF, and IFOREST also exhibit consistent or improved F1-scores with BERT and RoBERTa. However, for DEEPSVDD, the F1scores drop slightly with BERT to 0.9187 and even more with RoBERTa to 0.8999. Precision and recall also showcase similar trends.

The ANN baseline models generally perform better than the traditional outlier detection methods, and their performance is quite similar with only slight differences. Among these models, HNSWLIB-IP stands out with the highest F1 score (0.9765) and perfect recall (100%), which means it doesn't miss any actual anomalies. When we balance training time, precision, and recall, the BRUTEFORCE-BLAS models achieve the best precision and recall while needing less training time. This makes them suitable for scenarios where quick responses or limited resources are important.

⁵BERT implementation by Hugging Face - https://huggingface.co/docs/transformers/model_doc/bert

On the other hand, models like HNSWLIB-IP and ANNOY-MANHATTAN have slightly longer training times but achieve slightly higher F1 scores. The relatively slower performance of the MINKOWSKI distance metric in the BRUTEFORCE-BLAS model might be due to the more complicated calculations involved in the MINKOWSKI distance, especially when dealing with high-dimensional data [75]. The ANNOY model takes a different approach to constructing its search structure, which might explain its slightly slower training times compared to other models. ANNOY's method involves generating random projections and building binary trees for its search index, which requires significant computation to ensure effective projection dimensions that preserve data relationships [76]. Despite not having the highest F1 score, NMSLIB finds use in industries like Amazon Elasticsearch Service [77]. This indicates that although its accuracy might not be the absolute best compared to other ANN implementations, its simple deployment and easy integration align well with the requirements of real-world applications. The overall performance of the algorithm can be evaluated through the average outcomes of difference distance metrics and the algorithm parameters. As depicted in Figure 7, each algorithm utilizing FastText embeddings exhibited significantly swifter processing times compared to BERT and RoBERTa. FastText and CKDTREE attained the shortest average index build times (0.00584 seconds), whereas BALLTREE operated over 2.5 times slower despite employing the same embeddings. Within the top 8 fastest FastText algorithms, only BRUTEFORCE demonstrated favorable performance when applied to BERT and RoBERTa, achieving scores of 0.02745 and 0.03215, respectively. Conversely, ANNOY's performance was subpar for each language model. Regarding model accuracy, as illustrated in Figure 7, every algorithm displayed enhanced results when utilizing FastText, achieving F1-scores exceeding 97%. Similarly, the remaining algorithms also exhibited strong performance with F1-scores surpassing 96%. Generally, our framework achieved better accuracy compared to previous unsupervised and semi-supervised studies using the CSIC 2010 dataset, as shown in Table I.

The results for the ATRDF 2023 dataset, as can be seen from Table III, show that we observed a perfect classifier for most of ANN algorithms. With 100% F1-score, recall and precision, our framework exceeded the traditional outlier detection baseline requirements. Most of the models demonstrate the shortest training/building times, whereas AUTOENCODER, MCD and DEEPSVDD show significantly longer train times of average 5.3368, 109.6675 and 3.3173 seconds respectively. While NMSLIB-COS did not attain the briefest build time, it can still be regarded as relatively rapid. It is evident that BERT and RoBERTa result in extended training durations for the majority of models, with a few exceptions. LMDD, CBLOF, QMCD, HBOS, and AUTOENCODER exhibited comparatively swifter training completion when utilized with BERT and RoBERTa. Most of the traditional outlier detection baselines also performed well but struggled to predict all positive classes, which affected the precision score. LMDD obtained an average 49.41% in F1-Score, which is much worse than those tested. QMCD failed to predict when tested with BERT and RoBERTa. The comprehensive mean benchmark outcomes of the diverse distance metrics and algorithm parameters are presented in Figure 8. FastText and CKDTREE managed to achieve the briefest average index construction times (0.00007 seconds), whereas BALLTREE functioned more than twice as slowly even though it utilized the same embeddings. Generally, all the algorithms exhibited rapid performance, with the exception of ANNOY across all language models. As previously mentioned, all ANN algorithms demonstrated outstanding predictive accuracy.

VIII. DISCUSSION AND CONCLUSIONS

This paper suggests an innovative unsupervised few-shot anomaly detection framework that leverages a dedicated generic language model for API based on FastText embedding and uses ANN search in a Classification-by-retrieval approach. We showed that API attacks could be easily identified with no previous learning. To the best of our knowledge, this is the first work to utilize a Classification-by-retrieval framework based on the generalized approach of FastText embeddings combined with the approximate search to find anomalies in API traffic. We present a unique pre-processing technique to enhance input generalization and simplify API structure. This approach encompasses dividing input data into individual tokens, then constraining the vocabulary to a limited set of tokens. Consequently, the API structure becomes streamlined as the number of unique tokens diminishes, enabling input generalization and enables high detection accuracy even with minimal examples per class. We presented several state-of-theart models for this task, performed a comparative analysis and demonstrated the best accuracy on the CSIC 2010 and ATRDF 2023 datasets. We showcased multiple cutting-edge models for this objective through two other widely adopted language models BERT and RoBERTa. Our comprehensive analysis encompassed benchmarking various ANN search algorithms, where we illustrated our models' exceptional accuracy on the CSIC 2010 and ATRDF 2023 datasets. While we noted that our proposed dense cosine distance approach utilizing NM-SLIB did not yield the top F1 score among ANN algorithms, its straightforward implementation and seamless integration make it a suitable choice for practical applications, particularly those like Amazon Elasticsearch Service that prioritize realworld compatibility. One notable limitation of this and similar studies arises from the scarcity of up-to-date and representative network traffic datasets. Many research efforts rely solely on the CSIC 2010 dataset, raising concerns about the reliability and applicability of such data, consequently impacting the quality and generalizability of traffic models. While our evaluation focuses on measuring the impact of FT-ANN on the HTTP dataset, it is important to acknowledge that APIs exist in diverse forms, including REST, GraphQL, gRPC, and WebSockets, each catering to specific use cases and carrying common vulnerabilities. Our future work entails expanding the evaluation to encompass a wider range of API types and to assess the performance across various loads and volumes.

	Train Time (Sec)				F1-Score			Precision			Recall		
	BERT	Fast	Ro	BERT	Fast	Ro	BERT	Fast	Ro	BERT	Fast	Ro	
		Text	BERTa		Text	BERTa		Text	BERTa		Text	BERTa	
HNSWLIB-IP	4.4549	0.0978	3.6719	0.9443	0.9766	0.7548	0.8890	0.9547	0.6062	1.0000	1.0000	1.0000	
ANNOY-MANHATTAN	11.426	3.4422	11.924	0.9690	0.9728	0.9683	0.9507	0.9576	0.9496	0.9974	0.9941	0.9973	
FAISS	0.3592	0.0473	0.9377	0.9682	0.9725	0.9680	0.9493	0.9571	0.9491	0.9974	0.9940	0.9973	
BRUTEFORCE-BLAS-COSINE	0.0191	0.0005	0.0179	0.9682	0.9725	0.9680	0.9493	0.9571	0.9491	0.9974	0.9941	0.9972	
BRUTEFORCE-BLAS-CITYBLOCK	0.0132	0.0004	0.0122	0.9682	0.9724	0.9680	0.9493	0.9570	0.9491	0.9974	0.9941	0.9973	
BRUTEFORCE-BLAS-MANHATTAN	0.0176	0.0004	0.0165	0.9682	0.9724	0.9680	0.9493	0.9570	0.9491	0.9974	0.9941	0.9973	
KDTREE-CITYBLOCK	1.5269	0.0236	1.4969	0.9682	0.9724	0.9680	0.9493	0.9570	0.9491	0.9974	0.9941	0.9973	
KDTREE-MANHATTAN	1.5325	0.0285	1.4807	0.9682	0.9724	0.9680	0.9493	0.9570	0.9491	0.9974	0.9941	0.9973	
BALLTREE-CITYBLOCK	1.2906	0.0145	1.3317	0.9682	0.9724	0.9680	0.9493	0.9570	0.9491	0.9974	0.9941	0.9973	
BALLTREE-MANHATTAN	1.2704	0.0141	1.3043	0.9682	0.9724	0.9680	0.9493	0.9570	0.9491	0.9974	0.9941	0.9973	
CKDTREE	0.3944	0.0058	0.4961	0.9682	0.9723	0.9681	0.9493	0.9567	0.9492	0.9974	0.9942	0.9973	
KDTREE-EUCLIDEAN	1.5244	0.0214	1.5159	0.9682	0.9723	0.9680	0.9493	0.9567	0.9491	0.9974	0.9942	0.9973	
KDTREE-L2	1.5497	0.0250	1.5180	0.9682	0.9723	0.9680	0.9493	0.9567	0.9491	0.9974	0.9942	0.9973	
KDTREE-MINKOWSKI	1.5287	0.0347	1.5336	0.9682	0.9723	0.9680	0.9493	0.9567	0.9491	0.9974	0.9942	0.9973	
BALLTREE-EUCLIDEAN	1.2903	0.0154	1.2902	0.9682	0.9723	0.9680	0.9493	0.9567	0.9491	0.9974	0.9942	0.9973	
BALLTREE-L2	1.2916	0.0153	1.2997	0.9682	0.9723	0.9680	0.9493	0.9567	0.9491	0.9974	0.9942	0.9973	
BALLTREE-MINKOWSKI	1.2732	0.0154	1.3031	0.9682	0.9723	0.9680	0.9493	0.9567	0.9491	0.9974	0.9942	0.9973	
BRUTEFORCE-BLAS-EUCLIDEAN	0.0108	0.0005	0.0116	0.9682	0.9722	0.9680	0.9493	0.9566	0.9491	0.9974	0.9942	0.9973	
BRUTEFORCE-BLAS-MINKOWSKI	0.0765	0.1127	0.1025	0.9682	0.9722	0.9680	0.9493	0.9566	0.9491	0.9974	0.9942	0.9973	
NMSLIB-L2	0.9779	0.0473	1.0642	0.9680	0.9721	0.9674	0.9491	0.9568	0.9482	0.9973	0.9936	0.9972	
NMSLIB-L1	0.9580	0.0489	1.1008	0.9680	0.9721	0.9676	0.9491	0.9567	0.9488	0.9973	0.9937	0.9969	
ANNOY-ANGULAR	13.711	4.1185	13.759	0.9672	0.9720	0.9684	0.9477	0.9564	0.9497	0.9973	0.9941	0.9973	
ANNOY-EUCLIDEAN	12.177	4.5989	13.148	0.9680	0.9720	0.9686	0.9491	0.9563	0.9501	0.9974	0.9942	0.9973	
HNSWLIB-L2	6.5040	0.6606	6.8610	0.9673	0.9719	0.9659	0.9479	0.9562	0.9458	0.9973	0.9939	0.9970	
NMSLIB-COS (FT-ANN)	0.4458	0.0552	0.5626	0.9675	0.9713	0.9664	0.9470	0.9538	0.9465	0.9982	0.9954	0.9972	
GMM	3.3663	0.1052	3.3310	0.9380	0.9651	0.9686	0.9290	0.9395	0.9476	0.9494	0.9931	0.9948	
HNSWLIB-COSINE	6.4246	0.4612	7.2954	0.9462	0.9642	0.9433	0.9079	0.9414	0.9023	0.9994	0.9978	1.0000	
MCD	1269.3	6.3603	1261.3	0.9622	0.9572	0.9517	0.9377	0.9382	0.9159	0.9971	0.9774	0.9985	
CBLOF	2.8297	0.5747	2.7095	0.9404	0.9445	0.9365	0.9297	0.9318	0.9276	0.9531	0.9589	0.9477	
IFOREST	16.066	0.5734	15.980	0.9397	0.9419	0.9362	0.9289	0.9323	0.9288	0.9525	0.9538	0.9464	
HBOS	0.9967	0.8365	1.0126	0.9383	0.9393	0.9367	0.9289	0.9311	0.9274	0.9501	0.9502	0.9483	
PCA	27.829	0.0575	28.413	0.9380	0.9391	0.9349	0.9290	0.9304	0.9271	0.9494	0.9504	0.9454	
AUTOENCODER	82.873	75.064	84.402	0.9380	0.9389	0.9349	0.9290	0.9303	0.9271	0.9494	0.9502	0.9454	
KDE	86.801	3.6710	83.525	0.9370	0.9361	0.9338	0.9283	0.9296	0.9263	0.9483	0.9460	0.9441	
OCSVM	45.391	1.6392	50.025	0.9368	0.9360	0.9326	0.9283	0.9295	0.9255	0.9480	0.9459	0.9426	
FB	10.875	10.547	10.775	0.9355	0.9354	0.9319	0.9279	0.9303	0.9255	0.9460	0.9444	0.9415	
LOF	1.1774	1.0486	1.1147	0.9354	0.9350	0.9317	0.9279	0.9301	0.9255	0.9459	0.9439	0.9412	
DEEPSVDD	38.214	32.719	38.242	0.9187	0.9235	0.8999	0.9230	0.9381	0.9155	0.9210	0.9126	0.8954	
QMCD	9.9598	0.7783	10.251	0.0000	0.3500	0.0000	0.0000	0.8737	0.0000	0.0000	0.2259	0.0000	
LMDD	11883	225.87	11230	0.3292	0.3017	0.3101	0.5701	0.5280	0.5885	0.2476	0.2293	0.2250	

TABLE II: Performance comparisons of our framework (FT-ANN) on the CSIC 2010 dataset

0.35917

0.39443

0.40656

0.49607

1.12676

1.28321

1.30582

1.50904

1.53246

4.05321

5.79449

5.94277

12.43804

12.94397

0.93765 0.98512

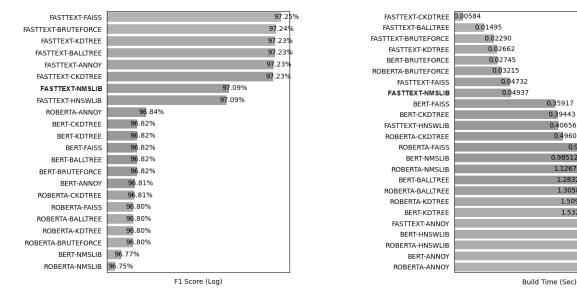
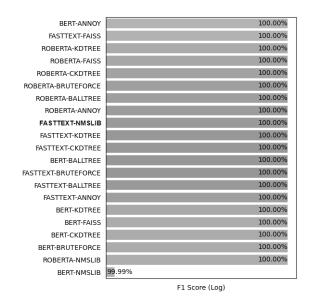


Fig. 7: Model level ANN benchmark on the CSIC 2010 dataset

	Train time (Sec.)				F1-score		Precision	l	Recall			
	BERT	FAST	Ro	BERT	FAST	Ro	BERT	FAST	Ro	BERT	FAST	Ro
		TEXT	BERTa		TEXT	BERTa		TEXT	BERTa		TEXT	BERTa
ANNOY-ANGULAR	0.9859	0.0908	1.0065	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
KDTREE-CITYBLOCK	0.0007	0.0001	0.0007	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
NMSLIB-L2	0.0026	0.0020	0.0025	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
KDTREE-EUCLIDEAN	0.0008	0.0002	0.0008	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
ANNOY-EUCLIDEAN	0.9808	0.0917	1.0144	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
KDTREE-L2	0.0008	0.0002	0.0008	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
KDTREE-MANHATTAN	0.0007	0.0001	0.0007	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
FAISS	0.0015	0.0010	0.0004	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
NMSLIB-COS (FT-ANN)	0.0039	0.0029	0.0042	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
CKDTREE	0.0005	0.0001	0.0005	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
KDTREE-MINKOWSKI	0.0007	0.0002	0.0008	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
BRUTEFORCE-BLAS-MINKOWSKI	0.0087	0.0028	0.0003	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
BRUTEFORCE-BLAS-MANHATTAN	0.0002	0.0001	0.0002	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
BRUTEFORCE-BLAS-EUCLIDEAN	0.0003	0.0001	0.0002	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
BRUTEFORCE-BLAS-COSINE	0.0002	0.0001	0.0002	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
BRUTEFORCE-BLAS-CITYBLOCK	0.0002	0.0001	0.0002	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
BALLTREE-MINKOWSKI	0.0005	0.0002	0.0005	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
BALLTREE-MANHATTAN	0.0005	0.0001	0.0005	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
BALLTREE-L2	0.0005	0.0001	0.0005	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
BALLTREE-EUCLIDEAN	0.0005	0.0002	0.0005	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
BALLTREE-CITYBLOCK	0.0005	0.0001	0.0005	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
NMSLIB-L1	0.0023	0.0019	0.0026	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
ANNOY-MANHATTAN	0.9944	0.0937	1.0303	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
HNSWLIB-L2	0.0010	0.0005	0.0010	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
DEEPSVDD	3.4848	3.1860	3.2811	0.9953	0.9960	0.9944	0.9908	0.9921	0.9889	1.0000	1.0000	1.0000
GMM	2.1158	0.1115	2.1114	0.9949	0.9953	0.9947	0.9899	0.9907	0.9896	1.0000	1.0000	1.0000
KDE	0.0043	0.0010	0.0044	0.9947	0.9946	0.9947	0.9896	0.9893	0.9896	1.0000	1.0000	1.0000
IFOREST	0.2578	0.1915	0.2597	0.9944	0.9946	0.9944	0.9888	0.9893	0.9888	1.0000	1.0000	1.0000
OCSVM	0.0028	0.0011	0.0028	0.9939	0.9946	0.9941	0.9879	0.9893	0.9884	1.0000	1.0000	1.0000
FB	0.0207	0.0144	0.0210	0.9944	0.9946	0.9944	0.9888	0.9893	0.9888	1.0000	1.0000	1.0000
PCA	0.0132	0.0015	0.0140	0.9951	0.9946	0.9951	0.9903	0.9893	0.9903	1.0000	1.0000	1.0000
AUTOENCODER	5.0431	6.0279	4.9394	0.9951	0.9946	0.9951	0.9903	0.9893	0.9903	1.0000	1.0000	1.0000
LOF	0.0016	0.0014	0.0016	0.9944	0.9946	0.9944	0.9888	0.9893	0.9888	1.0000	1.0000	1.0000
HBOS	0.4646	0.9127	0.4715	0.9938	0.9944	0.9947	0.9878	0.9888	0.9896	1.0000	1.0000	1.0000
MCD	151.30	3.6180	174.05	0.9939	0.9942	0.9886	0.9879	0.9885	0.9887	1.0000	1.0000	0.9898
CBLOF	0.0672	0.4408	0.0609	0.9949	0.9896	0.9957	0.9900	0.9795	0.9916	1.0000	1.0000	1.0000
HNSWLIB-COSINE	0.0011	0.0005	0.0011	0.9835	0.9785	0.9870	0.6119	0.8101	0.4654	1.0000	1.0000	1.0000
HNSWLIB-IP	0.0008	0.0004	0.0008	0.9627	0.9578	0.9866	0.4124	0.8958	0.5951	1.0000	1.0000	1.0000
QMCD	0.0379	0.5941	0.0431	0.0000	0.8946	0.0000	0.0000	0.9832	0.0000	0.0000	0.8240	0.0000
LMDD	0.3028	0.3387	0.3208	0.5641	0.2920	0.6261	1.0000	0.8237	1.0000	0.3982	0.1825	0.4628

TABLE III: Performance comparisons of our framework (FT-ANN) on the ATRDF 2023 dataset



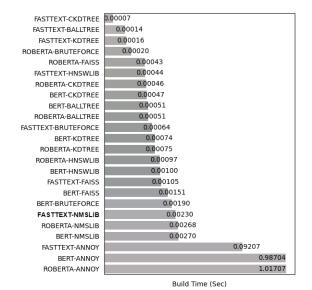


Fig. 8: Model level ANN benchmark on the ATRDF 2023 dataset

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REFERENCES

- [1] S. Balsari, A. Fortenko, J. A. Blaya, A. Gropper, M. Jayaram, R. Matthan, R. Sahasranam, M. Shankar, S. N. Sarbadhikari, B. E. Bierer et al., "Reimagining Health Data Exchange: An application programming interface—enabled roadmap for India," *Journal of Medical Internet Research*, vol. 20, no. 7, p. e10725, 2018.
- [2] J. Ofoeda, R. Boateng, and J. Effah, "Application programming interface (API) research: A review of the past to inform the future," *IJEIS*, vol. 15, no. 3, pp. 76–95, 2019.
- [3] A. Mendoza and G. Gu, "Mobile application web API reconnaissance: Web-to-mobile inconsistencies & vulnerabilities," in SP, 2018, pp. 756–769.
- [4] C. Benzaid and T. Taleb, "ZSM security: Threat surface and best practices," *IEEE Network*, vol. 34, no. 3, pp. 124–133, 2020.
- [5] IBM, "Innovation in the API economy: Building winning experiences and new capabilities to compete," 2016, https://www.ibm.com/downloads/cas/OXV3LYLO.
- [6] M. Reddy, API Design for C++. Elsevier, 2011.
- [7] R. Sun, Q. Wang, and L. Guo, "Research Towards Key Issues of API Security," in CNCERT, Beijing, China, July 20–21, 2021, pp. 179–192.
- [8] M. Coyne, "Zoom's Big Security Problems Summarized," https://www.forbes.com/sites/marleycoyne/2020/04/03/zooms-big-security-problems-summarized/?sh=46fc370f4641, 2020, forbes.
- [9] "Capital One data breach: Arrest after details of 106m people stolen," https://www.bbc.com/news/world-us-canada-49159859, 2019, bBC.
- [10] J. Greig, "Hilton denies hack after data from 3.7 million Honors customers offered for sale," https://therecord.media/hilton-denies-hackafter-data-from-3-7-million-honors-customer-offered-for-sale/, 2023, the Record
- [11] "Equifax Says Cyberattack May Have Affected 143 Million in the U.S." https://www.nytimes.com/2017/09/07/business/equifaxcyberattack.html, 2017, the New York Times.
- [12] D. Fett, R. Küsters, and G. Schmitz, "A comprehensive formal security analysis of OAuth 2.0," in SIGSAC CCCS, 2016, pp. 1204–1215.
- [13] A. Chan, A. Kharkar, R. Z. Moghaddam, Y. Mohylevskyy, A. Helyar, E. Kamal, M. Elkamhawy, and N. Sundaresan, "Transformer-based Vulnerability Detection in Code at EditTime: Zero-shot, Few-shot, or Fine-tuning?" arXiv preprint arXiv:2306.01754, 2023.
- [14] G. Baye, F. Hussain, A. Oracevic, R. Hussain, and S. A. Kazmi, "API security in large enterprises: Leveraging machine learning for anomaly detection," in *ISNCC*. IEEE, 2021, pp. 1–6.
- [15] E. Harlicaj et al., "Anomaly detection of web-based attacks in microservices," 2021.
- [16] F. Shen, Y. Mu, Y. Yang, W. Liu, L. Liu, J. Song, and H. T. Shen, "Classification by retrieval: Binarizing data and classifiers," in ACM SIGIR, 2017, pp. 595–604.
- [17] W. Shi, J. Michael, S. Gururangan, and L. Zettlemoyer, "Nearest neighbor zero-shot inference," arXiv preprint arXiv:2205.13792, 2022.
- [18] A. M. Qamar, E. Gaussier, J.-P. Chevallet, and J. H. Lim, "Similarity learning for nearest neighbor classification," in *ICDM*. IEEE, 2008, pp. 983–988.
- [19] J. J. Valero-Mas, A. J. Gallego, P. Alonso-Jiménez, and X. Serra, "Multilabel prototype generation for data reduction in k-nearest neighbour classification," *Pattern Recognition*, vol. 135, p. 109190, 2023.
- [20] A. S. Reddy and B. Rudra, "Evaluation of Recurrent Neural Networks for Detecting Injections in API Requests," in CCWC, 2021, pp. 0936– 0941.
- [21] J. Ombagi, "Time-Based Blind SQL Injection via HTTP Headers: Fuzzing and Exploitation." 2017.
- [22] I. Jemal, M. A. Haddar, O. Cheikhrouhou, and A. Mahfoudhi, "Performance evaluation of Convolutional Neural Network for web security," Computer Communications, vol. 175, pp. 58–67, 2021.
- [23] M. Gniewkowski, H. Maciejewski, T. R. Surmacz, and W. Walentynowicz, "HTTP2vec: Embedding of HTTP Requests for Detection of Anomalous Traffic," ArXiv, vol. abs/2108.01763, 2021.
- [24] I. Jemal, M. A. Haddar, O. Cheikhrouhou, and A. Mahfoudhi, "M-CNN: a new hybrid deep learning model for web security," in AICCSA, 2020, pp. 1–7.

- [25] Q. Niu and X. Li, "A high-performance web attack detection method based on CNN-GRU model," in *ITNEC*, vol. 1, 2020, pp. 804–808.
- [26] L. Yu, L. Chen, J. Dong, M. Li, L. Liu, B. Zhao, and C. Zhang, "Detecting malicious web requests using an enhanced textCNN," in COMPSAC. IEEE, 2020, pp. 768–777.
- [27] A. Moradi Vartouni, S. Mehralian, M. Teshnehlab, and S. Sedighian Kashi, "Auto-Encoder LSTM Methods for Anomaly-Based Web Application Firewall," *International Journal of Information and Communication Technology Research*, vol. 11, no. 3, pp. 49–56, 2019.
- [28] A. Moradi Vartouni, M. Shokri, and M. Teshnehlab, "Auto-threshold deep SVDD for anomaly-based web application firewall," 2021.
- [29] F. A. Research, "fastText library for efficient learning of word representations and sentence classification," https://github.com/facebookresearch/ fastText/, 2017, online; accessed 02-December-2017.
- [30] B. Bansal and S. Srivastava, "Sentiment classification of online consumer reviews using word vector representations," *Procedia Computer Science*, vol. 132, pp. 1147–1153, 2018.
- [31] S. TOPRAK and A. G. YAVUZ, "Web Application Firewall Based on Anomaly Detection Using Deep Learning," *Acta Infologica*, vol. 6, no. 2, pp. 219–244, 2022.
- [32] L. Xiao, S. Matsumoto, T. Ishikawa, and K. Sakurai, "SQL Injection Attack Detection Method Using Expectation Criterion," in 2016 Fourth International Symposium on Computing and Networking (CANDAR). IEEE, 2016, pp. 649–654.
- [33] Y. E. Seyyar, A. G. Yavuz, and H. M. Ünver, "An attack detection framework based on BERT and deep learning," *IEEE Access*, vol. 10, pp. 68 633–68 644, 2022.
- [34] E. Chávez, G. Navarro, R. Baeza-Yates, and J. L. Marroquín, "Searching in metric spaces," ACM Computing Surveys (CSUR), vol. 33, no. 3, pp. 273–321, 2001.
- [35] A. Ponomarenko, N. Avrelin, B. Naidan, and L. Boytsov, "Comparative analysis of data structures for approximate nearest neighbor search," in *DATA ANALYTICS*, 2014, pp. 125–130.
- [36] P. Indyk and R. Motwani, "Approximate nearest neighbors: towards removing the curse of dimensionality," in ACM Symposium on Theory of Computing, 1998, pp. 604–613.
- [37] K. Hajebi, Y. Abbasi-Yadkori, H. Shahbazi, and H. Zhang, "Fast approximate nearest-neighbor search with k-nearest neighbor graph," in AI, 2011.
- [38] R. Battle and E. Benson, "Bridging the semantic Web and Web 2.0 with representational state transfer (REST)," *Journal of Web Semantics*, vol. 6, no. 1, pp. 61–69, 2008.
- [39] W. J. Buchanan, S. Helme, and A. Woodward, "Analysis of the adoption of security headers in HTTP," *IET Information Security*, vol. 12, no. 2, pp. 118–126, 2018.
- [40] A. Joulin, E. Grave, P. Bojanowski, and T. Mikolov, "Bag of Tricks for Efficient Text Classification," arXiv preprint arXiv:1607.01759, 2016.
- [41] B. Li and L. Han, "Distance weighted cosine similarity measure for text classification," in *IDEAL*, China, Oct., 2013, pp. 611–618.
- [42] E. Techapanurak, M. Suganuma, and T. Okatani, "Hyperparameter-free out-of-distribution detection using cosine similarity," in ACCV, 2020.
- [43] Y.-C. Hsu, Y. Shen, H. Jin, and Z. Kira, "Generalized odin: Detecting out-of-distribution image without learning from out-of-distribution data," in CVF, 2020, pp. 10951–10960.
- [44] P. Xia, L. Zhang, and F. Li, "Learning similarity with cosine similarity ensemble," *Information Sciences*, vol. 307, pp. 39–52, 2015.
- [45] B. Naidan, L. Boytsov, Y. Malkov, and D. Novak, "Non-Metric Space Library (NMSLIB): An efficient similarity search library and a toolkit for evaluation of k-NN methods for generic non-metric spaces," https://github.com/nmslib/nmslib, 2014, online; accessed 14-July-2014.
- [46] J. E. Stone, K. S. Griffin, J. Amstutz, D. E. DeMarle, W. R. Sherman, and J. Günther, "ANARI: A 3-D Rendering API Standard," *Computing in Science & Engineering*, vol. 24, no. 2, pp. 7–18, 2022.
- [47] C. Torrano-Gimenez, H. T. Nguyen, G. Alvarez, S. Petrović, and K. Franke, "Applying feature selection to payload-based web application firewalls," in *IWSCN*, 2011, pp. 75–81.
- [48] B. Ware, "Analyzing Web Traffic ECML/PKDD 2007 Discovery Challenge," 2007, https://www.lirmm.fr/pkdd2007-challenge/comites.html.
- [49] UNB, "A collaborative project between the Communications Security Establishment (CSE) & the Canadian Institute for Cybersecurity (CIC)," 2018, https://www.unb.ca/cic/datasets/ids-2018.html.
- [50] B. Damele and M. Stampar, "SQLMAP: Automatic SQL injection and database takeover tool (2015)," http://sqlmap.org.
- [51] Icesurfer and Nico, "SQLNINJA: SQL Server injection & takeover tool (2007)," https://sqlninja.sourceforge.net.
- [52] S. Bennetts, "OWASP Zed attack proxy," AppSec USA, 2013.

- [53] Y. Fang, J. Peng, L. Liu, and C. Huang, "WOVSQLI: Detection of SQL injection behaviors using word vector and LSTM," in CSP, 2018, pp. 170–174.
- [54] C. T. Giménez, A. P. Villegas, and G. Á. Marañón, "HTTP data set CSIC 2010," CSIC, vol. 64, 2010.
- [55] S. Lavian, R. Dubin, and A. Dvir, "The API Traffic Research Dataset Framework (ATRDF)," 2023, https://github.com/ArielCyber/ Cisco_Ariel_Uni_API_security_challenge.
- [56] P. M. S. Sánchez, J. M. J. Valero, A. H. Celdrán, G. Bovet, M. G. Pérez, and G. M. Pérez, "A survey on device behavior fingerprinting: Data sources, techniques, application scenarios, and datasets," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 1048–1077, 2021.
- [57] B. R. Dawadi, B. Adhikari, and D. K. Srivastava, "Deep Learning Technique-Enabled Web Application Firewall for the Detection of Web Attacks," *Sensors*, vol. 23, no. 4, p. 2073, 2023.
- [58] H. Mac, D. Truong, L. Nguyen, H. Nguyen, H. A. Tran, and D. Tran, "Detecting attacks on web applications using autoencoder," in *ICT*, 2018, pp. 416–421.
- [59] J. Wang, Z. Zhou, and J. Chen, "Evaluating CNN and LSTM for web attack detection," in *ICMLC*, 2018, pp. 283–287.
- [60] M. Ito and H. Iyatomi, "Web application firewall using character-level convolutional neural network," in CSPA, 2018, pp. 103–106.
- [61] I. Jemal, M. A. Haddar, O. Cheikhrouhou, and A. Mahfoudhi, "Performance evaluation of Convolutional Neural Network for web security," Computer Communications, vol. 175, pp. 58–67, 2021.
- [62] L. Yan and J. Xiong, "Web-APT-Detect: a framework for web-based advanced persistent threat detection using self-translation machine with attention," *IEEE Letters of the Computer Society*, vol. 3, no. 2, pp. 66– 69, 2020.
- [63] V. L. Pochat, T. Van Goethem, S. Tajalizadehkhoob, M. Korczyński, and W. Joosen, "Tranco: A research-oriented top sites ranking hardened against manipulation," arXiv preprint arXiv:1806.01156, 2018.
- [64] Y. Zhao, Z. Nasrullah, and Z. Li, "PyOD: A python toolbox for scalable outlier detection," arXiv preprint arXiv:1901.01588, 2019.
- [65] M. Aumüller, E. Bernhardsson, and A. Faithfull, "ANN-Benchmarks: A benchmarking tool for approximate nearest neighbor algorithms," *Information Systems*, vol. 87, p. 101374, 2020.
- [66] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," arXiv preprint arXiv:1810.04805, 2018.
- [67] Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov, "RoBERTa: A robustly optimized BERT pretraining approach," arXiv preprint arXiv:1907.11692, 2019.
- [68] H. Guo, S. Yuan, and X. Wu, "Logbert: Log anomaly detection via bert," in 2021 International Joint Conference on Neural Networks (IJCNN). IEEE, 2021, pp. 1–8.
- [69] A. Arning, R. Agrawal, and P. Raghavan, "A Linear Method for Deviation Detection in Large Databases." in KDD, vol. 1141, no. 50, 1996, pp. 972–981.
- [70] T. Yu, H. Fei, and P. Li, "U-BERT for Fast and Scalable Text-Image Retrieval," in *Proceedings of the 2022 ACM SIGIR International Conference on Theory of Information Retrieval*, 2022, pp. 193–203.
- [71] J. Xin, R. Tang, Y. Yu, and J. Lin, "BERxiT: Early exiting for BERT with better fine-tuning and extension to regression," in *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, 2021, pp. 91–104.
- [72] A. Rücklé, G. Geigle, M. Glockner, T. Beck, J. Pfeiffer, N. Reimers, and I. Gurevych, "AdapterDrop: On the efficiency of adapters in transformers," arXiv preprint arXiv:2010.11918, 2020.
- [73] I. Tarunesh, S. Aditya, and M. Choudhury, "Trusting RoBERTa over BERT: Insights from checklisting the natural language inference task," arXiv preprint arXiv:2107.07229, 2021.
- [74] P. Rajapaksha, R. Farahbakhsh, and N. Crespi, "BERT, XLNet or RoBERTa: the best transfer learning model to detect clickbaits," *IEEE Access*, vol. 9, pp. 154704–154716, 2021.
- [75] Y. Jia, "Design of nearest neighbor search for dynamic interaction points," in 2021 2nd International Conference on Big Data and Informatization Education (ICBDIE). IEEE, 2021, pp. 389–393.
- [76] F. Cheng, R. J. Hyndman, and A. Panagiotelis, "Manifold learning with approximate nearest neighbors," ArXiv, 2021.
- [77] AWS, "Build k-Nearest Neighbor (k-NN) similarity search engine with Amazon Elasticsearch Service," 2020, https://aws.amazon.com/about-aws/whats-new/2020/03/
 - build-k-nearest-neighbor-similarity-search-engine-with-amazon-elastic search-service.



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