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A Comparative Performance Analysis of Explainable Machine Learning Models With And Without RFECV Feature Selection Technique Towards Ransomware Classification

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ABSTRACT Ransomware has emerged as one of the major global threats in recent days. The alarming increasing rate of ransomware attacks and new ransomware variants intrigue the researchers in this domain to constantly examine the distinguishing traits of ransomware and refine their detection or classification strategies. Among the broad range of different behavioral characteristics, the trait of Application Programming Interface (API) calls and network behaviors have been widely utilized as differentiating factors for ransomware detection, or classification. Although many of the prior approaches have shown promising results in detecting and classifying ransomware families utilizing these features without applying any feature selection techniques, feature selection, however, is one of the potential steps toward an efficient detection or classification Machine Learning model because it reduces the probability of overfitting by removing redundant data, improves the model's accuracy by eliminating irrelevant features, and therefore reduces training time. There have been a good number of feature selection techniques to date that are being used in different security scenarios to optimize the performance of the Machine Learning models. Hence, the aim of this study is to present the comparative performance analysis of widely utilized Supervised Machine Learning models with and without RFECV feature selection technique towards ransomware classification utilizing the API call and network traffic features. Thereby, this study provides insight into the efficiency of the RFECV feature selection technique in the case of ransomware classification which can be used by peers as a reference for future work in choosing the feature selection technique in this domain.

INDEX TERMS Explainable AI, Machine Learning, Feature Engineering, Ransomware Classification. Cyber Security

I. INTRODUCTION

R ANSOMWARE is a harmful software that applies symmetric and asymmetric cryptography to inscribe user information and poses a Denial-of-Service (DoS) attack on the intended user [1]. The unique functional process of ransomware attacks makes it more harmful than any malware attacks and causes irreversible losses. Crypto-viral Extortion', which is the functional process of ransomware, includes three main steps [2] as depicted in Figure 1. In the initial step, the attacker creates a key pair that incorporates a private key K1 and a public key K2, puts the public key

K2 in the ransomware, then, at that point, launches the ransomware. After entering a computer, in the second step, the ransomware activates itself and produces an arbitrary symmetric session key K3 to encrypt the victim's files or data. Next, the ransomware utilizes K2 to encrypt K3 and to create a small irregular ciphertext E1. Then, the ransomware zeroizes K3 and the plaintext from the person's drive. A communication bundle P1 containing previously generated E1, a payment note M, and a medium to contact the attacker, is then created. After that, the ransomware informs the victim of the attack and demands payment via a transaction medium

within a set amount of time in order to decrypt the files by displaying the payment note M. At the final step, as the payment is completed, the communication bundle P1 is adjusted to P2 containing just the deviated ciphertext E1 and steered back to the attacker. The attacker gets P2, decrypts E1 with K1, and gets K3 which is then sent back to the victim to decrypt the files. Finally, upon receiving K3, the victim decrypts the files. Usually, the victim pays the ransom using untraceable cryptocurrency [3]. However, paying the ransom doesn't guarantee that the decryption key could secure the encrypted files, which could be the worst scenario of any type of ransomware attack [4].

Supported by a report by Symantec in 2015, there are two types of ransomware [5]-

- Locker ransomware: denies access to the system or device
- · Crypto ransomware: denies access to the files or data

However, according to [6], based on the functionalities, ransomware is categorized into four groups-

- Encrypting ransomware: encrypts and denies access to the victim's files and data (i.e., AIDS Trojan, CryptoLocker, WannaCry, CryptoWall) [6]
- Non-encrypting ransomware: doesn't do encryption but rather threatens to try if the ransom is not paid (i.e., WinLock, NotPetya) [6]
- Leak-ware: doesn't do encryption instead claims to reveal stolen information from the victim's system if the ransom is not paid [7]
- Mobile ransomware: targets the Android platform [8]



FIGURE 1: Workflow of a ransomware

All these categories of ransomware are playing a vital role in the recent upsurge in the incidence of ransomware attacks. Due to the increasing number of ransomware variants and ransomware attacks, researchers have been earnestly involving themselves to look for efficient ways to improve the scenarios. While some researchers are analyzing the distinctive behaviors of ransomware by executing it in a secure environment called Dynamic Analysis [1], [9] - [13], some researchers are analyzing the ransomware without any execution, referred to as Static Analysis [14] - [16]. However, a good number of researchers are combining these two approaches and adopting a Hybrid Analysis Approach [17] - [19]. Although the static analysis technique takes less analysis time and facilitates the researchers by not requiring the execution of malicious files, this technique struggles to trace new ransomware variants because of the ever-evolving code obfuscation technique. On the other hand, although a dynamic analysis approach might take a longer time to process and analyze the ransomware program, this approach can detect ransomware with higher accuracy as it executes the ransomware program in a secure virtual environment and does real-time behavioral analysis. The main idea is that despite the changes in the new ransomware variants, they will still show the same behavioral patterns. Therefore, for this study, we have opted for the dynamic analysis approach for its ability to detect and classify ransomware families based on behavioral patterns regardless of the code obfuscation techniques deployed by the ransomware programmers [20], [21].

The main contributions of this study are:

- Developing a Web-Crawler, 'GetRansomware' to automate collecting the Windows Portable Executable (PE) files of 15 different ransomware families from the VirusShare repository. The Web-Crawler is essential to automate searching and downloading the samples and cutting down the manual workload.
- Examining and comparing the performance of six Supervised Machine Learning models with and without RFECV feature selection technique in case of classifying ransomware families. For this task, we construct two different datasets by analyzing two types of binaries, namely, Windows Portable Executables (PE) and Packet Capture (PCAP) files. Since our approach includes utilizing RFECV for selecting the optimum number of features and RandomSearchCV for selecting the optimum hyperparameter values for each classifier, therefore, this study attempts to optimize each model's performance in both scenarios before the comparison is made.
- Presenting the efficiency of the RFECV feature selection technique in ransomware classification with respect to the performance of the Machine Learning models. For this task, first, we utilize 'Shapley Additive exPlanations' to obtain the highly contributing features from the without feature selection scenario. Next, we obtain the RFECV-selected features from the with feature selection scenario. Finally, we report how the important set of features varies for each Machine Learning model in two scenarios and how they affect to the final outcome.

The rest of this paper is structured as follows: Section 2 presents the related works. Section 3 details our methodology. The experimental results and discussions are illustrated in Section 4. Section 5 concludes the paper with the direction for future works.

II. RELATED WORKS

In this section, we present several prior approaches to ransomware detection or classification. Although malware of a particular kind is called ransomware and many of the previous approaches include ransomware families in the malware dataset, our investigation mainly focuses on the binary and multiclass classification of ransomware through the dynamic analysis approach. First, we present recent research on API sequence and frequency-based ransomware detection and classification techniques. Next, we introduce a few investigations on network traffic features-based methods. Then, we mention several works that combine other significant features along with API call features and network traffic features towards ransomware detection and classification. All of these approaches are similar to our method since we consider both the API call features and network traffic features for comparing the performance of Machine Learning models with and without the RFECV feature selection technique.

A good number of researchers analyzed API call behaviors and proposed ransomware detection or classification methods based on the API call sequences or frequencies. Maniath et al. [10] analyzed the API call behavior of 157 Ransomware and presented LSTM-based ransomware detection that focuses on API call sequence and compensates for the ransomware that causes execution delays. However, this work lacks complete information about the ransomware families/variants and the number of benign software used for the experiment. Vinayakumar Kumar et al. [11] proposed an MLP-based ransomware detection method focusing on API call frequency but they deployed a simple MLP network that failed to distinguish CryptoWall and Cryptolocker. Z. Chen et al. [27] used API Call Flow Graph (CFG) generated from the extracted API sequence using the API monitor tool for detecting ransomware. Regardless, the work is based on a smaller dataset that includes only four ransomware families. Also, graphsimilarity analysis requires higher computational power that some systems may not provide. Takeuchi et al. [12] used API call sequences to identify zero-day ransomware attacks and the work involved kernel tricks for tuning Support Vector Machine. However, the accuracy of this work decreases while using standardized vector representation because of the less diverse dataset. Bae et al. [28] extracted the API call sequences using the Intel Pin Tool. Their sequential process includes generating an n-gram sequence, input vector, and Class Frequency Non-Class Frequency (CF-NCF) for every sample before fitting their model. Nevertheless, their work lacks complete information about the ransomware families/variants used for the experiment, and the work's accuracy can be improved with the help of deception-based techniques. Hwang et al. [13] analyzed API calls and used two Markov chains, one for ransomware and another for benign software to capture the API call sequence patterns. By using Random Forest, they compensate Markov Chains and control FPR and FNR to achieve better performance. However, their model produces high FPR that can be improved with the help of signature-based techniques.

In contrast to the API call behaviors, some researchers analyzed network traffic behaviors of different ransomware families. Cabaj et al. [29] proposed two real-time Software Defined Networking (SDN) based mitigation methods that were developed using OpenFlow to ensure the prompt reaction to the threat while not decreasing the overall network performance. However, the proposed method is only based on the features of CryptoWall ransomware. Tseng et al. [30] proposed a method that can identify specific network traffic types and detect in-network behavior sequences. Their approach detects ransomware before encryption starts. Regardless, the work lacks complete information about the ransomware families/variants as well as benign software used for the experiment. Alhawi et al. [31] used TShark for capturing and analyzing malicious network traffic activities followed by utilizing the WEKA ML tool to detect ransomware based on only 9 extracted features. Nonetheless, because of using fewer features of only 210 ransomware, the proposed method may fall short of recognizing the new ransomware variants. Almashhadani et al. [24] built a dedicated testbed for executing and capturing the network traffic of the sample ransomware and proposed a multi-classifier that works on two different levels: packet-based and flow-based classifiers. Their method employed a language-independent algorithm that can detect domain names from general sonic axioms. However, the proposed method is only based on the Locky ransomware.

Instead of considering only API call behavior or only the network traffic behavior, some researchers combined these two categories of behavior along with other malicious indicators (i.e., registry key operations, file extensions, files/directory operation, etc.) for their models. D. Sgandurra et al. [9] analyzed API calls, registry key operations, embedded strings, file extensions, files/directory operations, and dropped file extensions prior to developing their model. The features were selected using the mutual information criterion and their proposed method 'EldeRan' was able to deal with sophisticated encryption methods of ransomware at an early stage. However, the limitation of 'EldeRan' is that it produces a higher False Positive Rate. Continella et al. [32] analyzed filesystem operations and presented two models: process-centric trained on each process and system-centric trained on the whole system. They developed 'ShieldFS'a software on OS that can detect malicious file activities and roll back from the attack. However, their system-centric model produces high false positives, and the system may face performance degradation due to the add-on driver on the OS. T. Lu et al. [33] analyzed API calls, network features, registry operations, file operations, directory operations, and memory usage for developing a ransomware detection method based on the Artificial Immune System (AIS). They applied realvalued detector generation based on the V-detector negative selection while optimizing the AIS parameter (i.e., hypersphere detector distribution) to improve the ransomware detection rate. Regardless, their system also produces higher false alarms. Hasan et al. [1] considered API calls, network features, registry key operations. process operations, function length frequency, and printable string information for their model. They proposed a framework- 'RansHunt' that takes a hybrid approach to identify potential static and dynamic features for the SVM classifier that outperforms traditional AV tools. However, the proposed method only focuses on the Crypto category. So, it may not be effective for the Locker category.

Table 1 presents the synopsis of the previous research works conducted on the analysis, detection, and classification of ransomware.

III. METHODOLOGY

The methodology of our study consists of three subsequent steps as illustrated in Figure 2: Data Collection, Feature Engineering, and Classification.



FIGURE 2: Process overview of our methodology.

A. DATA COLLECTION

We have developed a Web-Crawler- 'GetRansomware' to automate collecting the Windows Portable Executable (PE) files of 15 different ransomware families from the VirusShare repository. [34]. We have also shared the Web-Crawler on our GitHub repository for public access [35]. About 95% of the PE files were collected from VirusShare using GetRansomware. The rest of the PE files were collected from theZoo [36] and Hybrid-Analysis.com [37]. In addition, we have collected the Packet Capture (PCAP) files of those ransomware families from the malware-traffic-analysis [38]. Every ransomware sample was downloaded as a passwordprotected compressed file. Table 2 presents the number of collected samples.

B. FEATURE ENGINEERING

The scarcity of the ransomware dataset is one of the major challenges that hinder the research work in this area [39]. Therefore, for this study, we construct two different datasets from two types of binaries through separate feature engineering processes. In the first process, we create the first dataset by analyzing the PE files while in the second process, we create the second dataset by analyzing the PCAP files.

1) Process 1: Creation of the first dataset- 'Data1'

The feature engineering step for the first process is composed of two phases. The phases are:

- Phase 1: Feature Extraction
- Phase 2: Feature Selection

TABLE 1: Synopsis of the Literature Review.

API Call Featu	res		
Reference	Dataset	Classifier	Accuracy %
Maniath et al. [10]	 157 Ransomware Unspecified number of benign software 	Long Short- Term Memory	96.67 %
Vinayakumar Kumar et al. [11]	 755 Ransomware 219 Benign Software 	Multilayer Per- ceptron	 100% (Binary Classifica- tion) 98% (Multi- class Classi- fication)
Z. Chen et al. [27]	 83 Ransomware 85 Benign Software	Simple Logis- tic	98.2%
Takeuchi et al. [12]	 276 Ransomware 312 Benign Software 	Support Vector Machine	97.48%
Bae et al. [28]	 1000 Ransomware 900 Malware 300 Benign software 	Random Forest	98.65%
Hwang et al. [13]	 1909 Ransomware 1139 Benign software 	Markov Chain, Random Forest (Two-stage de- tection model)	97.3%
Network Featu	res		
K. Cabaj et al. [29]	• 359 CryptoWall samples	N/A	N/A
Tseng et al. [30]	 155 Ransomware Unspecified number of benign software 	Deep Neural Network	93.92%
Alhawi et al. [31]	 210 Ransomware 264 Benign software	J48	97.1%
Almashhadani et al. [24]	 Locky ransomware Unspecified number of benign software 	Bayes Net	99.83%
API Call Featu	res, Network Features, and	d Other Features	0.010
D. Sgandurra et al. [9]	 582 Ransomware 942 Benign Software 	Regularized Logistic Regression	96.34%
A. Continella et al. [32]	 383 Ransomware 2245 Benign Software 	Random Forest	97.70%
T. Lu et al. [33]	 1000 Ransomware 1000 Benign Software 	V-detector	90%
Hasan et al. [1]	 360 Ransomware 532 Malware 460 Benign Software 	Support Vector Machine	97.10%

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TABLE 2:	Number	of colle	cted sam	ples.
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Ransomware	PE file	PCAP file
Cerber (c0)	95	58
Eris (c1)	95	55
CryptoWall (c2)	97	55
Eris (c3)	98	55
Hive (c4)	100	56
Jigsaw (c5)	95	60
Locky (c6)	95	60
Maze (c7)	100	55
Mole (c8)	100	56
Sage (c9)	100	56
Satan (c10)	100	60
Shade (c11)	98	57
TeslaCrypt (c12)	97	59
Virlock (c13)	95	57
WannaCry (c14)	95	57
Total	1460	856

a: Phase 1: Feature Extraction

From the wide range of distinct behavioral features, we have considered utilizing Application Programming Interface (API) call frequencies for our study. API calls are made by the application or program running at a user level to request services as depicted in Figure 3. It is the method through which data or information is exchanged between the sending device and the receiving device. The OS performs the requested services by issuing these calls, and the outcomes are returned to the caller user applications. Thus, API calls made by the ransomware program allow the attackers to explore and obtain control of the system and perform malicious activities. Since analyzing API call behavior leads researchers to better understand the program's behavior [40], [41], therefore, we have considered extracting the API call frequency by executing the PE files of the ransomware.





We have analyzed the PE files with the help of Hybrid-Analysis.com [37], powered by the CrowdStrike Falcon Sandbox [42]. To automate submitting malicious binaries, pull the analysis report after the analysis, and perform advanced or required search queries on the database, Falcon Sandbox provides a free, convenient, and efficient API key that one can obtain from an authorized user account. For analysis, we have used our API key and Falcon Sandbox Python API Connector- VxAPI wrapper [43] to automatically submit the binaries from the system. After submission, Falcon Sandbox runs the binaries in a Virtual Machine (VM) and captures the run-time behaviors as illustrated in Figure 4. Later, it shows the analysis results on the web interface.



FIGURE 4: Block diagram of the PE file execution process.

Contrary to the prior works where the analysis tasks were done using the Cuckoo Sandbox [1], [9] - [13], we have analyzed the PE files using the Falcon Sandbox that uses a VM (Windows 7 64-bit) to execute the PE files. Falcon Sandbox incorporates many other services, such as VirusTotal, Thug honeyclient, OPSWAT Metadefender, TOR, NSRL (Whitelist), Phantom, and a large number of antivirus engines to provide an integrated and in-depth analysis reports compared to other Sandboxes. While executing the binaries, we have set run-time to the maximum available duration in the Falcon Sandbox to deal with the delayed execution techniques deployed by the attackers. The total time for the analysis was (1460 PE files * 7 minutes) = 170 hours = 7 days approximately. Next, we obtained the analysis report by using the API key from which we have only sorted and computed the frequency of each API call. At the end of the PE files analysis process, we obtained our first dataset-'Data1' consisting of the different frequencies of 68 distinct API calls associated with the 15 ransomware families as presented in Table 3.

b: Phase 2: Feature Selection

At the beginning of the feature selection phase, we have evenly divided (stratified train-test split) our dataset into train data (80%) and test data (20%) to avoid data leakage. Next, we have applied Recursive Feature Elimination with Cross-Validation (RFECV) [48] to our train data. RFECV is a wrapper-style feature selection method that wraps a given ML model as depicted in Figure 5 and selects the optimal number of features for each model by recursively eliminating 0-n features in each loop. Next, it selects the best-performing subset of features based on the accuracy or the score of cross-validation. RFECV also removes the dependencies and collinearity existing in the model. By using RFECV, we have selected 6 distinct subsets of features for 6 ML classifiers. These features have been selected by setting 'min features to select' as 34 (half of the features), cv=5, and 'scoring'= 'accuracy' so that RFECV would select at least half of the



TABLE 3: List of features in the 'Data1' dataset.

API Call Features	
1. FindWindowExW	35. NtProtectVirtualMemory
2. LdrGetDllHandle	36. NtQueryAttributesFile
3. NtAdjustPrivilegesToken	37. NtQueryDefaultLocale
4. NtAlertThread	38. NtQueryDirectoryFile
5. NtAllocateVirtualMemory	39. NtQueryInformationFile
6. NtAlpcSendWaitReceivePort	40. NtQueryInformationProcess
7. NtConnectPort	41. NtQueryInformationToken
8. NtCreateEvent	42. NtQueryKey
9. NtCreateFile	43. NtQueryObject
10. NtCreateKey	44. NtQuerySystemInformation
11. NtCreateKeyEx	45. NtQueryValueKey
12. NtCreateMutant	46. NtQueryVirtualMemory
13. NtCreateSection	47. NtQueryVolumeInformationFile
14. NtCreateThreadEx	48. NtReadFile
15. NtCreateUserProcess	49. NtReadVirtualMemory
16. NtDelayExecution	50. NtRequestWaitReplyPort
17. NtDeleteValueKey	51. NtResumeThread
18. NtDeviceIoControlFile	52. NtSetContextThread
19. NtEnumerateKey	53. NtSetInformationFile
20. NtEnumerateValueKey	54. NtSetInformationKey
21. NtFsControlFile	55. NtSetInformationProcess
22. NtGetContextThread	56. NtSetInformationThread
23. NtMapViewOfSection	57. NtSetSecurityObject
24. NtNotifyChangeKey	58. NtSetValueKey
25. NtOpenDirectoryObject	59. NtTerminateProcess
26. NtOpenEvent	60. NtTerminateThread
27. NtOpenFile	61. NtUnmapViewOfSection
28. NtOpenKey	62. NtWaitForMultipleObjects
29. NtOpenKeyEx	63. NtWriteFile
30. NtOpenMutant	64. NtWriteVirtualMemory
31. NtOpenProcess	65. NtYieldExecution
32. NtOpenProcessToken	66. OpenSCManager
33. NtOpenSection	67. OpenServiceW
34 MtOpenThreadToken	68 SetWindowsHookEy

features based on the optimum accuracy over the 5-fold cross-validation.



FIGURE 5: RFECV feature selection technique.

2) Process 2: Creation of the second dataset- 'Data2' The feature engineering step for the second process is composed of four phases. The phases are:

- Phase 1: Feature Extraction
- Phase 2: Exploratory Data Analysis (EDA)
- Phase 3: Data Preprocessing
- Phase 4: Feature Selection

a: Phase 1: Feature Extraction

We have considered utilizing network traffic features for the second dataset for our study. The Transmission Control Protocol (TCP) refers to the set of standardized communication protocols that specify how computers communicate over the network. According to our literature review, the communication between the infected host machine (source) and the attacker (destination) is conducted through the transport layer [25]. Besides, HTTP GET or POST methods are also used to send back the information to the attacker [24]. Hence, we have opted for capturing the TCP traffic and the HTTP traffic information by analyzing the PCAP files of the ransomware.

Again, ransomware often spreads through spam emails containing malignant attachments as macro-enabled word documents. By executing a script, these attachments download the executable file of that ransomware from a URL and install it on the system. After the installation, the ransomware continuously tries to search and connect to its C&C servers to exchange the encryption key and launch the attack session. Firstly, it utilizes an encrypted list of IP addresses for creating a TCP session with the C&C servers. Upon failure due to the unreachable or blacklisted IP addresses or disrupted session, the ransomware then opts to find out its C&C server by executing the Domain Generation Algorithm (DGA) and recurrently produces a good number of pseudo-random domain names. Then, the ransomware continues sending the Domain Name System (DNS) request to those domain names until the actual C&C server is found as illustrated in Figure 6. Here, DNS converts human-readable domain names to machinereadable IP addresses. Upon successful establishment of a TCP session, the attacker guides the victim in delivering the payload. The characteristic of dispatching an extensive number of DNS requests looking for a real C&C server looks like an arbitrary set of characters. Meaningful statistical information can be derived from these requested domain names as well as the pattern of randomness found in them [22]. If the ransomware detection method can trace the randomness that occurs before finding out the actual C&C server, it can be stopped before the ransomware begins encrypting files. This is an efficient approach in case of a zero-day attack as deriving the information from the known ransomware is not required in this case. Therefore, we have opted for extracting DNS traffic information by analyzing the PCAP files of the ransomware.

We have analyzed the PCAP files using Wireshark- a network protocol analyzer [44], [45]. This manual process involved three identical systems with Wireshark installed and 2 volunteers for analyzing the PCAP files. We have extracted 18 network traffic features that according to [46], convey important statistical information that enhances the ability of the classification algorithms to classify ransomware. Then, these features have been merged resulting in 'Data2'. Table 4 presents the list of network traffic features.

b: Phase 2: Exploratory Data Analysis (EDA)

At the beginning of Phase 2, we have evenly divided (stratified train-test split) the dataset into train data (80%) and test data (20%) to avoid data leakage. Next, we have done exploratory data analysis to better understand the raw data so that the data could be preprocessed as per requirement. The findings from this phase are:



FIGURE 6: Finding out the actual C&C server by sending DNS requests.

TABLE 4: List of features in the 'Data2' dataset.

Network Traffic Features
1. IP and port of the client
2. IP and port of the server
3. Bytes sent from the client to the server
4. Bytes sent from the server to the client
5. RSTs in the TCP connection from client to server
6. RSTs in the TCP connection from server to client
7. FINs in the TCP connection from client to server
8. FINs in the TCP connection from server to client
9. Number of HTTP requests present in the connection
10. HTTP method (GET or POST) of the HTTP requests
11. Response code to the HTTP requests
12. URL requested in the HTTP request
13. Timestamp of the DNS request
14. IP and port of the client in the DNS request
15. IP and port of the DNS server
16. RCode of the DNS response (It is sent by the server
indicating whether it was able to settle the request or not)
17. DNS request
18. DNS response

- Categorical data: We have found 11 features containing categorical data. They are the IP and port of the client, IP and port of the server, Bytes sent from the client to the server, Bytes sent from the server to the client, HTTP method GET or POST of the HTTP requests, Response code to the HTTP requests, URL requested in the HTTP request, IP and port of the client.1, IP and port of the DNS server, DNS request, and DNS response. These categorical data need to be encoded into numerical values since the classifiers require the data to be understandable so that they can be trained on and make predictions.
- Random missing values: Since different ransomware families create different numbers of conversations over the network, the number of instances captured from the PCAP files was different for each ransomware sample. Hence, we have observed missing values in network

traffic information. Handling missing values is an essential part of the feature engineering process as the ML models may generate biased or inaccurate results if the missing values are not handled properly. There are two ways of dealing with missing values, such as deleting the missing values and imputing the missing values. Since deleting the missing values ends up deleting the entire row or column that contains the missing values, there is a probability of losing useful information in the dataset. So, we have opted for imputing the missing values.

c: Phase 3: Data Preprocessing

In the data preprocessing phase, firstly, we have encoded the categorical data into numerical data for which we have applied One-Hot Encoding [47] by using the '.get_dummies' attribute of Pandas data frame package that generates the dummy variables of those 11 features. For preventing the 'Dummy Variable Trap', we have set 'True' as 'drop_first' parameter. To normalize the data and to prevent the imputer from producing biased numerical replacements for the missing data, we have scaled the numerical values between 0 and 1. After normalizing the data, we have used Scikit-Learn's Impute package to apply KNNImputer to fill up the missing values.

d: Phase 4: Feature Selection

We have selected the network traffic features using RFECV by setting 'min_features_to_select' as 9 (half of the features), cv=5, and 'scoring'= 'accuracy' so that RFECV would select at least half of the features based on the optimum accuracy over the 5-fold cross-validation applied on our train data.

C. CLASSIFICATION

We have employed Supervised Machine Learning algorithms to classify 15 ransomware families into corresponding categories. Supervised learning algorithms are trained on the labeled dataset to make a decision in response to the unseen test dataset. These algorithms are generally of two types, such as classification-based and regression-based. The classification-based algorithms are used to accomplish both binary and multi-class classification where the instances from the test dataset are classified into one among an array of known classes, such as Naïve Bayes, Random Forest, K-Nearest Neighbor, etc. On the other hand, regression-based algorithms consider the relationship between independent features or input variables and dependent target class or continuous output variables to make a prediction, such as Linear Regression, Neural Network Regression, Lasso Regression, etc. As this study focuses on classifying 15 ransomware families, the following algorithms have been employed that are widely used for both binary and multi-class classification as per requirement:

• Logistic Regression (LR): is a type of statistical analysis that predicts the probability of a dependent variable

from a set of independent variables using their linear combination.

- Stochastic Gradient Descent (SGD): is an optimization algorithm to find the model parameters by updating them for each training data so that the best fit is reached between predicted and actual outputs.
- K-Nearest Neighbor (KNN): estimates the likelihood of a new data point being a member of a specific group by measuring the distance between neighboring data points and the new data point.
- Naïve Bayes (NB): is based on Bayes' theorem and predicts the probability of an instance belonging to a particular class.
- Random Forest (RF): constructs multiple decision trees during the training phase and finally determines the class selected by the maximum number of trees.
- Support Vector Machine (SVM): takes one or more data points from different classes as inputs and generates hyperplanes as outputs that best distinguish the classes.

Since this study focuses on multi-class classification and some classifiers are only designed for binary classification problems (i.e., Logistic Regression, Support Vector Machine, etc.), these cannot be directly applied to multi-class classification problems. Therefore, Heuristic Methods [52] can be applied to divide a multi-class classification problem into several binary classification problems. There are two types of heuristic methods as illustrated in Figure 7. The methods are:

- One-vs-Rest (OvR) which splits the dataset into one class against all other classes each time [53].
- One-vs-One (OvO) which splits the dataset into one class against every other class each time [54].

We have applied the OvR method for our experiment to reduce the time and computational complexities. All these classifiers are built along with 'RandomSearchCV' [51]a hyperparameter optimization technique, to find the best combination of hyperparameters for maximizing the performance of the models' output in a reasonable time. Instead of exhaustively searching for the optimal values of the hyperparameters through a manually determined set of values (i.e., Grid Search), RandomSearchCV randomly searches the grid space and selects the best combination of hyperparameter values based on the accuracy or the score of crossvalidation. Since we have used RFECV for feature selection and RandomSearchCV for hyperparameter optimization, the Nested Cross-Validation technique has been implemented in the pipeline to build each model.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

A. EXPERIMENTAL RESULTS

We have evaluated the models in terms of Precision, Recall, F1-score, and Accuracy. These performance metrics are measured as follows:

8



FIGURE 7: Heuristic methods: (a) One-vs-Rest and (b) One-vs-One.

$$\begin{aligned} Precision &= \frac{TP}{TP + FP} \\ Recall &= \frac{TP}{TP + FN} \\ F1 - score &= \frac{2 \times Precision \times Recall}{Precision + Recall} \\ Accuracy &= \frac{TP + TN}{TP + TN + FP + FN} \times 100 \end{aligned}$$

where, TP = True Positives, FP = False Positives (Type 1 Error), TN = True Negative, FN = False Negative (Type 2 Error).

Table 5 presents the performance comparison of Machine Learning models with and without feature selection for the 'Data1' dataset. It shows that with and without feature selection LR outperforms other classifiers securing 98.20% and 99.30% overall accuracy respectively. Although there is a slight performance degradation in all the classifiers in the with-feature selection scenario, remarkable improvement in the processing time has been observed. As shown in Table 6, with-feature selection, the average processing time of all the classifiers has been improved by 26.97%. We present the classification accuracy for each class of the best-performed supervised machine learning model from these classifiers in two different scenarios. Figure 8 illustrates the normalized confusion matrix of the LR classifier. As shown in Figure 8(a), when the features are not selected, among 15 classes, the classifier could distinguish 13 classes with 100% accuracy. However, the classifier produces 1% false negatives classifying CryptoLocker ransomware and 11% false positives classifying Shade ransomware. On the other hand, Figure 8(b) shows the confusion matrix of the LR classifier with feature selection. Although the classifier could distinguish 10 classes with 100% accuracy, the classifier produces 1% false negatives classifying Cerber, 22% false positives classifying CryptoLocker, 10% false positives classifying Mole, 10% false positives classifying Sage, and 11% false positives classifying Shade ransomware.

Table 7 presents the performance comparison of Machine Learning models with and without feature selection for the TABLE 5: Performance comparison between LR, SGD, KNN, NB, RF, and SVM with respect to the with-feature selection and without-feature selection using the 'Data1' dataset (W FS= With-Feature Selection, and W/O FS= Without-Feature Selection).

Performance		LR	S	GD	K	NN	-	NB		RF	S	VM
	W FS	W/O FS										
Accuracyavg	98.20	99.30	90.43	92.45	89.62	90.52	97.17	97.46	91.51	92.78	94.34	95.58
Precision _{avg}	98.53	99.37	98.86	100	94.33	94.08	97.82	98.77	100	99.79	99.15	99.21
Recallavg	98.22	99.30	91.36	92.45	89.62	90.52	97.17	97.46	91.51	92.78	94.34	95.58
F1-score _{avg}	98.20	99.29	94.61	95.85	90.78	91.27	97.21	98.02	95.23	95.87	96.40	97.19



FIGURE 8: Confusion matrix of (a) Logistic Regression without feature selection, and (b) Logistic Regression with feature selection for the 'Data1' dataset.

TABLE 6: Classifier's processing time comparison withoutfeature selection and with-feature selection using the 'Data1' dataset.

Classifier	Without-	With-feature	Improvement
	feature	selection (in	(%)
	selection	seconds)	
	(in seconds)		
LR	79.21	58.44	26.22
SGD	78.43	57.62	26.53
KNN	78.00	51.25	34.29
NB	76.39	55.67	27.12
RF	75.41	58.28	22.71
SVM	79.19	59.43	24.95
Average pro	26.97		

'Data2' dataset. It shows that with and without feature selection NB outperforms other classifiers securing 97.89% and 98.95% overall accuracy respectively. Even though all of the classifiers in the with-feature selection scenario show a minor performance deterioration, a notable improvement in processing time has been seen. As shown in Table 8, with-feature selection, the average processing time of all the classifiers has been improved by 34.72%. We present the classification accuracy for each class of the best-performed supervised machine learning model from these classifiers in two different scenarios. Figure 9 illustrates the normalized confusion matrix of the NB classifier. As shown in Figure 9(a), when the features are not selected, among 15 classes, the classifier could distinguish 10 classes with 100% accuracy. However, the classifier produces 2% false negatives classifying CryptoLocker and 1% false negatives classifying Maze ransomware. On the other hand, Figure 9(b) shows the confusion matrix of the NB classifier with feature selection. The classifier could distinguish 9 classes with 100% accuracy with no false negatives. However, with feature selection, the classifier produces higher false positives as compared to that without-feature selection.

B. DISCUSSIONS

In this section, we present the comparison between the RFECV-selected features in the with-feature selection scenario and the highly contributing features in the withoutfeature selection scenario to examine the efficiency of the RFECV feature selection technique toward ransomware classification. For this task, we apply 'Shapley Additive exPlanations', a tool for visualizing data that helps explain the results of machine learning models. SHAP is based on the coalition game theory that measures each feature's individual contribution to the final output while conserving the sum of contributions being the same as the final result [26]. When it comes to the performance evaluation of any model, knowing both 'What' and 'Why' the models have taken these decisions is equally important. The answer to 'What' presents the TABLE 7: Performance comparison between LR, SGD, KNN, NB, RF, and SVM with respect to the with-feature selection and without-feature selection using the 'Data2' dataset (W FS= With-Feature Selection, and W/O FS= Without-Feature Selection).

Performance		LR	S	GD	K	INN]	NB		RF	S	VM
	W FS	W/O FS										
$Accuracy_{avg}$	92.25	94.04	81.69	82.76	80.99	83.25	97.89	98.95	78.87	79.96	92.25	93.90
$Precision_{avg}$	98.21	97.81	90.96	93.27	92.05	92.56	98.21	99.05	100	99.90	98.73	98.89
$Recall_{avg}$	92.25	94.04	88.03	87.53	80.99	83.25	97.89	98.95	78.87	79.96	92.25	93.90
F1-score _{avg}	94.81	95.67	88.98	89.91	84.13	85.96	97.92	98.95	86.99	87.64	95.01	96.06



FIGURE 9: Confusion matrix of (a) Naïve Bayes without feature selection, and (b) Naïve Bayes with feature selection for the 'Data2' dataset.

TABLE 8: Classifier's processing time comparison withoutfeature selection and with-feature selection using the 'Data2' dataset.

Classifier	Without-	With-feature	Improvement
	feature	selection (in	(%)
	selection	seconds)	
	(in seconds)		
LR	88.19	56.88	35.5
SGD	85.31	54.66	35.9
KNN	85.44	54.30	36.4
NB	84.13	51.29	35.5
RF	85.27	56.78	33.4
SVM	83.18	56.93	31.6
Average pro	34.72		

results or outputs of the machine learning models while the answer to 'Why' explains the factors, or features affecting the results. While some predictive models may not require explainability because of their usage in a low-risk real-world environment, some models that deal with the real-world highrisk environment (i.e., ransomware detection/classification) need explanation. Unlike other explanation techniques that are limited to explaining specific models, SHAP values can be used to explain a wide variety of models, such as DeepExplainer to explain Deep Neural Networks (i.e., Multi-Layer Perceptron, Convolutional Neural Networks, etc.), TreeExplainer to explain tree-based models (i.e., Random Forest, XGBoost, etc.), and KernelExplainer to explain any model, etc. [49], [50]. For our study, we have used TreeExplainer to obtain highly contributing features from the Random Forest classifier, while for the other classifiers we have used Kernel-Explainer.

For the classification model, the SHAP value is regarded as a 2-D array where the columns represent the features used in the model and the rows represent individual predictions predicted by the model. So, each SHAP value in this array indicates a specific feature's contribution to that row's prediction output, as shown in Figure 10. Here, a positive SHAP value specifies that a feature is positively pushing the base value or expected value to the model output. On the other hand, the negative SHAP value specifies that the feature is negatively pushing the base value to the model output. The base value or the mean model output is computed based on the train data.

Passing the array of SHAP values to a 'summary plot' function creates a feature importance plot as shown in Figure 11. Here, we illustrate 40 highly contributing features (as RFECV selects the highest 40 features for the KNN classifier) for each classifier in the without-feature selection scenario for the 'Data1' dataset. Here, the x-axis denotes the mean of the absolute SHAP value for each feature which indicates the total contribution of the feature to the model and the y-axis denotes the features used for the classification.

array([[-0.01773837,	0.	,	0.	,,	0.	,
0. ,	-0.013749	94],				
[-0.08353088,	0.	,	0.	,,	0.	,
0.24198239,	-0.081196	506],				
[0.,	-0.085426	559,	-0.0150892	, <mark></mark> ,	0.	2
0. ,	-0.030209	981],				
[0.04899718,	0.082384	466,	0.05619304	,,	0.	,
0. ,	0.],				
[0.05624168,	0.	,	0.07758747	,,	0.	,
0. ,	0.],				
[0.,	0.	,	0.02306601	,,	0.	,
0. ,	0.	11)			

FIGURE 10: Array of SHAP values.

The features are organized in descending order from top to bottom by how strongly they influence the model's decision. As illustrated in Figure 11, the set of highly contributing features and their order varies for each classifier. However, for our study, we only examine the variation of the RFECVselected features with the highly contributing features of the corresponding classifiers. Table 9 presents the set of optimum features selected by RFECV for each ML classifier from the 'Data1' dataset and Table 10 presents the list of RFECVselected features for each ML classifier that is not present in the top 40 highly contributing features. By comparing these two tables, we get the features that are causing performance deterioration in the with-feature selection scenario and producing higher false alarms as compared to that withoutfeature selection.

TABLE 9: Set of optimum features selected by RFECV from the 'Data1' dataset for each ML classifier.

Selected API Call features	
Classifier:	
Total Selected Features:	38
NtDelayExecution	NtSetinformationThread
NtMapViewOfSection	NtNotifyChangeKey
NtTerminateProcess	NtOpenProcessToken
NtUnmapViewOfSection	NtAlertThread
NtFsControlFile	NtOpenThreadToken
NtSetinformationFile	NtCreateUserProcess
NtAIpcSendWaitReceivePort	NtOpenKeyEx
NtAllocateVirtualMemory	NtSetInformationKey
NtQueryInformationFile	NtYieldExecution
NtProtectVirtualMemory	NtResumeThread
NtQueryVirtualMemory	NtRequestWaitReplyPort
LdrGetDIlHandle	NtEnumerateKey
NtOpenEvent	NtQueryInformationProcess
NtOpenDirectoryObject	NtCreateEvent
NtWriteVirtualMemory	NtCreateKey
NtConnectPort	NtCreateThreadEx

TABLE 9: Set of optimum features selected by RFECV from the 'Data1' dataset for each ML classifier. (Continued)

Selected API Call features	
NtCreateSection	NtQuerykey
NtOpenProcess	NtOpenFile
NtOpenMutant	NtAdjustPrivilegesToken
Classifier:	SGD
Total Selected Features:	38
NtDelayExecution	NtSetinformationThread
NtNotifyChangeKey	NtAlertThread
NtAIpcSendWaitReceivePort	NtOpenThreadToken
NtQueryInformationFile	NtSetInformationFile
NtMapViewOfSection	NtAllocateVirtualMemory
NtSetinformationKey	NtYieldExecution
NtOpenProcessToken	NtOpenkey
NtProtectVirtualMemory	NtQueryValueKey
NtTerminateProcess	NtOpenProcess
NtFsControlFile	NtQueryInformationToken
NtOpenSection	NtCreateKey
NtCreateMutant	NtRequestWaitReplyPort
NtOpenMutant	NtReadFile
NtConnectPort	NtWriteVirtualMemory
NtCreateSection	NtCreateThreadEx
NtUnmapViewOfSection	NtCreateEvent
NtQueryAttributesFile	NtEnumerateKey
NtOpenEvent	NtQueryInformationProcess
NtSetContextThread	NtQueryDirectoryFile
Classifier:	KNN
Total Selected Features:	40
NtOpenSection	NtTerminateProcess
NtDelayExecution	NtMapViewOfSection
NtSetinformationFile	NtFsControlFile
NtSetinformationThread	NtCreateEvent
NtAIpcSendWaitReceivePort	NtCreateUserProcess
NtUnmapViewOfSection	NtQueryInformationFile
NtOpenDirectoryObject	NtAllocateVirtualMemory
NtCreateSection	NtOpenMutant
NtQueryValueKey	NtOpenKey
NtQueryInformationProcess	NtCreateThreadEx
NtProtectVirtualMemory	NtQueryAttributesFile
NtOpenFile	NtWriteVirtualMemory



FIGURE 11: Summary plot showing the top 40 highly contributing features of the 'Data1' dataset for each ML classifier in the without feature selection scenario.

TABLE 9: Set of optimum features selected by RFECV from the 'Data1' dataset for each ML classifier. (Continued)

Selected API Call features	
NtReadFile	NtQueryVolume- InformationFile
NtCreateMutant	NtResumeThread
NtEnumerateKey	NtSetInformationKey
NtOpenThreadToken	NtNotifyChangeKey
NtSetinformationProcess	NtWriteFile

TABLE 9: Set of optimum features selected by RFECV from the 'Data1' dataset for each ML classifier. (Continued)

Selected API Call features	
NtCreateFile	NtDeviceIoControlFile
NtAlertThread	NtGetContextThread
NtQueryDirectoryFile	NtSetContextThread
Classifier:	NB
Total Selected Features:	38
NtAllocateVirtualMemory	NtFsControlFile

TABLE 9: Set of optimum features selected by RFECV from the 'Data1' dataset for each ML classifier. (Continued)

Selected API Call features	
NtAlpcSendWaitReceivePort	NtReadFile
NtTerminateProcess	NtOpenThreadToken
NtOpenProcess	NtEnumerateKey
NtSetValueKey	NtSetinformationThread
NtCreateThreadEx	NtCreateEvent
NtQueryDirectoryFile	NtCreateUserProcess
NtNotifyChangeKey	NtQueryKey
NtCreateKey	NtOpenkey
NtYieldExecution	NtDeviceloControlFile
NtQueryObject	NtWriteVirtualMemory
NtWaitForMultipleObjects	NtDeleteValueKey
NtGetContextThread	NtOpenMutant
NtQueryInformationToken	NtDelayExecution
NtSetInformationKey	NtAdjustPrivilegesToken
NtResumeThread	OpenServiceW
NtAlertThread	NtOpenSection
NtCreateKeyEx	NtOpenEvent
NtQueryInformationFile	NtEnumerateValueKey
Classifier:	RF
Classifier: Total Selected Features:	RF 38
Classifier: Total Selected Features: NtEnumerateKey	RF 38 NtReadFile
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile	RF 38 NtReadFile NAdjustPrivilegesToken
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection NtCreateThreadEx	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution NtWriteFile
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection NtCreateThreadEx NtOpenThreadToken	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution NtWriteFile NtOpenEvent
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection NtCreateThreadEx NtOpenThreadToken NtTerminateProcess	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution NtWriteFile NtOpenEvent NtResumeThread
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection NtCreateThreadEx NtOpenThreadToken NtTerminateProcess NtSetinformationProcess	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution NtWriteFile NtOpenEvent NtResumeThread NtProtectVirtualMemory
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection NtCreateThreadEx NtOpenThreadToken NtTerminateProcess NtSetinformationProcess NtQuery DirectoryFile	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution NtWriteFile NtOpenEvent NtResumeThread NtProtectVirtualMemory NtAIpcSendWaitReceive- Port
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection NtCreateThreadEx NtOpenThreadToken NtTerminateProcess NtSetinformationProcess NtQuery DirectoryFile NtDelayExecution	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution NtWriteFile NtOpenEvent NtResumeThread NtProtectVirtualMemory NtAIpcSendWaitReceive- Port NtCreateEvent
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection NtCreateThreadEx NtOpenThreadToken NtTerminateProcess NtSetinformationProcess NtQuery DirectoryFile NtDelayExecution NtAllocateVirtualMemory	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution NtWriteFile NtOpenEvent NtResumeThread NtProtectVirtualMemory NtAIpcSendWaitReceive- Port NtCreateEvent NtQueryInformationFile
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection NtCreateThreadEx NtOpenThreadToken NtTerminateProcess NtSetinformationProcess NtQuery DirectoryFile NtDelayExecution NtAllocate VirtualMemory NtQueryKey	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution NtWriteFile NtOpenEvent NtResumeThread NtProtectVirtualMemory NtAIpcSendWaitReceive- Port NtCreateEvent NtQueryInformationFile NtWaitForMultipleObjects
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection NtCreateThreadEx NtOpenThreadToken NtTerminateProcess NtSetinformationProcess NtQuery DirectoryFile NtDelayExecution NtAllocateVirtualMemory NtQueryKey NtQueryVirtualMemory	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution NtWriteFile NtOpenEvent NtResumeThread NtProtectVirtualMemory NtAIpcSendWaitReceive- Port NtCreateEvent NtQueryInformationFile NtWaitForMultipleObjects NtAlertThread
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection NtOpenSection NtOpenThreadToken NtOpenThreadToken NtSetinformationProcess NtSetinformationProcess NtQuery DirectoryFile NtDelayExecution NtAllocate VirtualMemory NtQueryKey NtQueryVirtualMemory NtOpenFile	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution NtWriteFile NtOpenEvent NtResumeThread NtProtectVirtualMemory NtAIpcSendWaitReceive- Port NtCreateEvent NtQueryInformationFile NtWaitForMultipleObjects NtAlertThread NtOpenProcess Token
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection NtOpenSection NtCreateThreadEx NtOpenThreadToken NtTerminateProcess NtSetinformationProcess NtSetinformationProcess NtQuery DirectoryFile NtDelayExecution NtAllocateVirtualMemory NtQueryKey NtQueryVirtualMemory NtQueryFile NtOpenFile NtSetinformationKey	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution NtWriteFile NtOpenEvent NtResumeThread NtProtectVirtualMemory NtAIpcSendWaitReceive- Port NtCreateEvent NtQueryInformationFile NtQueryInformationFile NtWaitForMultipleObjects NtAlertThread NtOpenProcess Token NtDeviceloControlFile
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection NtOpenSection NtOpenThreadToken NtOpenThreadToken NtTerminateProcess NtSetinformationProcess NtSetinformationProcess NtQuery DirectoryFile NtDelayExecution NtAllocateVirtualMemory NtQueryKey NtQueryVirtualMemory NtQueryVirtualMemory NtOpenFile NtSetinformationKey NtQueryobject	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution NtWriteFile NtOpenEvent NtResumeThread NtProtectVirtualMemory NtAIpcSendWaitReceive- Port NtAIpcSendWaitReceive- Port NtQueryInformationFile NtQueryInformationFile NtQueryInformationFile NtAlertThread NtAlertThread NtOpenProcess Token NtDeviceloControlFile NtEnumerateValueKey
Classifier: Total Selected Features: NtEnumerateKey NtFsControlFile NtOpenSection NtOpenSection NtCreateThreadEx NtOpenThreadToken NtTerminateProcess NtSetinformationProcess NtSetinformationProcess NtQuery DirectoryFile NtDelayExecution NtAllocateVirtualMemory NtQueryKey NtQueryKey NtQueryVirtualMemory NtOpenFile NtSetinformationKey NtQueryobject NtQueryAttributesFile	RF 38 NtReadFile NAdjustPrivilegesToken NtYieldExecution NtWriteFile NtOpenEvent NtResumeThread NtProtectVirtualMemory NtAIpcSendWaitReceive- Port NtCreateEvent NtQueryInformationFile NtQueryInformationFile NtQueryInformationFile NtQueryInformationFile NtQueryInformationFile NtQueryInformationFile NtQueryInformationFile NtAlertThread

TABLE 9: Set of optimum features selected by RFECV from the 'Data1' dataset for each ML classifier. (Continued)

Selected API Call features	
NtCreateUserProcess	NtGetContextThread
NtQueryInformationProcess	NtMapViewOfSection
Classifier:	SVM
Total Selected Features:	37
NtDelayExecution	NtSetinformationThread
NtMapViewOfSection	NtQueryValueKey
NtOpenThreadToken	NtSetinformationKey
NtOpenSection	NtNotifyChangeKey
NtOpenProcessToken	NtAIpcSendWaitReceive- Port
NtTerminate rocess	NtUnmapViewOfSection
NtAlertThread	LdrGetDIlHandle
NtGetContextThread	NtSetinformationFile
NtOpenKey	NtCreateUserProcess
NtQueryVirtualMemory	NtAdjustPrivilegesToken
NtCreateThreadEx	NtCreateKey
NtWriteVirtualMemory	NtAllocateVirtualMemory
NtReadVirtualMemory	NtRequestWaitReplyPort
OpenSCManager	NtOpenDirectoryObject
NtFsControlFile	NtOpenFile
NtCreateEvent	NtCreateSection
NtOpenProcess	NtQueryInformationToken
NtEnumerateKey	NtSetContextThread
NtDeviceIoControlFile	

Similarly, for the 'Data2' dataset, we present the comparison between the RFECV-selected features in the withfeature selection scenario and the highly contributing features in the without-feature selection scenario. Figure 12 illustrates the features of the 'Data2' dataset in descending order from top to bottom by how strongly they influence the model's decision. For each classifier, the order of the features varies except for the 'Bytes sent from the client to the server' feature. However, similar to the previous step, we only examine the variation of the RFECV-selected features. Table 11 presents the set of optimum features selected by RFECV from the 'Data2' dataset for each ML classifier, and Table 12 presents the list of features that were not selected by the RFECV. By comparing these two tables, we get the features that are causing performance deterioration even with the best-performed ML classifier in the with-feature selection scenario and produce higher false alarms as compared to that without-feature selection.

TABLE 10: List of RFECV-selected features from the 'Data1' dataset for each ML classifier that is not present in the top 40 highly contributing features.

Classifier	API Call Features	Total	Average Performance Decrease with RFECV- selected features (%)
LR	NtEnumerateKey	3	1.10
	NtOpenEvent NtOpenEvent		
SGD	NtEnumerateKey	5	2.02
500	NtOpenEvent	5	2.02
	NtOuervInformationProcess		
	NtSetContextThread		
	NtQueryDirectoryFile		
KNN	NtDeviceIoControlFile	5	0.9
	NtAlertThread		
	NtGetContextThread		
	NtQueryDirectoryFile		
	NtSetContextThread		
NB	NtAllocateVirtualMemory	1	0.29
RF	NtCreateUserProcess	4	1.27
	NtGetContextThread		
	NtQueryInformationProcess		
	NtMapViewOfSection		
SVM	NtSetContextThread	2	1.24
	NtDeviceIoControlFile		

Although SHAP importance shows the effect of a given feature on the model output while disregarding the exactness of the prediction, our study, by comparing the highly contributing features in the without feature selection scenario and the RFECV selected features in the with feature selection scenario finds out that the RFECV feature selection technique, sometimes fails to select the features that have a high impact on the model output resulting in performance degradation. Again, for two different ransomware datasets, the selected features have been ranked 1, while the notselected features have been ranked greater than 1. Therefore, the order of the selected features based on their importance remains unknown in the RFECV feature selection technique making it less efficient in ransomware classification.

TABLE 11: Set of the optimum number of features selected by RFECV from the 'Data2' dataset for each ML classifier.

Selected Network Traffic Features

Classifier: LR

Number of Selected Network Traffic Features: 14

RSTs in the TCP connection from server to client RSTs in the TCP connection from client to server FINs in the TCP connection from client to server

FINs in the TCP connection from server to client

TABLE 11: Set of the optimum number of features selected by RFECV from the 'Data2' dataset for each ML classifier. (Continued)

Selected Network Traffic Features
Bytes sent from the client to the server
Bytes sent from the server to the client
DNS Request
DNS Response
IP and port of the client.1
IP and port of the client
HTTP method GET or POST of the HTTP request
IP and port of the server
Timestamp of the DNS request
RCode of the DNS response
Classifier: SGD
Number of Selected Network Traffic Features: 10
IP and port of the client.1
IP and port of the client
IP and port of the server
FINs in the TCP connection from server to client
URL requested in the HTTP request
RSTs in the TCP connection from client to server
Bytes sent from the client to the server
HTTP method GET or POST of the HTTP requests
Number of HTTP requests present in the connection
Response code to the HTTP requests
Classifier: KNN
Number of Selected Network Traffic Features: 10
Bytes sent from the client to the server
Bytes sent from the server to the client
HTTP method GET or POST of the HTTP requests
Response code to the HTTP requests
IP and port of the DNS server
RCode of the DNS response
URL requested in the HTTP request
IP and port of the client
RSTs in the TCP connection from client to server
Number of HTTP requests present in the connection
Classifier: NB
Number of Selected Network Traffic Features: 16
RCode of the DNS response
RSTs in the TCP connection from client to server



FIGURE 12: Summary plot showing the features of the 'Data2' dataset in descending order based on their contribution to each ML classifier's decision.

TABLE 11: Set of the optimum number of features selectedby RFECV from the 'Data2' dataset for eachML classifier. (Continued)

Selected Network Traffic Features
IP and port of the server
RSTs in the TCP connection from server to client
Number of HTTP requests present in the connection
IP and port of the DNS serve
DNS Request
DNS Response
Bytes sent from the server to the client
FINs in the TCP connection from client to server
Response code to the HTTP requests
Bytes sent from the client to the server
HTTP method GET or POST of the HTTP requests
IP and port of the client
URL requested in the HTTP request
FINs in the TCP connection from server to client
Classifier: RF
Number of Selected Network Traffic Features: 13
Timestamp of the DNS request
IP and port of the DNS server
Number of HTTP requests present in the connection
FINs in the TCP connection from server to client

TABLE 11: Set of the optimum number of features selected by RFECV from the 'Data2' dataset for each ML classifier. (Continued)

Selected Network Traffic Features
Bytes sent from the client to the server
Bytes sent from the server to the client
RCode of the DNS response
IP and port of the client.1
URL requested in the HTTP request
IP and port of the client
HTTP method GET or POST of the HTTP requests
DNS Response
RSTs in the TCP connection from server to client
Classifier: SVM
Number of Selected Network Traffic Features: 13
RSTs in the TCP connection from client to server
RSTs in the TCP connection from server to client
Bytes sent from the client to the server
Bytes sent from the server to the client
Number of HTTP requests present in the connection
IP and port of the client .1
HTTP method GET or POST of the HTTP requests
DNS Request
IP and port of the DNS server

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TABLE 11: Set of the optimum number of features selected
by RFECV from the 'Data2' dataset for each
ML classifier. (Continued)

Selected Network Traffic Features

Timestamp of the DNS request

IP and port of the server

RCode of the DNS response

DNS Response

TABLE 12:	List	of	features	from	the	'Data2'	dataset	that
	were	e no	t selected	d by th	ne R	FECV.		

Classifier	Not Selected Network Traffic Features	Total	Average Performance Decrease with RFECV- selected features (%)
LR	IP and port of the DNS server	4	1.79
	URL requested in the HTTP request		
	Number of HTTP requests present in the connection		
	Response code to the HTTP requests		
SGD	Timestamp of the DNS request	8	1.07
	DNS Request		
	DNS Response		
	RSTs in the TCP connection from server to client		
	IP and port of the DNS server		
	RCode of the DNS response		
	FINs in the TCP connection from client to server		
	Bytes sent from the server to the client		

TABLE 12:	List	of	features	from	the	'Data2'	dataset	that
	were	e nc	ot selected	d by th	ne R	FECV. (Continue	ed)

[, 	1	
Classifier	Not Selected Network Traffic Features	Total	Average Performance Decrease with RFECV- selected features (%)
KNN	FINs in the TCP connection from client to server	8	2.26
	RSTs in the TCP connection from server to client		
	IP and port of the server		
	DNS Response		
	FINs in the TCP connection from server to client		
	Timestamp of the DNS request		
	DNS Request		
	IP and port of the client .1		
NB	Timestamp of the DNS request	2	1.06
	IP and port of the client .1		
RF	FINs in the TCP connection from client to server	5	1.09
	RSTs in the TCP connection from client to server		
	IP and port of the server		
	DNS Request		
	Response code to the HTTP requests		
SVM	FINs in the TCP connection from client to server	5	1.65
	Response code to the HTTP requests		

TABLE 12:	List	of	features	from	the	'Data2'	dataset	that
	were	e nc	t selected	d by tł	ne R	FECV. (Continue	ed)

Classifier	Not Selected Network Traffic Features	Total	Average Performance Decrease with RFECV- selected features (%)
	FINs in the TCP connection from server to client IP and port of the client URL requested in the HTTP request		

V. CONCLUSION

In this paper, we present a comprehensive performance analysis of widely utilized Supervised Machine Learning models with and without RFECV to quantify the efficiency of this feature selection technique in ransomware classification. Our study finds out that although the classification accuracies are nearly similar in both scenarios, with RFECV the classifiers produce higher false alarms as compared to those without feature selection. In addition, the selected features have been ranked 1 for two separate ransomware datasets, whereas the not-selected features have been ranked higher. As a result, the RFECV feature selection approach does not reveal the importance-based order in which the features have been chosen. To summarize, by presenting this comparative study, this paper can provide future direction to the researchers in this domain who are looking for efficient feature selection techniques.

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